TIME SERIES FORECASTING WITH R: from CLASSICAL to MODERN Methods

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Department of Mathematics, Universitas Andalas, Padang
17-18 July 2017
TIME SERIES FORECASTING WITH R: from CLASSICAL to MODERN Methods

Department of Mathematics, Universitas Andalas, Padang
17-18 July 2017
25 years of time series forecasting
De Gooijer & Hyndman (International Journal of Forecasting, 2006)

- Introduction
- Exponential smoothing
  - Preamble
  - Variations
  - State space models
  - Method selection
  - Robustness
  - Prediction intervals
  - Parameter space and model properties
- ARIMA models
  - Preamble
  - Univariate
  - Transfer function
  - Multivariate
  - Seasonality
  - State space and structural models and the Kalman filter

Nonlinear models
- Preamble
- Regime-switching models
- Functional-coefficient model
- Neural nets
- Deterministic versus stochastic dynamics
- Miscellaneous
- Long memory models
- ARCH/GARCH models
- Count data forecasting
- Forecast evaluation and accuracy measures
- Combining
- Prediction intervals and densities
- A look to the future
- Acknowledgments
- References
Motivation

The M3-Competition: results, conclusions and implications

1. Statistically sophisticated or complex methods do not necessarily provide more accurate forecasts than simpler ones.
2. The relative ranking of the performance of the various methods varies according to the accuracy measure being used.
3. The accuracy when various methods are being combined outperforms, on average, the individual methods being combined and does very well in comparison to other methods.
4. The accuracy of the various methods depends upon the length of the forecasting horizon involved.

Makridakis & Hibon (International Journal of Forecasting, 2000)
Material

1. Time Series Regression (TSR) & ARIMA model
   - Seasonal models: Multiplicative, Additive, Subset
   - Multiple Seasonal models.

2. ARIMAX & Multivariate Time Series Model
   - Intervention Model & Outlier Detection
   - Calendar Variation Model, Transfer Function Model.

3. Nonlinear Time Series (Modern) Models
   - Non-linearity test, Neural Networks.

4. Hybrid Models
   - TSR-NN, ARIMA-NN, ARIMAX-NN.
Reference


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10 Scholars in Forecasting

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demography, population aging, economic demography, inter

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Forecasting, Decision Making, Medical Research

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Forecasting, Time series, Statistics, Machine learning, Data

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Econometrics, Time Series, Financial Econometrics, Forecasting

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## Indonesian Scholars in Time Series

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<td>1</td>
<td>SUHARTONO</td>
<td>Institut Teknologi Sepuluh November</td>
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<td>2</td>
<td>ANSAR SALEH AHMAR</td>
<td>Universitas Negeri Makassar</td>
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<tr>
<td>3</td>
<td>SUPARMAN</td>
<td>Universitas Ahmad Dahlan</td>
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<tr>
<td>1</td>
<td>DAYAR ARBAIN</td>
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<tr>
<td>2</td>
<td>RAHMIANA ZEIN</td>
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<td>3</td>
<td>DACHRIYANUS</td>
<td>Universitas Andalas</td>
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*Universitas Andalas*

Mathematics

[SINTA Score: 3](#)
(SINTA Score is composed based on quantity, quality and impact of published documents)

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Hybrid Model in Time Series Forecasting

Google

Time series forecasting using a hybrid

Cendekia

Sekitar 51.600 hasil (0,07 dtk)

Artikel

Koleksiku

Dinajapur 1417 kali Artikel terkait 10 versi Kutip Tersimpan

Kapan saja

Sejak 2017

Sejak 2016

Sejak 2013

Rentang khusus...

2000 —

Telusuri

Urutan menurut relevansi

Time series forecasting using a hybrid ARIMA and neural network model
GP Zhang - Neurocomputing, 2003 - Elsevier

Autoregressive integrated moving average (ARIMA) is one of the popular linear models in time series forecasting during the past three decades. Recent research activities in forecasting with artificial neural networks (ANNs) suggest that ANNs can be a promising technique...

Financial time series forecasting using support vector machines
K Kim - Neurocomputing, 2003 - Elsevier

... [15] showed the applicability of SVM to time-series forecasting. Recently, Tay and Cao [18] examined the predictability of financial time series including five time series data with ... Since we attempt to forecast the direction of daily price change in the stock price index, technical ... Dirirjak 1025 kali Artikel terkait 20 versi Kutip Simpan

Time-series forecasting using flexible neural tree model
Y Chen, B Yang, J Dong, A Abraham - Information sciences, 2005 - Elsevier

... A hybrid learning algorithm for evolving the neural tree models is given in Section 3. Section 4 presents some simulation results for two time-series forecasting problems ... reason for choosing the representation is that the tree can be created and evolved using the existing ... Dirirjak 274 kali Artikel terkait 65 versi Kutip Simpan
Hybrid Model in Time Series Forecasting

Hybrid methodology for tuberculosis incidence time-series forecasting based on ARIMA and a NAR neural network
KW Wang, C Deng, JP Li, YY Zhang, XY Li... - Epidemiology & ..., 2017 - cambridge.org
... Page 11. modelled by the NAR model. Moreover, this study compares the results obtained from the hybrid model with the forecast results from the single ARIMA model. ... Comparison of ARIMA, neural networks and hybrid models in time series: tourist arrival forecasting...
Arikel terkait 5 versi Kutip Simpan

Hybrid ARIMA-BPNN model for time series prediction of the Chinese stock market
L Xiong, Y Lu... - (ICIM), 2017 3rd International Conference on, 2017 - ieeexplore.ieee.org
Kutip Simpan

Hybrid DARIMA-NARX model for forecasting long-term daily inflow to Dez reservoir using the North Atlantic Oscillation (NAO) and rainfall data
ME Banihabib, A Ahmadian, FS Jamali - GeoResJ, 2017 - Elsevier... Autoregressive integrated moving average (ARIMA) models (classified as time series models) and artificial neural ... index (IIFFE) to assess mean absolute relative error (MARE), time to peak... forecaster has the most prominent influence on the increasing forecasting accuracy, while...
Arikel terkait Kutip Simpan

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"Padang" in Time Series Forecasting research

Google search for "peramalan di padang, indonesia"

PERAMALAN PASOKAN BAHAN BAKU DAN PENJUALAN SIR 20 DI PT. PERKEBUNAN NUSANTARA VII UNIT PADANG PELAWI KEC. SUKARAJA KAB. SELUMA
EM Manihuruk, MM Romdhon - JURNAL AGRISEP, 2016 - ejournal.unib.ac.id

... Dengan adanya perhitungan peramalan menggunakan software e-views dengan data pasokan ...
Perkebunan VII Unit Padang Pelawi diketahui bahwa metode Arima memiliki nilai ... yang menjadi masalah bagi perusahaan dalam memproduksi Standard Indonesia Rubber (SIR). ...
Artikel terkait 2 versi Kutip Simpan

Peramalan Kebutuhan Energi Jual pada PT Perusahaan Listrik Negara (PLN) Cabang Bukittinggi dengan Menggunakan Metode Dekomposisi Sensus II
S Wahyuni, H Helma, N Amalita - UNP Journal of Mathematics, 2014 - ejournal.unp.ac.id

Page 1. Peramalan Kebutuhan Energi Jual pada PT Perusahaan Listrik Negara (PLN) Cabang Bukittinggi dengan Menggunakan Metode Dekomposisi Sensus II Sujantri Wahyuni1, Helma2, Nonong Amalita3 1 Mathematics Department State University of Padang, Indonesia ...
Kutip Simpan
“Padang” in Time Series Forecasting research

Google search for "peramalan di padang, indonesia"

Peramalan Harga Ayam Broiler di Lima Kota di Sumatera Barat
A Amri - 2009 - repository.ipb.ac.id
... nilai MAD terkecil untuk meramalkan harga ayam broiler di Kota Padang dan Payakumbuh ...
Sedangkan model peramalan untuk Kota Solok dan Kabupaten Tanah Datar adalah winter aditif lag ...
Kutip, Simpan, Lainnya

