

New Models and Methods for Time Series for Time Series Analysis in Big Data Era

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Big Data Era



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Graduate starting salary

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- How popular is this topic?
Number of tweets

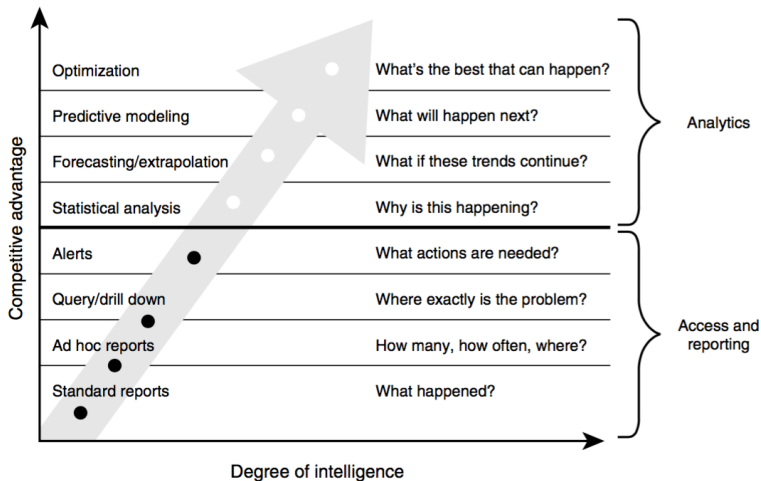
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IMDb rating, box office
- How popular is this topic?
Number of tweets
- How much does the man love this woman?

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Graduate starting salary
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IMDb rating, box office
- How popular is this topic?
Number of tweets
- How much does the man love this woman?
The carat of the diamond

Level of Intelligence



-Gorman, M. F., Klimberg, R. K. (2014). Benchmarking academic programs in business analytics. *Interfaces*. **44(3)**, 329-341.

Time series

- A sequence of data points observed over time
- Successive data points are usually expected to be dependent
- Examples: the daily weight, the daily return of stocks, the three-minute traffic volume, historical financial data of a firm

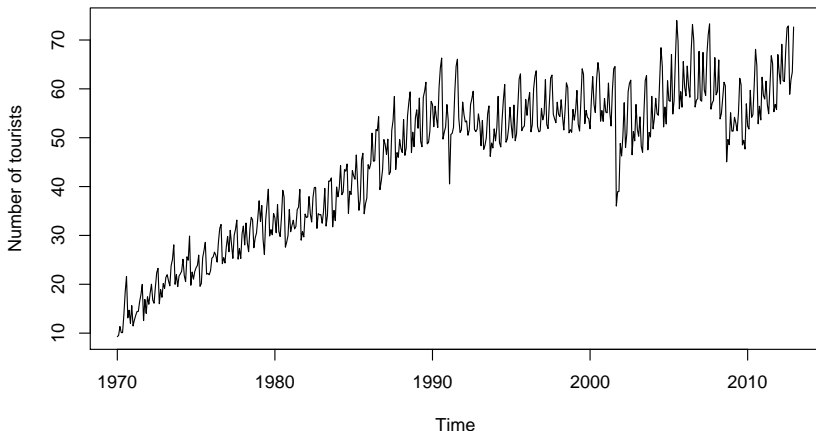
Why to study time series?

- Understanding the underlying mechanism driving the process (why is this happening?)
- Forecasting (what will happen next?)

- Traditional time series analysis deals with scalar or vector observations
 - Linear: ARIMA and seasonal ARIMA models
- In big data era, information available becomes massive and complex. My research focuses on time series data in
 - nonlinear dynamics
 - functional form
 - high dimension

Hawaii Tourism Data: 1970-2012

Number of tourists visiting Hawaii (monthly)



We re-scale the data by dividing 10^5 .

Source: Hawaii Visitors Bureau.

Questions: how to understand and predict the number of tourists? why is it so important?

- Tourism is the largest single source of the state GDP, representing about \$14 billion, 21% of its entire economy
- Tourism contributed \$1.5 billion in total state tax revenue in 2013
- Most local service industries rely heavily on tourism , for example, airlines, hotels, casinos, shopping malls, theaters
- It is important for state budget and for supply chain management of local firms

Seasonal ARIMA model:

$$(1 - \phi_1 B)(1 - \phi_{12} B^{12})(1 - B^{12})X_t = \varepsilon_t,$$

where B is backshift operator, i.e. $B^q X_t = X_{t-q}$.

