Stock Price Prediction using Hierarchical Network Structure

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Abstract

Stock price prediction using the conventional time series techniques often falls, sensitively reacting to irregular and external interventions propagated from global economical issues. To cope with this, we propose to employ a network structure for time series prediction. The network can include many time series indices within a unified framework and represent the relationship between two indices with various forms of connections such as simple, causal, and hierarchical links.

Keywords: Stock Price Prediction, Hierarchical Structure, Technical Indicators, Semi-Supervised Learning (SSL).

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Outline

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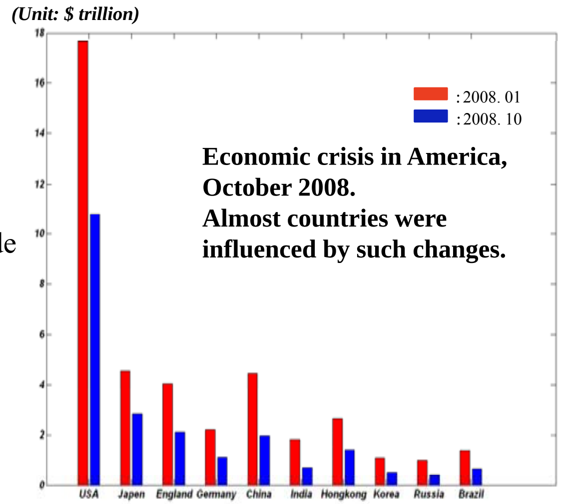
- Proposed Method
  - Hierarchical Relationship Implementation using Semi-Supervised Learning Graph
- Experiment
  - Data
  - Comparison of Accuracy(AUC)
    - $SSL_{\_HR}$(Proposed method)
    - SSL
    - SVM
    - ANN
  - Comparison of Profit(ROI)
- Conclusion

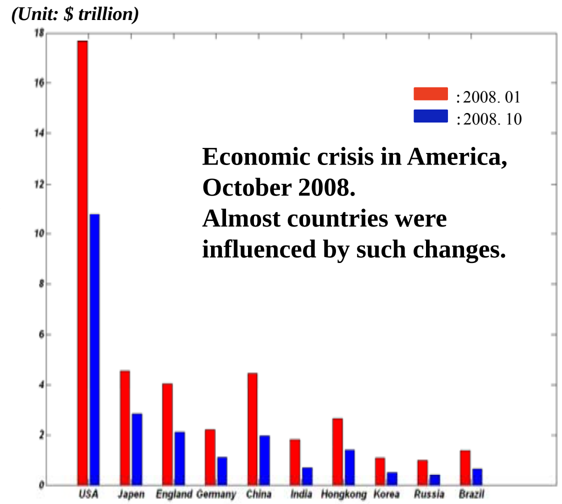
Motivation: Close Interrelation among Stock Markets

- **Sudden fluctuation**
  - Stock prices represent sudden fluctuations according to worldwide close relations.



Motivation: Close Interrelation among Stock Markets

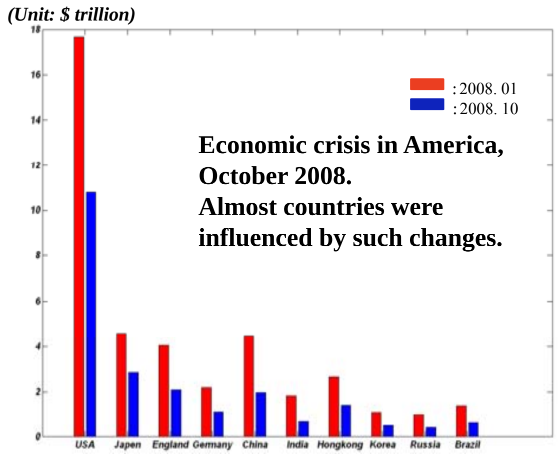
- **Sudden fluctuation**
  - Such fluctuations significantly affect the economy of the countries in the world as a huge scale.



Motivation: Close Interrelation among Stock Markets

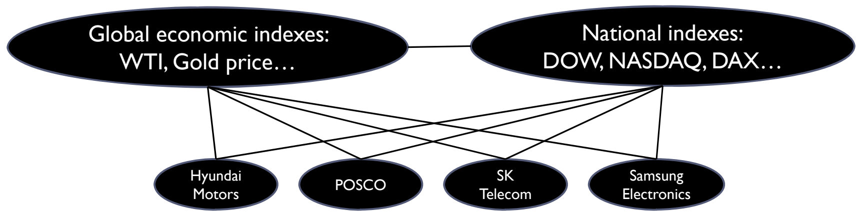
➢ Interrelation importance with major stock markets

- Therefore, it is very important to use not only domestic economy situations but also stock price indexes in world major stock markets for predicting ups and downs in domestic stock price indexes.