[doc] Teknik baru statistika dalam peramalan curah hujan ekstrim untuk penentuan musim tanam produk-produk pertanian
M Irfan, A Santoso - 2011 - repository.ipb.ac.id
... iklim ditengarai menyebabkan sekitar 400 hektare sawah di Kabupaten Padang Pariaman tidak ...
penggunaan metode alternative statistika ini akan mampu melakukan peramalan lebih akurat ...
sebelumnya dengan melihat nilai RMSE dari masing – masing hasil peramalan nya ...
Kutip, Simpan, Lainnya

PROGRAM KREATIVITAS MAHASISWA

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“Padang” in Time Series Forecasting research
“Padang” in Time Series Forecasting research

Google search results:

1. **Peramalan** Kebutuhan Manajemen Logistik Pada Usaha Depot Air Minum Isi Ulang Al-Fitrah
   - H Yulius - Jurnal EDik Informatika, 2017 - ejournal.stkip-pgri-sumbar.ac.id
   - ISSN : 2407-0491 E-ISSN : 2541-3716
   - Kebutuhan Manajemen Logistik Pada Usaha Depot Air Minum Isi Ulang Al-Fitrah
   - Henny Yulius 1, Isami Yetti 2 Universitas Putra Indonesia "YPTK" Padang
   - henny_yulius27@yahoo.com

2. **Pengendalian Perencanaan Produksi Premium Dan Harga Pesan Crude Oil Ekonomis Menggunakan Metode Peramalan** Dan Economic Order Quantity (Studi Kasus ...)
   - H Yulius - Jurnal EDik Informatika, 2017 - ejournal.stkip-pgri-sumbar.ac.id
   - Raya Lubuk Begalung Padang – Sumatera Barat E-mail : henny_yulius27@yahoo.com, daviddeska_p@yahoo.com
   - hasil perbandingan tabel tersebut diatas dengan nilai SEE yang terkecil maka dapat diketahui peramalan perencanaan produksi ...

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“Padang” in Time Series Forecasting research

Google search results for "peramalan di padang, indonesia"

[PDF] PENENTUAN RESIKO INVESTASI DENGAN MODEL GARCH PADA INDEKS HARGA SAHAM PT. INDOFOOD SUKSES MAKMUR TBK.
L Mahlindiani, H Yozza - Jurnal Matematika UNAND, 2017 - jmua.fmipa.unand.ac.id
... dan Ilmu Pengetahuan Alam, Universitas Andalas, Kampus UNAND Limau Manis Padang, Indonesia, email: laramahlindiani@yahoo ... Perusahaan ini juga ter-gabung di Bursa Efek Indonesia ... Berikutnya akan dihitung nilai peramalan return, peramalan variaran dan volatili- tas. ...
Kutip  Simpan  Lainnya

[PDF] PEMODELAN DAN PERAMALAN DATA DERET WAKTU DENGAN METODE SEASONAL ARIMA
A ul Ukhra - Jurnal Matematika UNAND, 2014 - jmua.fmipa.unand.ac.id
... Fakultas Matematika dan Ilmu Pengetahuan Alam, Universitas Andalas, Kampus UNAND Limau Manis Padang, Indonesia, annisa.ulukhara25@gmail.com ... dengan model peramalanannya adalah ... Pemodelan dan Peramalan Data Deret Waktu dengan Metode Seasonal ARIMA 65 ... Artikel terkait  Kutip  Simpan  Lainnya

Jurnal Matematika UNAND Vol. VI No. 1 Hal. 25 – 32

18  Inspiring Creative & Innovative Minds – Dept. of Mathematics, UNAND
TIME SERIES FORECASTING WITH R: from CLASSICAL to MODERN Methods
DOUBLE SEASONAL ARIMA MODEL
WITH R, MINITAB AND SAS

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Department of Mathematics, Universitas Andalas, Padang
17-18 July 2017
Motivation

- Develop the best forecast ARIMA model for Short-term Electricity Load Data
- **MINITAB**: Descriptive evaluation about the pattern of DOUBLE Seasonal Time Series Data
- **R**: Theoretical ACF and PACF of DOUBLE Seasonal ARIMA model
- **MINITAB**: The Data: identification of stationary & tentative order of DOUBLE Seasonal ARIMA
- **SAS**: Estimation & Diagnostic check.
- Discussion
Multiple Seasonal ARIMA models: 
Double Seasonal ARIMA, Triple Seasonal ARIMA model.
Kehlog Albran

“The Profit (1973)”

I have seen the future
and it is just like the present, only longer.
**Problem:** Prediction of half hourly load data
MINITAB Descriptive: half hourly load data
MINITAB Descriptive: half hourly load data
MINITAB Descriptive: half hourly load data
MINITAB Identification: half hourly load data
MINITAB Identification: half hourly load data
**MINITAB Identification:** half hourly load data
MINITAB Identification: half hourly load data
MINITAB Identification: half hourly load data
MINITAB Identification: half hourly load data
MINITAB Identification: half hourly load data

ACF for d1-D336-D48-Y(t)

Lag

Autocorrelation

-1.0
-0.8
-0.6
-0.4
-0.2
0.0
0.2
0.4
0.6
0.8
1.0

240
288
336
432
MINITAB Identification: half hourly load data
ARIMA, SARIMA, DSARIMA model

- ARIMA model
  \[ \phi_p(B)(1 - B)^d Z_t = \theta_0 + \theta_q(B)a_t \]

- SARIMA model
  \[ \phi_p(B)\Phi_p(B^s)(1 - B)^d (1 - B^s)^D \dot{Z}_t = \theta_q(B)\Theta_Q(B^s)a_t \]

- DSARIMA model
  \[ \phi_p(B)\Phi_{P_1}(B^{s_1})\Phi_{P_2}(B^{s_2})(1 - B)^d (1 - B^{s_1})^{D_1} (1 - B^{s_2})^{D_2} Z_t = \theta_q(B)\Theta_{Q_1}(B^{s_1})\Theta_{Q_2}(B^{s_2})a_t \]
o SARIMA(0,0,1)(0,0,1)²₄ model

\[ \rho_k = \begin{cases} 
1, & k = 0, \\
-\frac{\theta_1}{(1 + \theta_1^2)}, & k = 1, \\
\frac{\theta_1 \theta_{24}}{(1 + \theta_1^2)(1 + \theta_{24}^2)}, & k = 23 \text{ and } 25, \\
-\frac{\theta_{24}}{(1 + \theta_{24}^2)}, & k = 24, \\
0, & k \text{ others.} 
\end{cases} \]
DSARIMA(0,0,1)(0,0,1)_{24}(0,0,1)_{168}

\[ \rho_k = \begin{cases} 
1, & k = 0, \\
-\frac{\theta_1}{1 + \theta_1^2}, & k = 1, \\
\frac{\theta_1 \theta_{24}}{(1 + \theta_1^2)(1 + \theta_{24}^2)}, & k = 23 \text{ and } 25, \\
-\frac{\theta_{24}}{1 + \theta_{24}^2}, & k = 24, \\
-\frac{\theta_1 \theta_{24} \theta_{168}}{(1 + \theta_1^2)(1 + \theta_{24}^2)(1 + \theta_{168}^2)}, & k = 143, 145, 191 \text{ and } 193, \\
\frac{\theta_{24} \theta_{168}}{(1 + \theta_1^2)(1 + \theta_{24}^2)(1 + \theta_{168}^2)}, & k = 144, \\
\frac{\theta_1 \theta_{168}}{(1 + \theta_1^2)(1 + \theta_{168}^2)}, & k = 167 \text{ and } 169, \\
-\frac{\theta_{168} (1 + \theta_{24}^2 + \theta_1^2 \theta_{24}^2)}{(1 + \theta_1^2)(1 + \theta_{24}^2)(1 + \theta_{168}^2)}, & k = 168, \\
\frac{\theta_{24} \theta_{168}}{(1 + \theta_{24}^2)(1 + \theta_{168}^2)}, & k = 192, \\
0, & k \text{ others}.
\end{cases} \]
# Program to calculate ACF and PACF theoretically
theta = c(-0.6, rep(0, 22), -0.5, 0.3)
acf arma = ARMAacf(ar=0, ma=theta, 168)
pacf arma = ARMAacf(ar=0, ma=theta, 168, pacf=T)
acf arma = acf arma[2:169]
c1 = acf arma
c2 = pacf arma
arma = cbind(c1, c2)
arma # ACF and PACF theoretically
par(mfrow=c(1, 2))
plot(acf arma, type="h", xlab="lag", ylim=c(-1, 1))
abline(h=0)
plot(pacf arma, type="h", xlab="lag", ylim=c(-1, 1))
abline(h=0)
# Program to calculate ACF and PACF theoretically
theta = c(-0.6, rep(0, 22), -0.5, 0.3, rep(0, 143), -0.4, 0.24, rep(0, 12), 0.2, -0.12)
acf.arma = ARMAacf(ar=0, ma=theta, 200)
pacf.arma = ARMAacf(ar=0, ma=theta, 200, pacf=T)
acf.arma = acf.arma[2:201]
c1 = acf.arma
c2 = pacf.arma
arma = cbind(c1, c2)
arma  # ACF and PACF theoretically
par(mfrow=c(1,2))
plot(acf.arma, type="h", xlab="lag", ylim=c(-1,1))
abline(h=0)
plot(pacf.arma, type="h", xlab="lag", ylim=c(-1,1))
abline(h=0)
**R**: the result - ACF of DSARIMA