Define time series Y_t by taking a seasonal difference,

$$Y_t = (1 - B^{12})X_t = X_t - X_{t-12}.$$

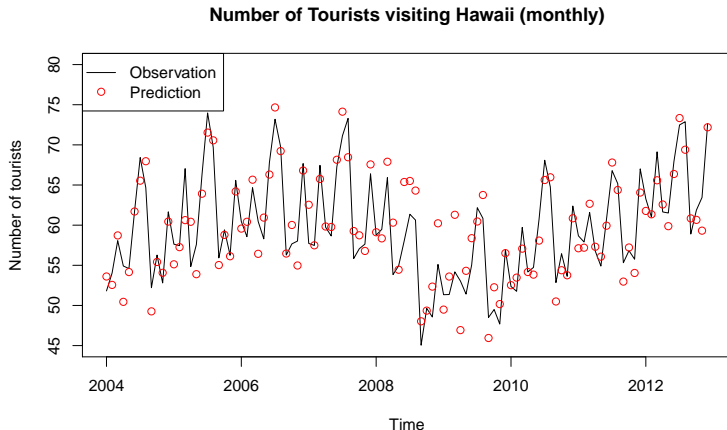
Then

$$(1 - \phi_1 B)(1 - \phi_{12} B^{12})Y_t = \varepsilon_t$$

$$Y_t = \phi_1 Y_{t-1} + \phi_{12} Y_{t-12} + \phi_1 \phi_{12} Y_{t-13} + \varepsilon_t.$$

Hawaii Tourism Data: Seasonal ARIMA models

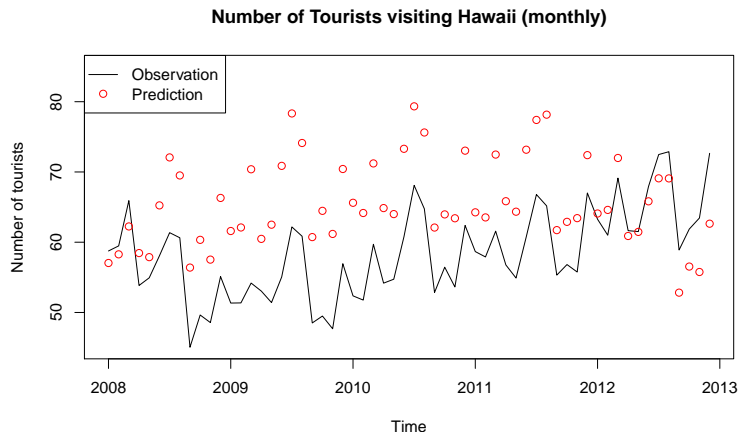
One month ahead out-sample forecasting from 2005 to 2012.



Mean squared error is 6.8475.

Hawaii Tourism Data: Seasonal ARIMA models

Four years ahead out-sample forecasting from 2008 to 2012.



Mean squared error is 89.8845.

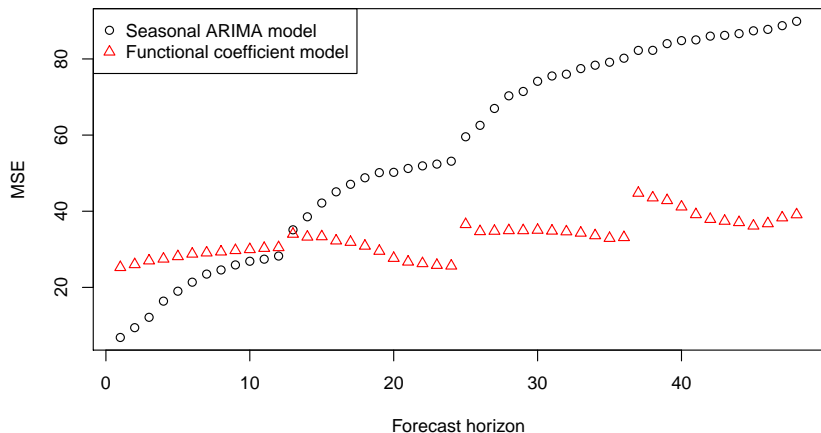
- Long term prediction does not work
- The impact of the past on the present changes, and nonlinear dynamics exists
- Some exogenous variables may help

The growth rate of annual personal disposable income (PDI) of U.S. and Japan are added as $\{x_{1t}\}$ and $\{x_{2t}\}$, respectively, since U.S. and Japan contribute more than 80% of the tourists in Hawaii.

$$y_{tj} = [\alpha_0(s_t) + \beta_{0j}(s_t)] + [\alpha_1(s_t) + \beta_{1j}(s_t)]x_{1t} + [\alpha_2(s_t) + \beta_{2j}(s_t)]x_{2t} + e_{tj}$$

h is selected by generalized cross-validation.

