# Time Series Analysis 时间序列分析

Yongfeng Zhang, Tsinghua University zhangyf07@gmail.com





### Outline

- ➤什么是时间序列分析(Time Series Analysis)
- ▶常见模型和基本手段
  - ➤ 趋势(Trend Component)
  - ➤ 周期性(Seasonal Component)
  - ➤ 随机性(Random Component)
- ▶简单示例
  - ➤ Modeling a Time Series
- ➤常用模型 ARMA
  - > AR (Auto Regressive)
  - ➤ MA (Moving Average)
  - ➤ ARIMA (Auto Regressive Integrated Moving Average)
- ▶应用示例
  - ➤ Google Trends

Information Retriever @ Tsingitus University

### Outline

- ➤什么是时间序列分析(Time Series Analysis)
- ▶常见模型和基本手段
  - ➤ 趋势(Trend Component)
  - ➤周期性(Seasonal Component)
  - ➤ 随机性(Random Component)
- ▶简单示例
- ▶常用模型 ARMA
  - > AR (Auto Regressive)
  - ➤ MA (Moving Average)
  - ➤ ARIMA (Auto Regressive Integrated Moving Average)



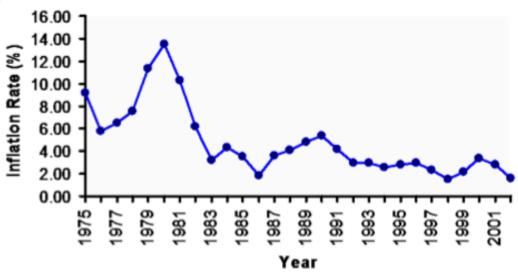
### Time Series

What is Time Series

A time-series plot is a two-dimensional plot of time series data

- the vertical axis measures the variable of interest
- the horizontal axis corresponds to the time periods



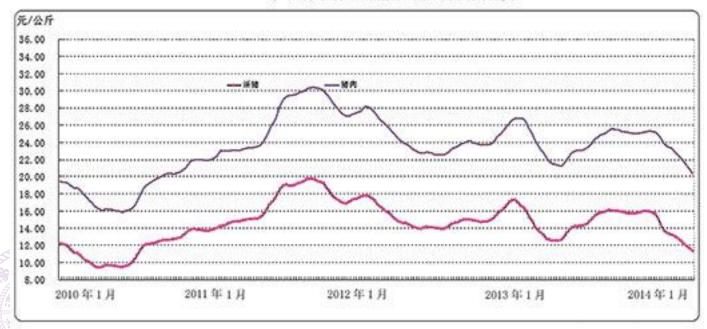


# Time Series (cont.)

#### ➤ Other Examples

- ➤ Governments forecast **unemployment rates**, **income taxes** for policy purposes.
- Marketing executives forecast demand, sales, and consumer preferences for strategic planning
- > etc...

#### 2010年以来全国活猪和猪肉价格趋势



### Types of Time Series

- Types of time series
  - continuous
  - discrete
- Discrete means that observations are recorded in discrete times it says nothing about the nature of the observed variable
- The time intervals can be annually, quarterly, monthly, weekly, daily, hourly, etc.
- Continuous means that observations are recorded continuously -e.g. temperature and/or humidity in some laboratory
- Again, time series can be continuous regardless of the nature of the observed variable





# Types of Time Series (cont.)

- Discrete time series can result when continuous time series are sampled.
- Sometimes quantities that don't have an instantaneous value get aggregated also resulting in a discrete time series e.g. daily rainfall
- We will mostly study discrete time series in this course. Note that discrete time series are often the result of discretization of continuous time series (e.g. monthly rainfall)

#### Example

Year	2000	2001	2002	2003	2004
Sales	75.3	74.2	78.5	79.7	80.2





# Time Series Analysis – Objectives

- ➤ Objectives of time series analysis:
  - ➤ description summary statistics, graphs
  - ➤ analysis and interpretation find a model to describe the time dependence in the data, can we interpret the model?
  - ➤ forecasting or prediction given a sample from the series, forecast the next value, or the next few values
  - > control adjust various control parameters to make the series fit closer to a target