- SARIMA\((0,0,1)(0,0,1)^{24}(0,0,1)^{168}\) model with
  \[\theta_1 = 0.8, \quad \theta_{24} = 0.65, \text{ and } \theta_{168} = 0.45\]
R: the result - PACF of DSARIMA

- SARIMA(0,0,1)(0,0,1)^24(0,0,1)^168 model with
  \( \theta_1 = 0.8, \quad \theta_{24} = 0.65, \) and
  \( \theta_{168} = 0.45 \)

![PACF Plot](image-url)
R: the result - ACF of DSARIMA

- SARIMA$(1,0,0)(1,0,0)^{24}(1,0,0)^{168}$ model with $\phi_1 = 0.7$, $\phi_24 = 0.4$, and $\phi_{168} = 0.8$
R: the result - PACF of DSARIMA

- **SARIMA(1,0,0)(1,0,0)$$^{24}$$(1,0,0)$$^{168}$$** model with
  - $$\varphi_1 = 0.7$$,
  - $$\varphi_{24} = 0.4$$, and
  - $$\varphi_{168} = 0.8$$

---

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SAS Program: Estimation DSARIMA

data listrik;
  input y;
cards;
  12123.6
  ...
  11947.8
;
proc arima data=listrik out=b1;
  /*** IDENTIFICATION Step ***/
  identify var=y(1,48,336) nlag=12;
  run;
  /*** PARAMETER ESTIMATION & DIAGNOSTIC CHECK Step ***/
  estimate p=(5,8) q=(1)(24)(168) noconstant;
  run;
  /*** FORECASTING Step ***/
  forecast lead=336 out=b2 noprint;
  run;

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SAS Program: Estimation DSARIMA

```
proc arima data=listrik out=b1;
    /***  IDENTIFICATION Step  ****/
    identify var=y(1,48,336) nlag=12;
    run;
    /***  PARAMETER ESTIMATION & DIAGNOSTIC CHECK Step  ****/
    estimate p=(5,8) q=(1)(24)(168) noconstant;
    run;
    /***  FORECASTING Step  ****/
    forecast lead=336 out=b2 noprint;
    run;

proc export data= work.b2
    outfile= "D:\results1.xls"
    dbms=excel2000 replace;
    sheet="om_41";
    run;
```

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This paper shows that R, MINITAB and SAS must be used comprehensively for model building of DSARIMA from certain time series data.

- **R**: To calculate the theoretical ACF and PACF from DOUBLE Seasonal ARIMA models
- **MINITAB**: Descriptive evaluation & Identification step.
- **SAS**: Parameter Estimation, Diagnostic check, and Forecasting steps.
Two Levels Regression Modeling of **Trading Day** and **Holiday Effects** for Forecasting Retail Data

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17-18 July 2017
Outline

• **Introduction**: General time series “pattern”
• **The aims of this paper**: Develop two levels calendar variation model
• **Data**: Monthly men’s jeans and women's trousers sales in a retail company
• **Modeling method**: Based on time series regression
• **Results, analysis and evaluation**: forecast accuracy
• **Conclusion and future works**
General time series “PATTERN”

- Stationer
- Trend: linear & nonlinear
- Seasonal: additive & multiplicative
- Cyclic
- Calendar Variation
Introduction

- Two kinds of calendar variation effects:
  1. Trading day effects
     The levels of economics or business activities may change depending on the day of the week. The composition of days of the week varies from month to month and year to year.
  2. Holiday (traditional festivals) effects
     Some traditional festivals or holidays, such as Eid ul-Fitr, Easter, Chinese New Year, and Jewish Passover are set according to lunar calendars and the dates of such holidays may vary between two adjacent months in the Gregorian calendar from year to year.
Introduction

(a). Y1: Men's jeans sales in Boyolali shop

Inspiring Creative & Innovative Minds – Dept. of Mathematics, UNAND
**Eid holidays for the period 2002 to 2011**

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Introduction cont'

(b). Y2: Women's trouser sales in Boyolali shop

Inspiring Creative & Innovative Minds – Dept. of Mathematics, UNAND
Fig. 2. Bar chart of Eid effects on the women’s trouser sales in the month during and one month prior to the Eid celebration in Boyolali shop.
The aims

- To develop *two levels calendar variation model* based on *time series regression method* for forecasting sales data with the *Eid ul-Fitr* effects.

- To compare the *forecast accuracy* with other forecasting methods, i.e.
  - ARIMA model
  - Feed-forward Neural Networks (FFNN)
Modeling method

• Model for linear trend:

\[ y_t = \beta_0 + \beta_1 t + w_t \quad \ldots (1) \]

• Regression with dummy variable for seasonal pattern:

\[ y_t = \beta_0 + \beta_{1,t} + \beta_{2,S_{s,t}} + \cdots + \beta_{s,S_{s,t}} + w_t \quad \ldots (2) \]

• Regression for calendar effects:

\[ y_t = \beta_0 + \beta_{1,V_{1,t}} + \beta_{2,V_{2,t}} + \cdots + \beta_{p,V_{p,t}} + w_t \quad \ldots (3) \]
The Proposed Model

- Model at the first level:

\[ Y_t = \delta_1 t + \beta_1 S_{1,t} + \beta_2 S_{2,t} + \cdots + \beta_s S_{s,t} + \sum_j \alpha_j D_{j,t} + \sum_j \gamma_j D_{j,t-1} + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + \varepsilon_t. \]

- Model at the second level:

1. **Linear model**
   
   \[ \hat{\alpha}_j = \nu_0 + \nu_1 j, \]
   \[ \hat{\gamma}_j = \omega_0 + \omega_1 j. \]

2. **Exponential model**
   
   \[ \hat{\alpha}_j = \nu_0 e^{\nu_1 j}, \]
   \[ \hat{\gamma}_j = \ln(\omega_0 + \omega_1 j). \]
Background of Two Levels

**Fig. 2.** Bar chart of Eid effects on the women’s trouser sales in the month during and one month prior to the Eid celebration in Boyolali shop.
## Dummy at Two Levels

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The proposed procedure

**Step 1**: Determination of dummy variable for calendar variation period.

**Step 2**: Determination of deterministic trend and seasonal model.

**Step 3**: Simultaneous estimation of calendar effects and other patterns.

**Step 4**: Diagnostic checks on error model. If error is not white noise, add significant lags (autoregressive order) based on ACF and PACF plots of error model.

**Step 5**: Re-estimate calendar effect, other pattern (trend, seasonal), and appropriate lags (autoregressive order) simultaneously for the first level model.