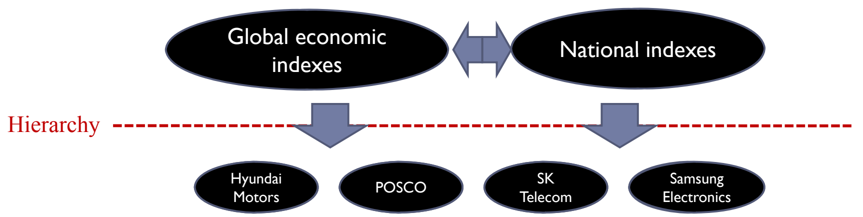
Motivation: Hierarchical Structure

- There is a certain relationship between domestic individual stock prices and other countries' stock information and economy indexes.



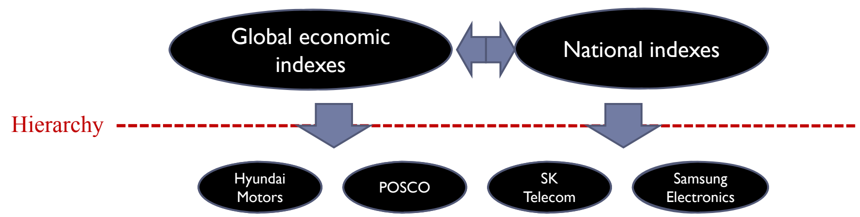
Motivation: Hierarchical Structure

- In addition, a causal hierarchical structure between economy and various financial indexes also exists.
  - ex) Global indexes such as CD interests, gold prices, exchange rates, and oil prices affect stock markets in most countries and that leads to decrease in domestic individual stock prices.



Motivation: Hierarchical Structure

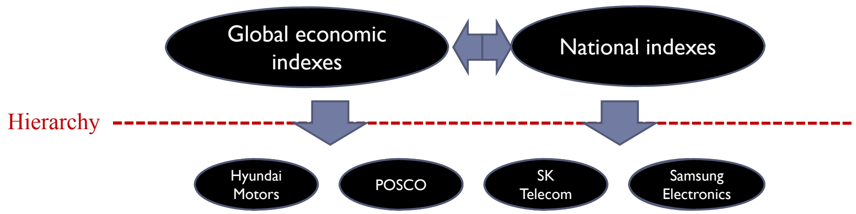
- Therefore, we can say that the correlation between the economy and national indexes and the domestic individual stock prices is not a mutually equal but a hierarchical structure.



Motivation: Hierarchical Structure Advantage

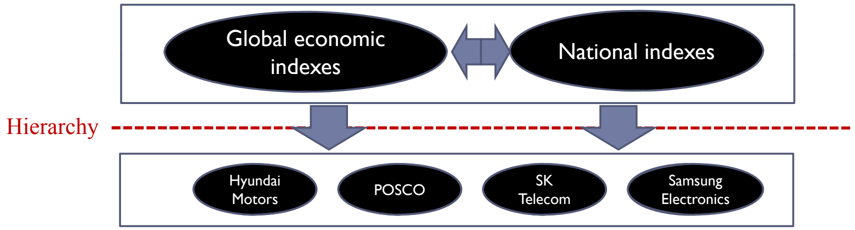
- Advantages in the hierarchical structure
  - Advantages in the hierarchical structure represent a simultaneous consideration for both the microscopic analysis of national and social figures and the analysis in and between hierarchies.

    - As if it shows a general overview for observing geographical features to users by varying its scale in the Google-map.



Motivation: Challenge

- In this paper, we propose a domestic individual stock price prediction method by considering different national and economy indexes interrelation using hierarchical structure.

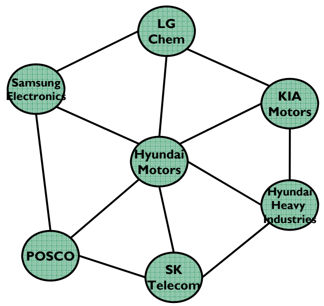


Proposed Method:

Hierarchical Relationship Implementation using Semi-Supervised Learning Graph

Method: Semi-Supervised Learning Overview

- Semi-Supervised Learning



a data point

the similarity between data points

$$w_{ij} = \begin{cases} \exp\left(-\frac{(x_i - x_j)^T (x_i - x_j)}{\sigma^2}\right) & \textit{if} \quad i \sim j, \\ 0 & \textit{otherwise} \end{cases}$$

k-nearest neighbor

Method: Semi-Supervised Learning Overview

- Objective function

$$\boxed{\min_f (f-y)^T (f-y) + \mu f^T L f}$$

$$y = (y_1, \cdots, y_l, 0, \cdots, 0)^T \quad y_l \in \{-1, 1\} \quad y_u \in \{0\}$$

$$L = D - W \quad d_i = \sum_j w_{ij} \quad D = diag(d_i)$$

  - **Loss condition**: in labeled nodes, final output should be closed to the given label.
  - **Smoothness condition**: final output should not be too different from the adjacent node's output.