### Outline

- ➤什么是时间序列分析(Time Series Analysis)
- ▶常见模型和基本手段
  - ➤数值变换(Transformations)
  - ➤ 趋势(Trend Component)
  - ▶季节性(Seasonal Component)
  - ➤ 周期性(Cyclical Component)
  - ➤ 随机性(Random Component)
- ▶简单示例
- ▶常用模型 ARMA
  - > AR (Auto Regressive)
  - ➤ MA (Moving Average)
  - ARIMA (Auto Regressive Integrated Moving Average)



### **Transformation**

- To stabilize the variance. For example, if the standard deviation is proportional to the mean, log transform can be used
- To make the seasonal effect additive.
  - multiplicative vs additive noise- if the noise is also multiplicative, the transformation will also help stabilize the variance
- To make the data normally distributed useful for a variety of reasons to be discussed later

#### Example

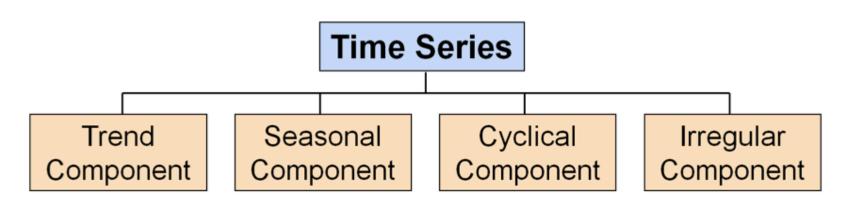
logarithmic, square root, reciprocal square root, Box-Cox as a general approach

In general, transforming the data is usually not a great idea except where doing so makes physical sense. Example: percentage data transformed using a log transform





# Major Types of Variation



Overall, persistent, longterm movement Regular periodic fluctuations, usually within a 12-month period Repeating swings or movements over more than one year Erratic or residual fluctuations





# Major Types of Variation (cont.)

#### **Types of Variation**

1 Seasonal variation: sales figures and temperature readings exhibit variation that is annual in period.

#### **Example**

Unemployment is typically "high" in winter and "lower" in summer.

- 2 Cyclic variation:
  - variation at other fixed periods.

#### **Example**

Daily variation in temperature "high" at noon, "low" at night.

O Some time series exhibit oscillations without a fixed period, they are predictable to some extent.

#### **Example**

Economic data are affected by business cycles.

# Major Types of Variation (cont.)

3 Trend: long-term change in the mean level "long term" relative to the number of observations.

#### **Example**

Climate variables exhibit cyclic variation over long periods.

- 4 Irregular fluctuations: after trend and cyclic variations have been removed, a series of residuals may or may not be "random".
  - any cyclic variation is still left.
  - Probability models such as moving average (MA) or autoregressive (AR).

Stationary Time Series: If there is no systematic change in mean (no trend), variance and if periodic variations have been removed.

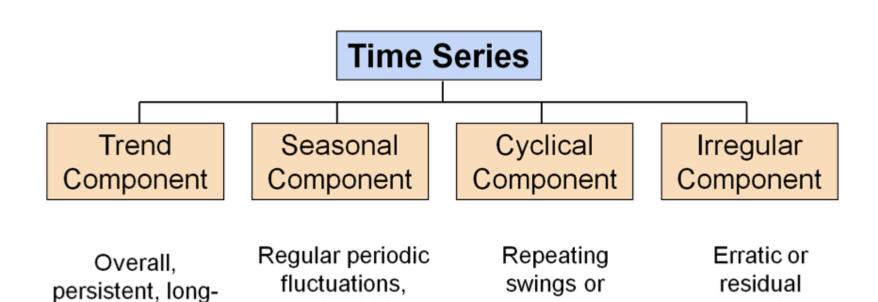




# Major Types of Variation (cont.)

usually within a

12-month period



movements over

more than one

year

fluctuations

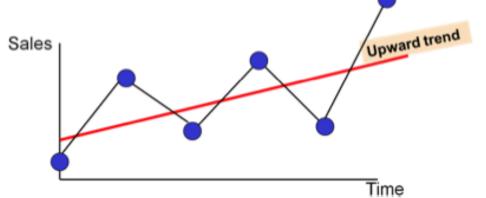


term movement

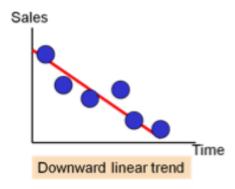


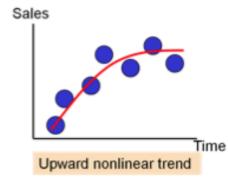
### Trend Component

- Long-run increase or decrease over time (overall upward or downward movement)
- Data taken over a long period of time