**Step 6**: Estimate the second level model to predict the effects of calendar variation in every possibility number of days before Eid ul-Fitr celebration.
Step 1

- Based on the time series plot, two dummy variables are used for evaluating calendar variation effect, i.e.
  - The months prior to Eid ul Fitr,
    \[ D_{j,t-1} = \text{dummy variable for ONE month prior to Eid ul-Fitr celebration.} \]
  - During the month of Eid ul Fitr celebration,
    \[ D_{j,t} = \text{dummy variable for during the month of Eid ul-Fitr celebration.} \]
  - \( j \) = number of days before Eid ul-Fitr celebration
Step 2-3

- Model for linear trend:
  \[ y_t = \beta_0 + \beta_1 t + \epsilon_t \]

- Regression with dummy variable for seasonal pattern:
  \[ y_t = \beta_0 + \beta_1 S_{1,t} + \beta_2 S_{2,t} + \cdots + \beta_s S_{s,t} + \epsilon_t \]

- Regression for calendar effects and other patterns:
  \[ Y_t = \delta_1 t + \beta_1 S_{1,t} + \beta_2 S_{2,t} + \cdots + \beta_s S_{s,t} + \sum_j \alpha_j D_{j,t} + \sum_j \gamma_j D_{j,t-1} + \epsilon_t \]
Step 4-6

- Model at the first level:
  \[ Y_t = \delta_1 t + \beta_1 S_{1,t} + \beta_2 S_{2,t} + \cdots + \beta_s S_{s,t} + \sum_j \alpha_j D_{j,t} + \sum_j \gamma_j D_{j,t-1} + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + \varepsilon_t. \]

- Model at the second level:
  1. **Linear model**
     \[ \hat{\alpha}_j = \nu_0 + \nu_1 j \]
     \[ \hat{\gamma}_j = \omega_0 + \omega_1 j \]
  2. **Exponential model**
     \[ \hat{\alpha}_j = \nu_0 e^{\nu_1 j} \]
     \[ \hat{\gamma}_j = \ln(\omega_0 + \omega_1 j) \]
Results: monthly sales of men’s jeans

a. The first level model

\[ Y_{t,t} = 0.197M_{1,t} + 0.201M_{2,t} + 0.238M_{3,t} + 0.281M_{4,t} + 0.240M_{5,t} + 0.291M_{6,t} + 0.318M_{7,t} + 0.346M_{8,t} + 0.359M_{9,t} + 0.462M_{10,t} + 0.162M_{11,t} + 0.283M_{12,t} + 0.605D_{2,t} + 0.825D_{5,t} + 0.627D_{11,t} + 1.32D_{13,t} + 1.12D_{22,t} + 1.60D_{24,t} + 0.917D_{2,t-1} + 1.02D_{5,t-1} + 0.215D_{13,t-1} + \varepsilon_t. \]  

(16)

b. The second level model

b.1. Linear form

\[ \hat{\alpha}_j = 0.408 + 0.0473 j, \]  

(17a)

\[ \hat{j}_j = 0.946 - 0.0458 j. \]  

(17b)

b.2. Exponential form

\[ \hat{\alpha}_j = \ln(1.614 + 0.098 j), \]  

(18a)

\[ \hat{j}_j = 2.103 e^{-0.038 j} - 1. \]  

(18b)
Results: monthly sales of women’s trouser

a. The first level model

\[ Y_{2,t} = 0.00126 t + 0.225 M_{1,t} + 0.217 M_{2,t} + 0.331 M_{3,t} + 0.284 M_{4,t} + 0.285 M_{5,t} + \\
0.366 M_{6,t} + 0.346 M_{7,t} + 0.338 M_{8,t} + 0.345 M_{9,t} + 0.280 M_{10,t} + 0.202 M_{11,t} + \\
0.257 M_{12,t} + 0.408 D_{2,t} + 0.507 D_{5,t} + 1.211 D_{11,t} + 1.14 D_{13,t} + 1.29 D_{22,t} + \\
1.53 D_{24,t} + 1.26 D_{2,t-1} + 0.963 D_{5,t-1} + 0.41 D_{11,t-1} + 0.590 D_{13,t-1} + \\
0.118 D_{22,t-1} + 0.217 D_{24,t-1} + \epsilon_t. \]

b. The second level model

b.1. Linear form

\[ \hat{\alpha}_j = 0.552 + 0.0361 j, \]
\[ \hat{\gamma}_j = 1.20 - 0.0469 j. \]

b.2. Exponential form

\[ \hat{\alpha}_j = \ln(1.203 + 0.138 j), \]
\[ \hat{\gamma}_j = 1.519 e^{-0.094 j}. \]
**Results:** monthly sales of women’s trouser

**Fig. 3.** The fitted line of the second level model regression in Eq. (13a)-(14b) for monthly sales of women’s trouser data
## Results

<table>
<thead>
<tr>
<th>Method</th>
<th>$Y_{1,t} =$ men’s jeans</th>
<th></th>
<th>$Y_{2,t} =$ women trouser</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>in-sample</td>
<td>out-sample</td>
<td>in-sample</td>
<td>out-sample</td>
</tr>
<tr>
<td>ARIMA</td>
<td>0.1408</td>
<td>0.2634</td>
<td>0.1685</td>
<td>0.4235</td>
</tr>
<tr>
<td>FFNN: no skip layer</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3-1-1</td>
<td>0.1188</td>
<td>0.3847</td>
<td>0.0845</td>
<td>0.3290</td>
</tr>
<tr>
<td>3-2-1</td>
<td>0.0809</td>
<td>4.3466</td>
<td>0.0741</td>
<td>0.3844</td>
</tr>
<tr>
<td>3-3-1</td>
<td>0.0786</td>
<td>0.3375</td>
<td>0.0657</td>
<td>0.2789</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>3-9-1</td>
<td>0.0709</td>
<td>11.7676</td>
<td>0.0551</td>
<td>1.7997</td>
</tr>
<tr>
<td>3-10-1</td>
<td>0.0894</td>
<td>5.6064</td>
<td>0.0598</td>
<td>10.6219</td>
</tr>
<tr>
<td>FFNN: with skip layer</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3-1-1</td>
<td>0.1148</td>
<td>0.4159</td>
<td>0.0889</td>
<td>0.3273</td>
</tr>
<tr>
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<td>0.0809</td>
<td>0.5659</td>
<td>0.0710</td>
<td>0.3383</td>
</tr>
<tr>
<td>3-3-1</td>
<td>0.0708</td>
<td>0.6290</td>
<td>0.0663</td>
<td>0.2855</td>
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<td>...</td>
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<td>...</td>
</tr>
<tr>
<td>3-9-1</td>
<td>0.1245</td>
<td>2.6E+01</td>
<td>0.0616</td>
<td>2.6E+01</td>
</tr>
<tr>
<td>3-10-1</td>
<td>0.1087</td>
<td>1.9E+07</td>
<td>0.0561</td>
<td>8.2E+01</td>
</tr>
<tr>
<td>Two levels regression</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$2^{nd}$ linear model</td>
<td>0.0686</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$2^{nd}$ exponential model</td>
<td></td>
<td>0.2424</td>
<td></td>
<td>0.0929</td>
</tr>
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Graphical Results

(a2). ARIMA method

Variable
- Actual
- ARIMA

Y1 (Thousands unit)

Month
Year
Jan 2008
Jan 2009
Jan 2010
Jan 2011

1/2 Oct 08
21/22 Sep 09
10/11 Sep 10
30/31 Aug 11
Graphical Results

(b2). Neural Networks method

Variable
Actual
NN: 3-3-1

Y1 (Thousands unit)

Month Year
Jan 2008
Jan 2009
Jan 2010
Jan 2011

1/2 Oct 08
Sep/2009
Sep/2010
Aug/2011
Conclusion

- The proposed two levels calendar variation model based on time series regression yield better prediction for out-sample data, compared to those of ARIMA model and neural networks.

- The application of ARIMA model usually yield spurious results, particularly about seasonal pattern and the presence of outliers.