- Solution

$$\boxed{f = (I + \mu L)^{-1} y}$$

$$f = (f_1, \cdots, f_l, f_{l+1}, \cdots, f_{n=l+u})^T$$

Method: Semi-Supervised Learning Overview

1. How to make Labels?

2. How to make similarity matrix?

Method: Semi-Supervised Learning Overview

- Objective function

$$\boxed{\min_f (f-y)^T (f-y) + \mu f^T L f}$$

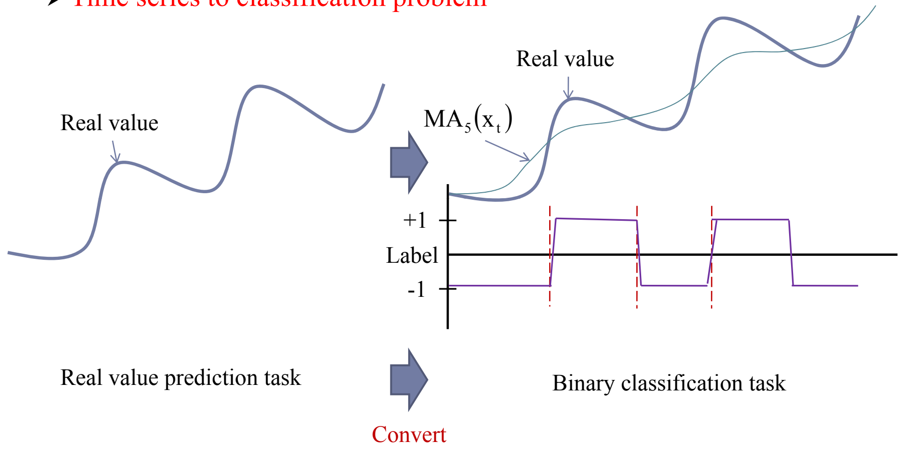
$$\boxed{y_l \in \{-1, 1\}}$$

Semi-Supervised learning is classification method.
But time series data is continuous.

How to apply classification rule to continuous data?

Method: Semi-Supervised Learning Overview

- Time series to classification problem

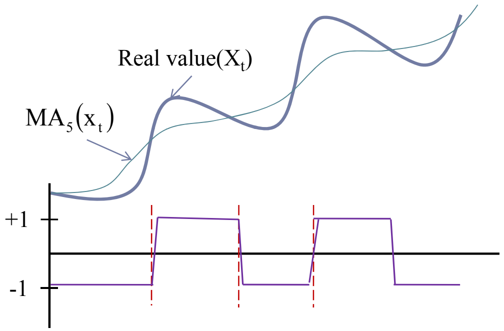


Method: Semi-Supervised Learning Overview

- How to Make Labels?

How to Make Labels?

$$y = sign(X_t - MA_5(X_t))$$



Method: Semi-Supervised Learning Overview

- Label Interpretation

Interpretation

$$\text{sign}\ (X_t - MA_5(X_t)) > 0,$$

$$X_t - MA_5(X_t),$$

$$where\ \ MA_k(X_t) = \frac{1}{k}(X_t) + \frac{k-1}{k} MA_k(X_{t-1})$$

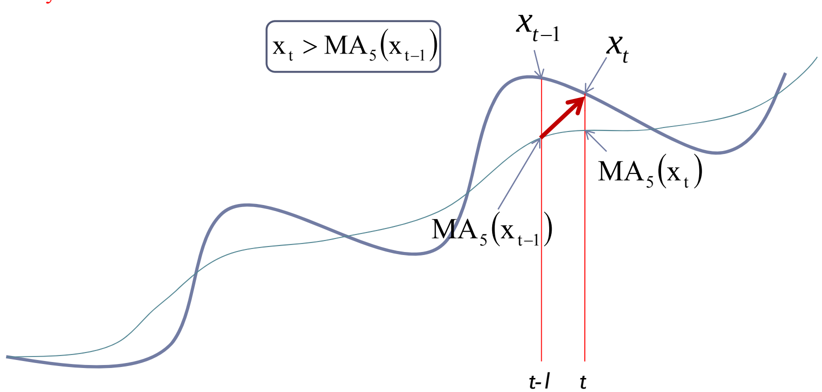
$$X_t > \frac{1}{3} X_t + \frac{2}{3} MA_5(X_t),$$

$$X_t > MA_5(X_{t-1})$$

Method: Semi-Supervised Learning Overview

- Label Interpretation

The result implies,
" The price of today will increase relatively to the MA(moving average) of the previous five days."