- Trend can be upward or downward
- Trend can be linear or non-linear





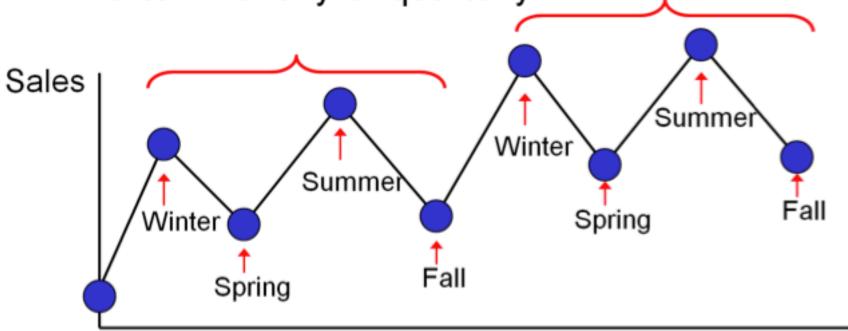




### Seasonal Component

- Short-term regular wave-like patterns
- Observed within 1 year

Often monthly or quarterly



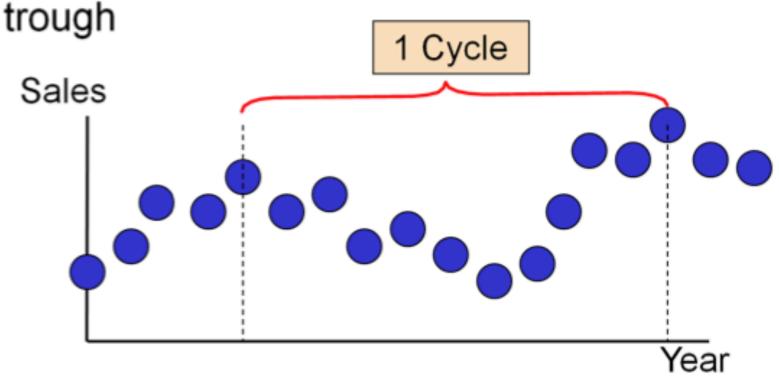
Time (Quarterly)





# Cyclical Component

- Long-term wave-like patterns
- Regularly occur but may vary in length
- Often measured peak to peak or trough to







### Irregular Component

- Unpredictable, random, "residual" fluctuations.
- "Noise" in the time series.
- Stochastic factors.

#### Does The Time-Series have a Trend Component?

- A time-series plot should help answer this question.
- Often it helps if you "smooth" the time series data to help answer this question.
- Two popular smoothing methods are moving averages and exponential smoothing.





### Outline

- ➤什么是时间序列分析(Time Series Analysis)
- ▶常见模型和基本手段
  - ▶数值变换(Transformations)
  - ➤ 趋势(Trend Component)
  - ▶季节性(Seasonal Component)
  - ➤ 周期性(Cyclical Component)
  - ➤ 随机性(Random Component)
- ▶简单示例
  - ➤ Modeling a Time Series
- ▶常用模型 ARMA
  - > AR (Auto Regressive)
  - ➤ MA (Moving Average)
  - > ARIMA (Auto Regressive Integrated Moving Average)
- > 应用示例
  - > Google Trends

# Modeling a Time Series

The simplest model is given by

$$X_t = \alpha + \beta t + \epsilon_t,$$

where  $\epsilon_t \sim N\left(0, \sigma_{\epsilon_t}^2\right)$ .

model = linear trend + noise.

The mean level at time t is given by  $\mu_t = E(X_t) = \alpha + \beta t$ .