- Whereas, neural networks perform well only for in-sample data.
References


Two Levels ARIMAX and Regression Models for Forecasting Time Series Data with Calendar Variation Effects

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Email: suhartono@statistika.its.ac.id, gmsuhartono@gmail.com

Department of Mathematics, Universitas Andalas, Padang
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  - Calendar Variation

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Introduction

(a) Y1: Men's jeans sales in Boyolali shop

Unit sales (Thousands)

Month Year
Jan 2002
Jan 2003
Jan 2004
Jan 2005
Jan 2006
Jan 2007
Jan 2008
Jan 2009

Dec '02
Nov '03
Nov '04
Nov '05
Oct '06
Oct '07
Oct '08
Sep '09

Inspiring Creative & Innovative Minds – Dept. of Mathematics, UNAND
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  \[ y_t = \beta_0 + \beta_1 t + w_t \]  
  \[ \ldots (1) \]

- Regression with dummy variable for **seasonal pattern**: 
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  \[ \ldots (2) \]

- Regression for **calendar effects**: 
  \[ y_t = \beta_0 + \beta_1 V_{1,t} + \beta_2 V_{2,t} + \cdots + \beta_p V_{p,t} + w_t \]  
  \[ \ldots (3) \]
The Two Levels Regression Model

- Model at the **first level**:

\[ Y_t = \delta_1 t + \beta_1 S_{1,t} + \beta_2 S_{2,t} + \ldots + \beta_s S_{s,t} + \sum_j \alpha_j D_{j,t} + \sum_j \gamma_j D_{j,t-1} + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_p Y_{t-p} + \varepsilon_t. \]

- Model at the **second level**:

1. **Linear model**

   - \[ \hat{\alpha}_j = \nu_0 + \nu_1 j \]
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2. **Exponential model**

   - \[ \hat{\alpha}_j = \nu_0 e^{\nu_1 j} \]
   - \[ \hat{\gamma}_j = \ln(\omega_0 + \omega_1 j) \]
The **PROPOSED Model**

- Model at the **first level** → **ARIMAX-1**: stochastic TREND-SEASONAL
  \[ Y_t = \sum_j \alpha_j D_{j,t} + \sum_j \gamma_j D_{j,t-1} + \frac{\theta_q(B)\Theta_Q(B^S)}{\phi_p(B)\Phi_P(B^S)(1-B)^d(1-B^S)^D} \epsilon_t \]

- Model at the **first level** → **ARIMAX-2**: deterministic TREND-SEASONAL
  \[ Y_t = \delta_1 t + \beta_1 M_{1,t} + \beta_2 M_{2,t} + \cdots + \beta_s M_{s,t} + \sum_j \alpha_j D_{j,t} + \sum_j \gamma_j D_{j,t-1} + \frac{\theta_q(B)}{\phi_p(B)} \epsilon_t \]

- Model at the **second level**:
  
  ✓ **Linear** model

  - \[ \hat{\alpha}_j = \nu_0 + \nu_1 j \]
  - \[ \hat{\gamma}_j = \omega_0 + \omega_1 j \]

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<td>2008</td>
<td>01-02 October</td>
<td>$D_{0,t} = \text{October, and } D_{0,t-1} = \text{September}$</td>
</tr>
<tr>
<td>2009</td>
<td>21-22 September</td>
<td>$D_{20,t} = \text{September, and } D_{20,t-1} = \text{August}$</td>
</tr>
<tr>
<td>2010</td>
<td>10-11 September</td>
<td>$D_{9,t} = \text{September, and } D_{9,t-1} = \text{August}$</td>
</tr>
<tr>
<td>2011</td>
<td>30-31 August</td>
<td>$D_{29,t} = \text{September, and } D_{29,t-1} = \text{August}$</td>
</tr>
</tbody>
</table>
The Proposed Procedure

**Step 1:** Determination of dummy variable for calendar variation period.

**Step 2:** Remove the calendar variation effect from the response by fitting
\[ Y_t = \beta_0 + \sum_j \alpha_j D_{j,t} + \sum_j \gamma_j D_{j,t-1} + N_t \]
for model with stochastic trend and seasonal model, or fitting
\[ Y_t = \delta_1 t + \beta_1 M_{1,t} + \beta_2 M_{2,t} + \cdots + \beta_s M_{s,t} + \sum_j \alpha_j D_{j,t} + \sum_j \gamma_j D_{j,t-1} + N_t \]
simultaneously for model with deterministic trend and seasonal, to obtain the error, \( N_t \).

**Step 3:** Find the best ARIMA model of \( N_t \) using Box-Jenkins procedure.

**Step 4:** Simultaneously fit the model from step 2 and 3. This model is the first level of calendar variation model based on ARIMAX method.

**Step 5:** Test the significance of parameter and perform diagnostic check.

**Step 6:** Estimate the second level model to predict the effects of calendar variation in every possibility number of days before Eid ul-Fitr.
Step 1

- Based on the time series plot, **TWO DUMMY VARIABLES** are used for evaluating calendar variation effect, i.e.
  - **The months prior to Eid ul Fitr**, 
    \[ D_{j,t-1} = \text{dummy variable for ONE month prior to Eid ul-Fitr celebration.} \]
  - **During the month of Eid ul-Fitr celebration**, 
    \[ D_{j,t} = \text{dummy variable for during the month of Eid ul-Fitr celebration.} \]
  - \[ j = \text{number of days before Eid ul-Fitr celebration} \]
Step 2 - 6

• Model at the first level → ARIMAX-1: stochastic TREND-SEASONAL

\[ Y_t = \sum \alpha_j D_{j,t} + \sum \gamma_j D_{j,t-1} + \frac{\theta_q(B)\Theta_Q(B^S)}{\phi_p(B)\Phi_P(B^S)(1-B)^d(1-B^S)^D} \epsilon_t \]

• Model at the first level → ARIMAX-2: deterministic TREND-SEASONAL

\[ Y_t = \delta_1 t + \beta_1 M_{1,t} + \beta_2 M_{2,t} + \ldots + \beta_s M_{s,t} + \sum \alpha_j D_{j,t} + \sum \gamma_j D_{j,t-1} + \frac{\theta_q(B)}{\phi_p(B)} \epsilon_t \]

• Model at the second level:
  ✓ Linear model

\[ \hat{\alpha}_j = \nu_0 + \nu_1 j \]

\[ \hat{\gamma}_j = \omega_0 + \omega_1 j \]
Results: monthly sales of men’s jeans

a. ARIMAX-1 method

a.1. The first level model

\[ Y_{t} = 0.109871 + 0.51153D_{2,t} + 0.79284D_{5,t} + 0.89457D_{11,t} + 1.21885D_{13,t} + \\
1.31881D_{22,t} + 1.44439D_{24,t} + 1.07963D_{24,t-1} + 0.80625D_{5,t-1} + \\
0.18174D_{11,t-1} + 0.38253D_{13,t-1} + 0.12689D_{24,t-1} + \frac{(1 + 0.57B^{12})}{(1 - 0.60498B)} \varepsilon_{t}. \]

a.2. The second level model

\[ \hat{\alpha}_{j} = 0.537 + 0.0385j, \]
\[ \hat{\gamma}_{j} = 0.983 - 0.0431j. \]
Results: monthly sales of men’s jeans

b. ARIMAX-2 method

b.1. The first level model

\[ Y_{1,t} = 0.21334M_{1,t} + 0.21110M_{2,t} + 0.24403M_{3,t} + 0.28412M_{4,t} + 0.24168M_{5,t} + 0.29194M_{6,t} + 0.31880M_{7,t} + 0.34575M_{8,t} + 0.33287M_{9,t} + 0.44423M_{10,t} + 0.12521M_{11,t} + 0.27299M_{12,t} + 0.69022D_{2,t} + 0.85376D_{3,t} + 0.67169D_{4,t} + 1.38182D_{5,t} + 1.10961D_{6,t} + 1.61269D_{7,t} + 0.94901D_{8,t} + 1.05741D_{9,t} + 0.5262D_{10,t} + 0.24495D_{11,t} + \frac{1}{(1-0.58642B)} \epsilon_t \]