Hawaii Tourism Data



Plots of mean squared error for our model and seasonal ARIMA model

Other applications

- Scalar time series data with seasonality and nonlinear dynamics
- Example: electricity consumption, airline traffic volume, etc

Why is volatility important?

- Volatility is a very popular topic in finance, and crucial for option pricing.
- Many hedging strategies depend on the volatility of assets.

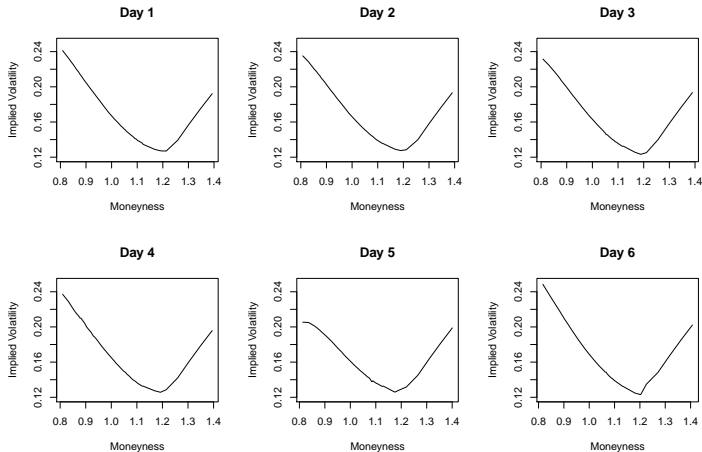
What is implied volatility?

- Black-Scholes model is the world's most well-known pricing model. Scholes won the Nobel Prize for this work in 1997.
- Volatility derived from Black-Scholes model is implied volatility
- Volatility smile: plot of implied volatility against moneyness (strike price/underlying asset price) yields a 'smile'

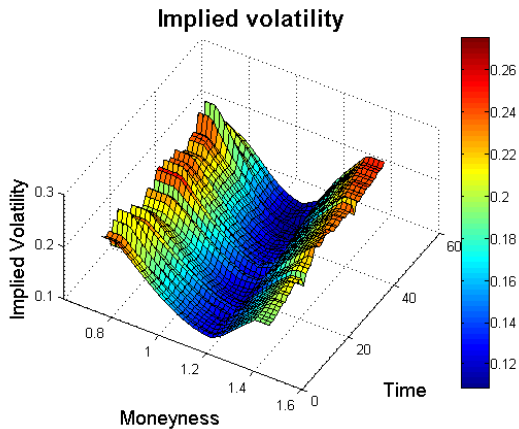
Volatility is treated as a function of moneyness, and our aim is to predict volatility curve.

Volatility Smiles

Daily implied volatilities of European call options of the S & P 500 index from July 9, 2004 to Sep 20, 2004. The expiration date is Dec 18, 2013. The strike prices range from 950 to 1550.



Volatility Smiles



Functional time series data are widely observed in many fields.

- Finance: yield curve
- Demography: age-specific mortality rate, birth rate
- Meteorology: temperature, participation, and cloud cover in a region

Convolutional FAR(p) Models

$$X_t(s) = \sum_{i=1}^p \int_0^1 \phi_i(s-u) X_{t-i}(u) du + \varepsilon_t(s) \text{ where } s \in [0, 1]$$

- $\phi(\cdot)$ is defined on $[-1, 1]$.
 - Finite support for integration of estimated $\phi(\cdot)$.
 - $w_s(u) = \phi(s-u)$ is the weight function for s .
- Noise process $\{\varepsilon_t(\cdot), t = 1, \dots, T\}$ is assumed to be i.i.d following an Ornstein-Uhlenbeck process

$$d\varepsilon_t(s) = -\rho\varepsilon_t(s)ds + \sigma dW_t(s)$$

with $\text{Var}(\varepsilon_t(s)) = \sigma^2/2\rho$, $\text{Cor}(\varepsilon_t(s_1), \varepsilon_t(s_2)) = \exp\{-\rho|s_1 - s_2|\}$.

Table: Out-of-sample forecasting MSEs for different models

MSE1(CFAR model)	MSE2(FAR model)	MSE3(random walk)
$8.7134e - 05$	$1.1010e - 04$	$1.1938e - 04$