#### Types of Trend

- Global trend
  - Polynomial: linear trend quadratic trend
  - Exponential
  - O Logistic





### How to describe Trend (Moving Average)

- ➤ 1. Curve Fitting
  - ➤ Assume a curve function and conduct regression over observed time series.

#### **Approaches to Describe Trend**

**1** Curve fitting  $\rightarrow$  Regression.

#### **Example**

Polynomial curve  $X_t = \alpha + \beta t \rightarrow X_t = 0.4 + 2t$ .

#### **Example**

**Gompertz** curve  $\log X_t = a + b \cdot r^t \rightarrow \log X_t = 3 + 2 \cdot 0.5^t$ .

#### **Example**

**Logistic** curve  $X_t = \frac{a}{1+be^{-ct}} \rightarrow X_t = \frac{0.7}{1+0.3e^{-2t}}$ .



### How to describe Trend (Moving Average)

### ➤ 2. Filtering (Moving Average)

> measure trend and remove seasonal variation

#### **Linear Filter**

$$Y_t = \sum_{r=-a}^{s} a_r \cdot X_{t+r}.$$

 $Y_t$  is the linear operator,  $a_r$  is the set of weights.

If  $\sum a_r = 1 \to \text{smooth out local fluctuations} \to \text{moving average}$ . MA is often symmetric s = q and  $a_j = a_{-j}$ .

#### Example

 $a_r=rac{1}{2q+1}$  for  $r=-q,\cdots,+q$ . The smoothed value of  $X_t$  is given by

$$Y_t = Sm(X_t) = \frac{1}{2q+1} \sum_{r=-q}^{q} X_{t+r}.$$

### How to describe Trend (Moving Average)

Used for smoothing a series of arithmetic means over time.

Result dependent upon choice of L=2q+1 (length of period for computing means).

#### **Example**

$$Y_t = Sm(X_t) = \frac{1}{5}(X_{t-2} + X_{t-1} + X_t + X_{t+1} + X_{t+2}).$$

First average:

$$Y_3 = MA(5) = \frac{X_1 + X_2 + X_3 + X_4 + X_5}{5}$$

Second average:

$$Y_4 = MA(5) = \frac{X_2 + X_3 + X_4 + X_5 + X_6}{5}$$



### Outline

- ➤ 什么是时间序列分析(Time Series Analysis)
- ▶常见模型和基本手段
  - ➤ 数值变换(Transformations)
  - ➤ 趋势(Trend Component)
  - ➤ 季节性(Seasonal Component)
  - ➤ 周期性(Cyclical Component)
  - ➤ 随机性(Random Component)
- ▶简单示例
  - ➤ Modeling a Time Series
- ➤ 常用模型 AR, MA, ARMA, ARIMA
  - > AR (Auto Regressive)
  - > MA (Moving Average)
  - ➤ ARMA (Auto Regressive Moving Average)
  - ➤ ARIMA (Auto Regressive Integrated Moving Average)

### **Basic Definitions**

➤ Stationary

#### **Strictly Stationary**

The overall behavior of random process  $X_t$  is described by a point distribution function of the process  $\{X_{t_1}, X_{t_2}, \cdots, X_{t_k}\}$  at finite number of points  $t_1, t_2, \cdots, t_k$  for any positive integer k. This function is

$$F_{t_1,t_2,\cdots,t_k}(X_1,X_2,\cdots,X_k) = P(X_{t_1} < X_1,\cdots,X_{t_k} < X_k).$$

#### Definition

A time series  $X_t$  is **strictly stationary** if  $\{X_{t_1}, X_{t_2}, \cdots, X_{t_k}\}$  and  $\{X_{t_1+\tau}, X_{t_2+\tau}, \cdots, X_{t_k+\tau}\}$  have the same point distribution for any positive integer  $n \geq 1$  and any integer  $\tau$   $(t_1, t_2, \cdots, t_n, \tau)$ , i.e. the joint distribution function is invariant under time shifts.