b.2. The second level model

\[ \hat{\alpha}_j = 0.626 + 0.0333j, \]

\[ \hat{\gamma}_j = 1.018 - 0.0481j. \]
## Results

<table>
<thead>
<tr>
<th>Method</th>
<th>( Y_{1,t} )</th>
<th>( Y_{2,t} )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>in-sample</td>
<td>out-sample</td>
</tr>
<tr>
<td>ARIMA</td>
<td>0.1408</td>
<td>0.2634</td>
</tr>
<tr>
<td>FFNN: no skip layer</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3-1-1</td>
<td>0.1188</td>
<td>0.3847</td>
</tr>
<tr>
<td>3-2-1</td>
<td>0.0809</td>
<td>4.3466</td>
</tr>
<tr>
<td>3-3-1</td>
<td>0.0786</td>
<td>0.3375</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>3-10-1</td>
<td>0.0894</td>
<td>5.6064</td>
</tr>
<tr>
<td>FFNN: with skip layer</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3-1-1</td>
<td>0.1148</td>
<td>0.4159</td>
</tr>
<tr>
<td>3-2-1</td>
<td>0.0809</td>
<td>0.5659</td>
</tr>
<tr>
<td>3-3-1</td>
<td>0.0708</td>
<td>0.6290</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>3-10-1</td>
<td>0.1087</td>
<td>1.9E+07</td>
</tr>
<tr>
<td>Two levels regression</td>
<td>0.0686</td>
<td>0.2434</td>
</tr>
<tr>
<td>Two levels ARIMAX-1</td>
<td>0.0671</td>
<td>0.2169</td>
</tr>
<tr>
<td>Two levels ARIMAX-2</td>
<td>0.0606</td>
<td>0.2599</td>
</tr>
</tbody>
</table>
Graphical Results

(a2). ARIMA method

Y1 (Thousands unit)

Month Year
Jan 2008  Jan 2009  Jan 2010  Jan 2011

Variable
Actual
ARIMA

1/2 Oct 08  21/22 Sep 09  10/11 Sep 10  30/31 Aug 11
Graphical Results

(b2). Neural Networks method

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(c2). Time Series Regression method

Graphical Results
Graphical Results

(d2). The 1st ARIMAX method
Graphical Results

(e2). The 2nd ARIMA method

Variable
- Actual
- 2nd ARMAX

Y1 (Thousands unit)

Month Year
Jan 2008
Jan 2009
Jan 2010
Jan 2011

1/2 Oct 08
21/22 Sep 09
10/11 Sep 10
30/31 Aug 11

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Conclusion

- The proposed two levels calendar variation model based on ARIMAX and Regression method yield better prediction for out-sample data, compared to those of ARIMA model and neural networks.

- The application of ARIMA model usually yield spurious results, particularly about seasonal pattern and the presence of outliers.

- Whereas, Neural Networks perform well only for in-sample data.
References

References


Applying Data Analytics Using Neural Networks

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Department of Mathematics, Universitas Andalas, Padang
17-18 July 2017
Outline

- **Introduction**: Background, Motivation, Jargons, Goals.
- **Architecture of Neural Networks**: Supervised & Unsupervised networks
- **Model selection in Neural Networks**: Inputs, Number of hidden neurons, Activation function, Preprocessing method.
- **Application and Development**: Forecasting and Classification problems.
Neural Networks – NN

- Sven F. Crone:

- Halbert L. White:
  - http://weber.ucsd.edu/~hwhite/

- Warren S. Sarle:
During the last few decades,

1. modeling to explain nonlinear relationship between variables, and
2. some procedures to detect this nonlinear relationship

have grown in a spectacular way and received a great deal of attention.

Granger, C.W.J. and Terasvirta, T., (1993)

Due to computational advances and increased computational power, nonparametric models that do not make assumptions about the parametric form of the functional relationship between the variables to be modelled have become more easily applicable.
Today’s research is largely motivated by the possibility of using NN model as an instrument to solve a wide variety of application problems such as:

- pattern recognition (classification), signal processing,
- process control, and forecasting.

The use of the NN model in applied work is generally motivated by a mathematical result stating that under mild regularity conditions, a relatively simple NN model is capable of approximating any Borel-measureable function to any given degree of accuracy.

(see e.g. Hornik, Stichombe and White (1989, 1990), White (1990); Cybenko (1989))
The use of NN ...

[Sarle, 1994]

1. as models of biological nervous systems and “intelligence”,
2. as real-time adaptive signal processors or controllers implemented in hardware for applications such as robots,
3. as data analytic methods.

 эту paper is concerned with NN for DATA ANALYSIS.
Chart of Neural Networks

http://www.asimovinstitute.org/neural-network-zoo/

A mostly complete chart of Neural Networks

Backfed Input Cell
Input Cell
Noisy Input Cell
Hidden Cell
Probabilistic Hidden Cell
Spiking Hidden Cell
Output Cell
Match Input Output Cell
Recurrent Cell
Memory Cell
Different Memory Cell
Kernel
Convolution or Pool

Deep Feed Forward (DFF)
Perceptron (P)
Feed Forward (FF)
Radial Basis Network (RBF)
Recurrent Neural Network (RNN)
Long / Short Term Memory (LSTM)
Gated Recurrent Unit (GRU)
Auto Encoder (AE)
Variational AE (VAE)
Densising AE (OAE)
Sparse AE (SAE)
Supervised vs Unsupervised networks

- **Supervised Learning**
  - Continuous
    - regression
  - Discrete
    - classification or categorization

- **Unsupervised Learning**
  - dimensionality reduction
  - clustering

**Dependence Methods**

**Interdependence Methods**

Multivariate Data Analysis

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Chart of Neural Networks

http://www.asimovinstitute.org/neural-network-zoo/

Figure 1: Simple Linear Regression

Figure 2: Simple Nonlinear Perceptron = Logistic Regression

Source: Sarle (1994)
Feed Forward Neural Networks

 Economist perceptron (MLP), also known as feedforward neural networks (FFNN), is probably the most commonly used NN architecture in engineering application.

 Typically, applications of NN for regression, time series modeling and classification (discriminant analysis) are based on the FFNN architecture.
Neural Networks & Statistical Jargon

<table>
<thead>
<tr>
<th>Neural Networks</th>
<th>Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>▪ features</td>
<td>▪ variables</td>
</tr>
<tr>
<td>▪ inputs</td>
<td>▪ independent variables</td>
</tr>
<tr>
<td>▪ outputs</td>
<td>▪ predicted values</td>
</tr>
<tr>
<td>▪ targets or training values</td>
<td>▪ dependent variables</td>
</tr>
<tr>
<td>▪ errors</td>
<td>▪ residuals</td>
</tr>
<tr>
<td>▪ training, learning, adaptation</td>
<td>▪ estimation</td>
</tr>
<tr>
<td>▪ patterns or training pairs</td>
<td>▪ observations</td>
</tr>
<tr>
<td>▪ weights</td>
<td>▪ parameter estimates</td>
</tr>
<tr>
<td>▪ supervised learning</td>
<td>▪ regression &amp; discriminant</td>
</tr>
<tr>
<td>▪ unsupervised learning</td>
<td>▪ data reduction</td>
</tr>
<tr>
<td>▪ adaptive vector quantization</td>
<td>▪ cluster analysis</td>
</tr>
<tr>
<td>▪ generalization</td>
<td>▪ interpolation &amp; extrapolation</td>
</tr>
</tbody>
</table>

$x_1, x_2, \ldots, x_p \rightarrow y$
FFNN as Nonlinear regression

- FFNN includes estimated weights between the inputs and the hidden layer, and the hidden layer uses nonlinear activation functions such as the logistic function, the FFNN becomes genuinely nonlinear model, i.e., nonlinear in the parameters.

- In this case, FFNN can be seen as nonlinear regression. FFNN can have multiple inputs and outputs (This figure is multiple inputs with single output), and this architecture is similar to multiple nonlinear regression.
FFNN as Logistic Regression and Discriminant Analysis

- FFNN with nonmetric data (dichotomous/polyothomous) in target values is identical to logistic regression and nonlinear discriminant analysis.

- In this case, FFNN often use a multiple logistic function to estimate the conditional probabilities of each class. A multiple logistic function is called a softmax activation function in the NN literature.
FFNN as Nonlinear AR(p) model

\[ y_t = \beta_0 + \sum_{j=1}^{q} \beta_j f \left( \sum_{i=1}^{p} \gamma_{ij} y_{t-i} + \gamma_{0j} \right) + \varepsilon_t \]
FFNN as Nonlinear AR(p) model

- Model building strategy that proposed by Terasvirta et al. (1994)
  
  1. Test $Y_t$ for linearity, using linearity test (neglected nonlinearity).
  
  2. If linearity is rejected, consider a small number of alternative parametric models and/or nonparametric models.
  
  3. These models should be estimated in-sample and compared out-of-sample.
FFNN: the main problems !!!

1. How many nodes (neurons) in hidden layer?
2. What is the best inputs (features selection)?
3. What is the best pre-processing method?
4. What is the best activation function in hidden and output layer?

Model selection in Neural Networks
FFNN: the main problems !!!

1. What is the best inputs (features selection)?
2. How many nodes (neurons) in hidden layer?
3. What is the best pre-processing method?
4. What is the best activation function in hidden and output layer?

Model selection in Neural Networks

In Time Series Forecasting

1. What is the best inputs (features selection)?
2. How many nodes (neurons) in hidden layer?
3. What is the best pre-processing method?
4. What is the best activation function in hidden and output layer?
Nonlinear relationship Concept

Nonlinear Time Series

Nonlinear Time Series

Lag plot: $Y_{t-1}$ vs $Y_t$

Logistic Model

$p = \frac{1}{1 + e^{-(b_0 + b_1 x)}}$
Model Selection in Neural Network

- In general, there are **two procedures** usually used to find **the best FFNN model** or **the optimal architecture**, those are “general-to-specific” or “top-down” and “specific-to-general” or “bottom-up” procedures.

- “**Top-down**” procedure is started from complex model and then applies an algorithm to reduce number of parameters (number of input variables and unit nodes in hidden layer) by using some stopping criteria, whereas “**bottom-up**” procedure works from a simple model.
Neural Networks

Training of neural networks

**Description**

neuralnet is used to train neural networks using backpropagation, resp. (Riedmiller, 1994) or without weight backtracking (Riedmiller and Braun, 1992) version (GRPROP) by Anastasiadis et al. (2005). The function allows for error and activation function. Furthermore the calculation of generalized is implemented.

**Usage**

```r
neuralnet(formula, data, hidden = 1, threshold = 0.03, 
            stepmax = 1e-05, rep = 1, startweights = NULL, 
            learningrate.limit = NULL, 
            learningrate.factor = list(minus = 0.5, plus = 1), 
            learningrate.null = NULL, lifesign = "none", 
            lifesign.step = 1000, algorithm = "rprop", 
            err.fct = "sse", act.fct = "logistic", 
            linear.output = TRUE, exclude = NULL, 
            constant.weights = NULL, likelihood = FALSE)
```

**Fit Neural Networks**

**Description**

Fit single-hidden-layer neural network, possibly with skip-layer connections.

**Usage**

```r
nnet(x, ...) 
```

```r
## S3 method for class 'formula'
nnet(formula, data, weights, ..., 
      subset, na.action, contrasts = NULL)
```

```r
## Default S3 method:
nnet(x, y, weights, size, Wts, mask, 
     linout = FALSE, entropy = FALSE, softmax = FALSE, 
     censored = FALSE, skip = FALSE, rang = 0.7, decay = 0, 
     maxit = 100, Hess = FALSE, trace = TRUE, MaxNWts = 1000, 
     abstol = 1.0e-4, reltol = 1.0e-8, ...)
```
Neural Networks “software”

---

**Lag plot:** $Y_{t-7}$ vs $Y_t$

Nonlinear Time Series

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Neural Networks “software”

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Application: NN for Classification

- **Source:** bankloan.sav from SPSS

<table>
<thead>
<tr>
<th>Variable</th>
<th>Notation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Y</td>
<td>default (Yes = 1, No = 0)</td>
</tr>
<tr>
<td>X₁</td>
<td>age</td>
</tr>
<tr>
<td>X₂</td>
<td>ed (categorical)</td>
</tr>
<tr>
<td>X₃</td>
<td>employ</td>
</tr>
<tr>
<td>X₄</td>
<td>address</td>
</tr>
<tr>
<td>X₅</td>
<td>income</td>
</tr>
<tr>
<td>X₆</td>
<td>debtinc</td>
</tr>
<tr>
<td>X₇</td>
<td>creddebt</td>
</tr>
<tr>
<td>X₈</td>
<td>othdebt</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Name</th>
<th>Type</th>
<th>Width</th>
<th>Decimals</th>
<th>Label</th>
</tr>
</thead>
<tbody>
<tr>
<td>age</td>
<td>Numeric</td>
<td>4</td>
<td>0</td>
<td>Age in years</td>
</tr>
<tr>
<td>ed</td>
<td>Numeric</td>
<td>4</td>
<td>0</td>
<td>Level of education</td>
</tr>
<tr>
<td>employ</td>
<td>Numeric</td>
<td>4</td>
<td>0</td>
<td>Years with current employer</td>
</tr>
<tr>
<td>address</td>
<td>Numeric</td>
<td>4</td>
<td>0</td>
<td>Years at current address</td>
</tr>
<tr>
<td>income</td>
<td>Numeric</td>
<td>8</td>
<td>2</td>
<td>Household income in thousands</td>
</tr>
<tr>
<td>debtinc</td>
<td>Numeric</td>
<td>8</td>
<td>2</td>
<td>Debt to income ratio (x100)</td>
</tr>
<tr>
<td>creddebt</td>
<td>Numeric</td>
<td>8</td>
<td>2</td>
<td>Credit card debt in thousands</td>
</tr>
<tr>
<td>othdebt</td>
<td>Numeric</td>
<td>8</td>
<td>2</td>
<td>Other debt in thousands</td>
</tr>
<tr>
<td>default</td>
<td>Numeric</td>
<td>4</td>
<td>0</td>
<td>Previously defaulted</td>
</tr>
</tbody>
</table>

Level of education

1 = "Did not complete high school"
2 = "High school degree"
3 = "Some college"
4 = "College degree"
5 = "Post-undergraduate degree"
Application: NN for Classification

- Source: bankloan.sav from SPSS

<table>
<thead>
<tr>
<th>Input variables</th>
<th>All Input</th>
<th>$X_1, X_2, \ldots, X_8$: age, ed, \ldots, othdebt</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Best Input</td>
<td>employ, address, debtinc, and creddebt</td>
</tr>
<tr>
<td>Number of neurons</td>
<td>1 – 25</td>
<td></td>
</tr>
<tr>
<td>Activation Function</td>
<td>Logistic Sigmoid vs Tangent Hyperbolic</td>
<td></td>
</tr>
<tr>
<td>Preprocessing Method</td>
<td>None, Standardized, Normalized, Adjusted Normalized</td>
<td></td>
</tr>
</tbody>
</table>

1. What is the best inputs (features selection)?
2. How many nodes (neurons) in hidden layer?
3. What is the best activation function in hidden and output layer?
4. What is the best pre-processing method?