### Basic Definitions (cont.)

- ➤ Autocovariance (自协方差)
- ➤ Autocorrelation(自相关系数)
- The autocovariance function (acv.f.)  $\gamma_{t_1,t_2}$  or  $\gamma(t_1,t_2)$  of  $X_{t_1}$  with  $X_{t_2}$  is defined by

$$\gamma_{t_1,t_2} = E\left[ (X_{t_1} - \mu_{t_1})(X_{t_2} - \mu_{t_2}) \right]$$

$$= \int \int (X_1 - \mu_{t_1})(X_2 - \mu_{t_2}) \cdot f_{t_1,t_2}(X_1,X_2) \,\, dX_1 dX_2.$$

- When  $t=t_1=t_2$  we get  $Var(X_t)=\sigma_t^2$ .
- The autocorrelation function (ac.f.)  $\rho_{\tau}$  is defined by

$$\rho_{ au} = \frac{\gamma_{ au}}{\gamma_0}.$$





# Basic Definitions (cont.)

For the stationary stochastic process X(t) or  $X_t$  we have

$$ho_{ au}=rac{\gamma_{ au}}{\gamma_0}$$

- **1**  $\rho_0 = 1$ .
- ② Covariance is symmetric,  $\rho_{\tau} = \rho_{-\tau}$ .

$$\gamma_{\tau} = cov\left(X_{t}, X_{t+\tau}\right) = \gamma_{-\tau}.$$

Since  $X_t$  is stationary.

- **3**  $|\rho_{\tau}| \leq 1$ .
- A stochastic process ⇒ unique ac.f. The converse is not necessarily true (≠).





# Moving Average (MA) Process

> MA(q)

**3** Moving average processes MA(q):  $\{Z_t\} \sim IID(0, \sigma^2)$ .

$$X_t = \beta_0 Z_t + \beta_1 Z_{t-1} + \beta_2 Z_{t-2} + \dots + \beta_q Z_{t-q}.$$

We may rescale  $Z_t$  so that  $\beta_0 = 1$ .

#### Mean and Variance

$$E(X_t) = 0, \qquad Var(X_t) = \sigma_Z^2 \sum_{i=0}^q \beta_i^2.$$





# Moving Average (MA) Process (cont.)

> Feature of MA

For 
$$X_t = Z_t + \beta_1 Z_{t-1} + \beta_2 Z_{t-2} + \cdots + \beta_q Z_{t-q}$$
, show that:

$$\gamma_k = \left\{ egin{array}{ll} 0, & k > q. \\ \sigma^2 \sum_{i=0}^{q-k} eta_i eta_{i+k}, & k = 0, 1, \cdots, q. \\ \gamma_{-k}, & k < 0. \end{array} 
ight.$$

$$ho_k = \left\{ egin{array}{ll} 0, & k > q. \ 1, & k = 0. \ rac{\sum_{i=0}^{q-k}eta_ieta_{i+k}}{\sum_{i=0}^qeta_i^2}, & k = 1, 2, \cdots, q. \ 
ho_{-k} & k < 0. \end{array} 
ight.$$

• The ac.f. cuts off at lag q, a feature/benchmark of MA(q) process.





# Auto Regressive (AR) Process

> AR(p)

### 4 Autoregressive Process AR(p).

Let  $\{Z_t\} \stackrel{iid}{\sim} \left(0, \sigma_Z^2\right)$  be the white noise. The **autoregressive process** with parameter p is given by

$$X_t = \alpha_1 X_{t-1} + \dots + \alpha_p X_{t-p} + Z_t.$$





# Auto Regressive (AR) Process (cont.)

- Stationary of AR(p) process
  - The backward shift operator B is defined by  $BX_t = X_{t-1}$ .

•

$$B^2X_t = B(BX_t) = BX_{t-1} = X_{t-2}.$$

In general,

$$B^j X_t = X_{t-j}, \quad \forall \ j.$$

$$X_t = \alpha_1 X_{t-1} + \dots + \alpha_p X_{t-p} + Z_t.$$

$$X_t = (\alpha_1 B + \cdots + \alpha_p B^p) X_t + Z_t.$$

Let 
$$\phi(B) = 1 - \alpha_1 B - \cdots - \alpha_p B^p$$
. Then,

$$\phi(B)\cdot X_t=Z_t.$$

AR(p) process is stationary if the roots of  $\phi(B)=1-\alpha_1B-\cdots-\alpha_pB^p=0$  are all outside the unit circle.