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### Application: NN for Classification

- **Source:** bankloan.sav from SPSS

<table>
<thead>
<tr>
<th>Input variables</th>
<th>All Input</th>
<th>X₁, X₂, …, X₈: age, ed, …, othdebt</th>
</tr>
</thead>
<tbody>
<tr>
<td>Best Input</td>
<td></td>
<td>employ, address, debtinc, and creddebt</td>
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</table>

<table>
<thead>
<tr>
<th>Stepwise Discriminant</th>
<th>Logistic Regression</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Variable</strong></td>
<td><strong>F</strong></td>
</tr>
<tr>
<td>Debtinc</td>
<td>30,531</td>
</tr>
<tr>
<td>Employ</td>
<td>73,671</td>
</tr>
<tr>
<td>Creddebt</td>
<td>43,584</td>
</tr>
<tr>
<td>Address</td>
<td>9,560</td>
</tr>
<tr>
<td>Debtinc</td>
<td>20,129</td>
</tr>
<tr>
<td>Address</td>
<td>9,560</td>
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<tr>
<td>Creddebt</td>
<td>35,799</td>
</tr>
</tbody>
</table>
Application: NN for Classification

- Source: bankloan.sav from SPSS

Percentage **correct** of classification

**Number of neurons** in hidden layer

**The effect of INPUTS and number of NEURONS in hidden layer**
Application: NN for Classification

The effect of PREPROCESSING method & number of NEURONS

Percentage correct of classification

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Application: NN for Classification

- Source: bankloan.sav from SPSS

Percentage correct of classification

The effect of ACTIVATION function method & number of NEURONS

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Application: NN for Classification

- Source: bankloan.sav from SPSS

Summary of the results:

(1) More sophisticated or complex methods do not necessarily provide more accurate classification than simpler ones, particularly at testing dataset.

(2) The performance of the various NN methods for classification problem depends upon:

- Inputs,
- Number of neurons in hidden layer,
- Pre-processing method, and
- Activation function.
Application: NN for Time Series Forecasting

- Source: simulation study using ESTAR(1) model

\[ x_t = 6.5x_{t-7}\exp(-0.25x_{t-7}^2) + e_t, \quad e_t \sim N(0, 0.5) \]
Application: NN for Time Series Forecasting

- Source: simulation study using ESTAR(1)\(^7\) model

<table>
<thead>
<tr>
<th>Input variables</th>
<th>Many Inputs</th>
<th>include lag 7 (X(_{t-7})) and without lag 7</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Best Input</td>
<td>only using lag 7 or X(_{t-7})</td>
</tr>
<tr>
<td>Number of neurons</td>
<td>1,2,3,4,5,10,15</td>
<td></td>
</tr>
<tr>
<td>Activation Function</td>
<td>Logistic Sigmoid vs Tangent Hyperbolic</td>
<td></td>
</tr>
<tr>
<td>Preprocessing Method</td>
<td>None, Standardized, Normalized, Adjusted Normalized</td>
<td></td>
</tr>
</tbody>
</table>

1. What is the best **inputs** (features selection)?
2. How many **nodes** (neurons) in hidden layer?
3. What is the best **activation function** in hidden and output layer?
4. What is the best **pre-processing** method?
Application: NN for Time Series Forecasting

- Source: simulation study using ESTAR(1) model

Identification the appropriate lag inputs: use LAG PLOT in R
Application: NN for Time Series Forecasting

- Source: simulation study using ESTAR(1) model

RMSE

The effect of INPUTS and number of NEURONS in hidden layer

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Application: NN for Time Series Forecasting

- Source: simulation study using ESTAR(1) model

The effect of ACTIVATION function and number of NEURONS

RMSE

Number of neurons in hidden layer

Inspiring Creative & Innovative Minds – Dept. of Mathematics, UNAND
Application: NN for Time Series Forecasting

- **Source**: simulation study using \( \text{ESTAR}(1) \) model

### Result

<table>
<thead>
<tr>
<th>Number of neurons in hidden layer</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training</td>
<td></td>
</tr>
<tr>
<td>Testing</td>
<td></td>
</tr>
</tbody>
</table>

The effect of PREPROCESSING method & number of NEURONS
Summary of the results:

(1) More sophisticated or complex methods do not necessarily provide more accurate forecast than simpler ones.

(2) The performance of the various NN methods for time series forecasting problem depends upon:

- Inputs or lag variables,
- Number of neurons in hidden layer,
- Pre-processing method.

Source: simulation study using ESTAR(1) model

Inspiring Creative & Innovative Minds – Dept. of Mathematics, UNAND
25 years of time series forecasting
De Gooijer & Hyndman (International Journal of Forecasting, 2006)

Inspiring Creative & Innovative Minds – Dept. of Mathematics, UNAND
The M3-Competition: results, conclusions and implications

1. Statistically sophisticated or complex methods do not necessarily provide more accurate forecasts than simpler ones.

2. The relative ranking of the performance of the various methods varies according to the accuracy measure being used.

3. The accuracy when various methods are being combined outperforms, on average, the individual methods being combined and does very well in comparison to other methods.

4. The accuracy of the various methods depends upon the length of the forecasting horizon involved.

Makridakis & Hibon (International Journal of Forecasting, 2000)
Recent development of NN for forecasting

**Hybrid Model - Combined - Ensemble**

Model Selection in Neural Networks by Using Inference of R2 Incremental, PCA, and SIC Criteria for Time Series Forecasting

<table>
<thead>
<tr>
<th>Authors</th>
<th>Suhartono, Subanar, S Guritno</th>
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<tbody>
<tr>
<td>Publication date</td>
<td>2006</td>
</tr>
<tr>
<td>Journal</td>
<td>JOURNAL OF QUANTITATIVE METHODS: Journal Devoted to The Mathematical and Statistical Application in Various Fields</td>
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</table>

New Procedures for Model Selection in Feedforward Neural Networks for Time Series Forecasting

<table>
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THE EFFECT OF DECOMPOSITION METHOD AS DATA PREPROCESSING ON NEURAL NETWORKS MODEL FOR FORECASTING TREND AND SEASONAL TIME SERIES

<table>
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<th>Subanar Subanar, Suhartono Suhartono</th>
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<td>2007/2/1</td>
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<td>Jurnal Teknik Industri</td>
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Recent development of NN for forecasting

Hybrid Model – Combined – Ensemble

Two-level seasonal model based on hybrid ARIMA-ANFIS for forecasting short-term electricity load in Indonesia

<table>
<thead>
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<tbody>
<tr>
<td>Suhartono ; Indah Puspitasari ; M. Sjahid Akbar ; Muhammad Hisyam Lee</td>
</tr>
</tbody>
</table>

Design of Experiment to Optimize the Architecture of Wavelet Neural Network for Forecasting the Tourist Arrivals in Indonesia

Authors: Bambang W Otok, Suhartono, Brodjol SS Ulama, Afonsus J Endharta
Publication date: 2011/11/14
Conference: International Conference on Informatics Engineering and Information Science

Seasonal Time Series Data Forecasting by Using Neural Networks Multiscale Autoregressive Model

Suhartono, B.S.S. Ulama and A.J. Endharta
Department of Statistics, Faculty of Mathematics and Natural Sciences, Institute Technology Sepuluh Nopember, Surabaya 60111, Indonesia
Recent development of NN for forecasting

Hybrid Model - Combined - Ensemble

Forecasting currency circulation data of Bank Indonesia by using hybrid ARIMAX-ANN model
I. Gede Surya Adi Prayoga, Suhartono, and Santi Puteri Rahayu

Citation: AIP Conference Proceedings 1842, 030029 (2017); doi: 10.1063/1.4982867

Forecasting electricity load demand using hybrid exponential smoothing-artificial neural network model
Winita Sulandari, Subanar Subanar, Suhartono Suhartono, Herni Utami

Quality & Quantity
November 2015, Volume 49, Issue 6, pp 2633–2647

Artificial neural networks and fuzzy time series forecasting: an application to air quality

Authors and affiliations:
Conclusion

偏差 Statistical models and NN are not competing methodologies for data analysis. There is considerable many similarities between the two models.

偏差 NN include several models, such as FFNN, that are useful for statistical applications.

偏差 Statistical methodology is directly applicable to NN in a variety of ways, including estimation criteria, optimization algorithm, testing hypothesis and diagnostic check.
Main References

Neural Networks and Statistical Models
Proceedings of the Nineteenth Annual SAS Users Group International Conference, April, 1994
Warren S. Sarle, SAS Institute Inc., Cary, NC, USA

neuralnet: Training of Neural Networks
by Frauke Günther and Stefan Fritsch
provides functions to visualize the results or in gen-

Model Selection in Neural Networks
Ulrich Anders, Olaf Korn
Centre for European Economic Research (ZEW), Mannheim