### Auto Regressive Moving Average (ARMA) Process

➤ The ARMA(p,q) Process

A mixed autoregressive moving average process containing p AR terms and q MA terms is said to be an ARMA process of order (p,q), i.e. ARMA(p,q), and is given by

$$X_t = \alpha_1 X_{t-1} + \dots + \alpha_p X_{t-p} + Z_t + \beta_1 Z_{t-1} + \dots + \beta_q Z_{t-q}.$$

The ARMA(p,q) can be expressed in terms of the back-shift operator:

$$\phi(B)X_t = \theta(B)Z_t,$$

where 
$$\phi(B)=1-\alpha_1B-\cdots-\alpha_pB^p$$
, and  $\theta(B)=1+\beta_1B+\cdots+\beta_qB^q$ .





### Auto Regressive Integrated Moving Average (ARIMA) Process

➤ The ARIMA(p,d,q) Process

 $X_t$  is called an autoregressive integrated moving average (ARIMA) process of order (p,d,q) denoted  $\{X_t\} \sim ARIMA(p,d,q)$ , where  $d \geq 1$  is an integer if its d-th difference  $W_t = \nabla^d X_t = (1-B)^d X_t$  is an ARMA(p,q) process, i.e.

$$W_t = \alpha_1 W_{t-1} + \dots + \alpha_p W_{t-p} + Z_t + \dots + \beta_q Z_{t-q},$$

or

$$\phi(B) \cdot W_t = \theta(B) \cdot Z_t.$$

$$\phi_p(B) \cdot (1 - B)^d \cdot X_t = \theta_q(B) \cdot Z_t.$$





### Auto Regressive Integrated Moving Average (ARIMA) Process

> Why such a definition?

Most data in reality is non-stationary. If the time series is non-stationary in the mean, we can difference "differentiate" the series

$$\nabla X_t = (1 - B)X_t.$$

$$\nabla^2 X_t = (1 - B)^2 X_t.$$

i

$$\nabla^d X_t = (1 - B)^d X_t.$$





# Example of ARIMA(p,d,q)

Let  $W_t = (1-B)^d X_t$ . If  $W_t \sim ARMA(p,q)$  then  $X_t \sim ARIMA(p,d,q)$ .

$$\phi(B) \cdot (1-B)^d \cdot X_t = \theta(B) \cdot Z_t.$$

Note that B=1 is one of the roots with multiplicity d.

#### Example

Random Walk:  $X_t = X_{t-1} + Z_t \sim IID(\mu, \sigma^2)$ . This is an

ARIMA(0,1,0).

$$E(X_t) = t\mu \implies$$
 not stationary.

$$X_t = BX_t + Z_t$$
.

$$(1-B)^{d=1} \cdot X_t = Z_t.$$

$$\phi(B) = 1 = B^0 \to p = 0, \qquad \theta(B) = 1 = B^0 \to q = 0.$$





### Outline

- ➤ 什么是时间序列分析(Time Series Analysis)
- ▶常见模型和基本手段
  - ➤ 数值变换(Transformations)
  - ➤ 趋势(Trend Component)
  - ➤ 季节性(Seasonal Component)
  - ➤ 周期性(Cyclical Component)
  - ➤ 随机性(Random Component)
- ▶简单示例
  - ➤ Modeling a Time Series
- ➤ 常用模型 AR, MA, ARMA, ARIMA
  - > AR (Auto Regressive)
  - ➤ MA (Moving Average)
  - ➤ ARMA (Auto Regressive Moving Average)
  - ➤ ARIMA (Auto Regressive Integrated Moving Average)
- > 应用示例
  - ➤ Google Trends

### Problem Statement

- ➤ Government agencies and other organizations produce monthly reports on economic activity
  - ➤ House Sales, Automotive Sales, Unemployment
- Problems with reports
  - Compilation delay of several weeks
- Google Trends releases daily and weekly index of search queries by industry vertical
- Can Google Trends data help predict *current* economic activity?





### HongKong Visitor Arrival Statistics

### Visitors Arrival Statistics from Hong Kong Tourism Board

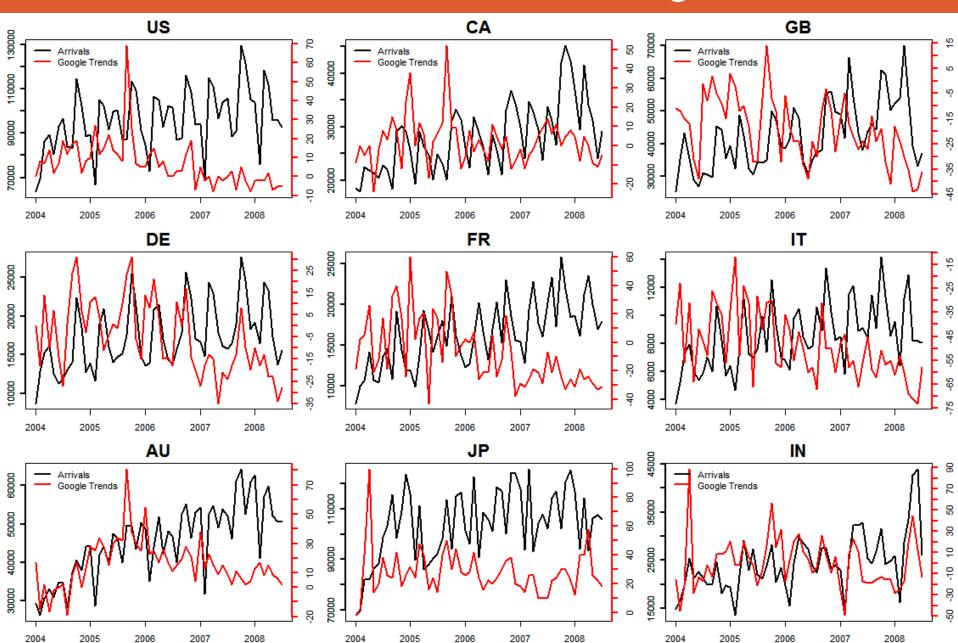
- Monthly summaries release with 1 month lag
- Reports Country/Territory of Residence of visitors
- Data available 2004-2008



#### **Google Trends Travel by Category**

- Hotels & Accommodations
- Air Travel
- Car Rental & Taxi Services
- Cruises & Charters
- Attractions & Activities
- Vacation Destinations
  - Australia
  - Caribbean Islands
  - Hawaii
  - Hong Kong
  - Las Vegas
  - Mexico
  - New York City
  - Orlando
- Adventure Travel
- Bus & Rail

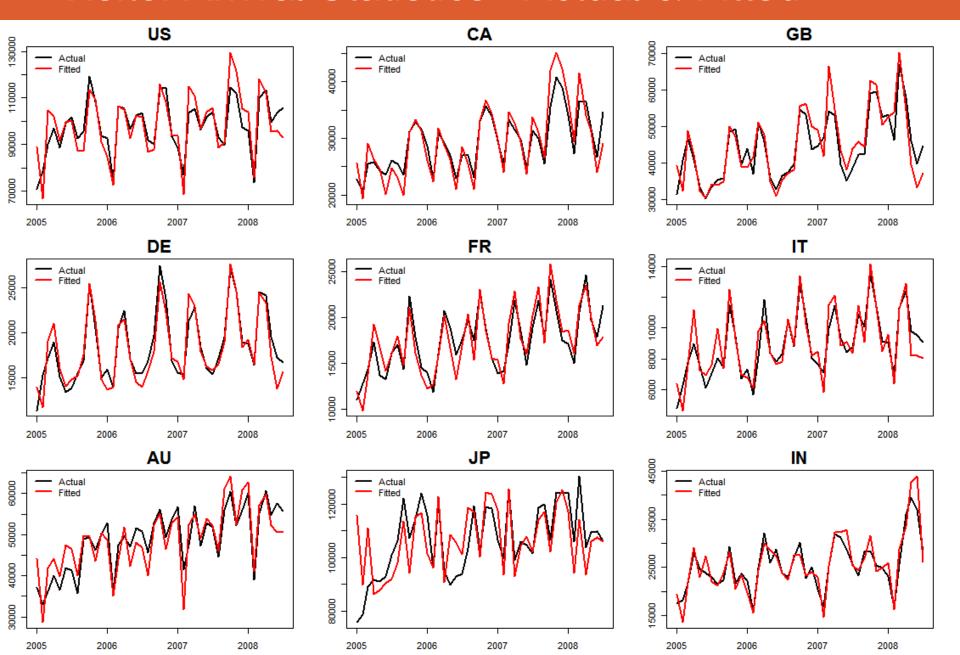
### Visitors Arrival Statistics vs. Google Trends



### **Analysis and Forecasting**

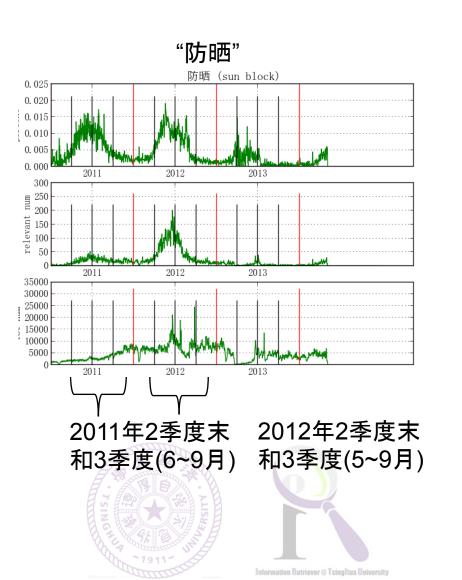
- ➤ Model: ARMA(12,0,1)
- $\log(Y_{i,t}) = 0.664 + 0.113 * \log(Y_{i,t-1}) + 0.828 * \log(Y_{i,t-12}) + 0.001 * X_{i,t,2} + 0.001 * X_{i,t,3} + 0.005 * FXrate_{i,t} + \eta_i, + e_{i,t}$   $e_{i,t} \sim N(0, 0.0938^2), \ \eta_i \sim N(0, 0.0228^2)$ 
  - > Y<sub>i.t</sub> = Arrival to Hong Kong at month t and from i-th country
  - $\succ X_{i,t,1}$  = Google Trend Search at 1st week of month t and from i-th country
  - $> X_{i,t,2}$  = Google Trend Search at 2nd week of month t and from i-th country
  - > X<sub>i,t,3</sub> = Google Trend Search at 3rd week of month t and from i-th country
  - ➤ FXrate <sub>i,t</sub> = Hong Kong Dollar per one unit of i-th country's local currency at month t. Average of first week's FX rate is used as a proxy to FX rate per each month.

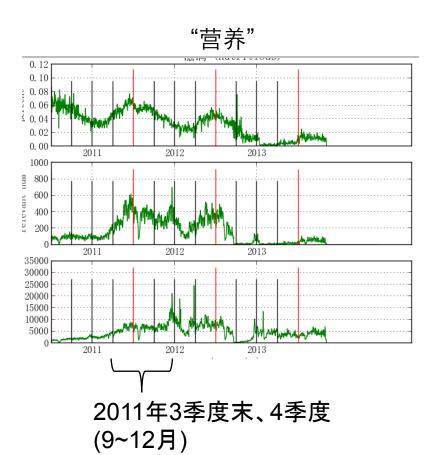
### Visitor Arrival Statistics - Actual & Fitted



### Share some of Our Finding

京东商城化妆品领域用户评论属性词频率的时间统计





### Time-Dependent Recommendation

- ▶用户对物品属性的关心可能具有时间性
  - ▶周期性(Cyclic)
  - ▶季节性(Seasonal)
- ▶目前的推荐策略
  - ▶根据用户的全部历史评论和评分构建用户模型
  - ▶过于依赖用户的全部或近期行为
  - ▶ 较少考虑特定产品领域内在的规律性(时间和周期性)
- > 考虑时间信息的个性化推荐
  - ▶将领域内的规律性与个性化相结合
  - ▶因人而异、因时而异





# Thanksi