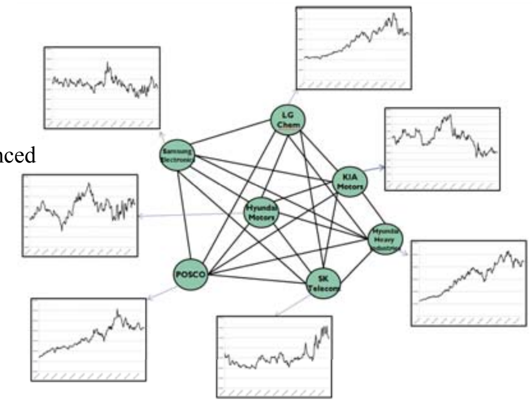


Method: Semi-Supervised Learning Overview

- How to make similarity

- Graph Representation

- SSL performance are influenced similarity matrix



Method: Semi-Supervised Learning Overview

➢ Similarity matrix

	Hyundai motors	POSCO	LG Chem	SK Telecom	…
Hyundai motors	-	-	-	-	-
POSCO	-	-	-	-	-
LG Chem	-	-	-	-	-
SK Telecom	-	-	-	-	-
…	-	-	-	-	-

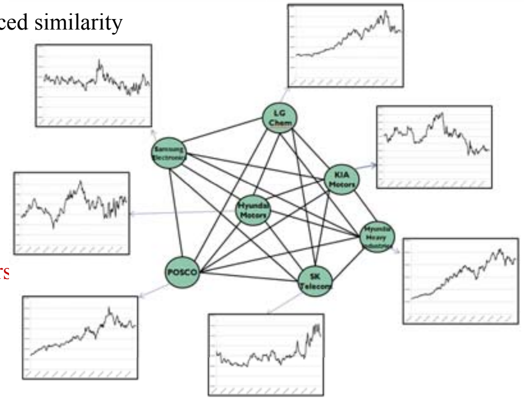
Method: Semi-Supervised Learning Overview

➢ Graph Representation

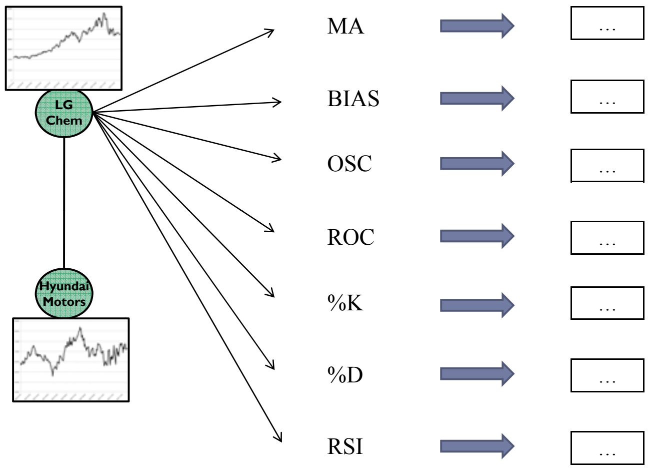
SSL performance are influenced similarity matrix

Time series data have noise

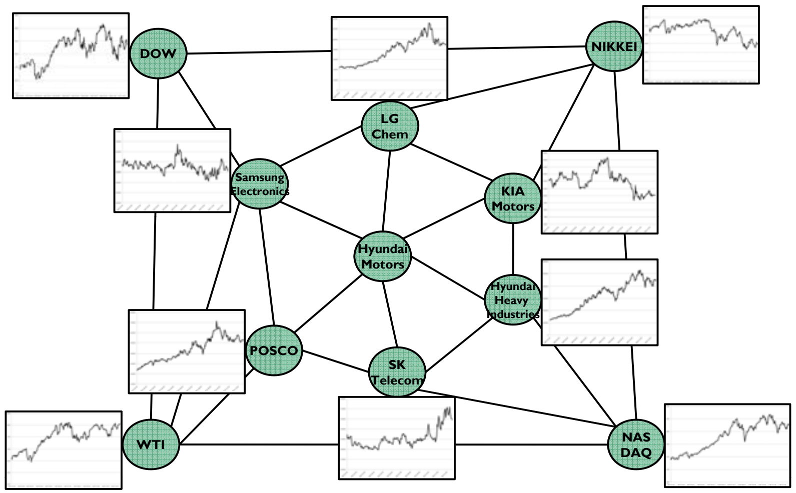
- Original data transforms into Technical Indicators
- Building similarity matrix "W" using Technical Indicators

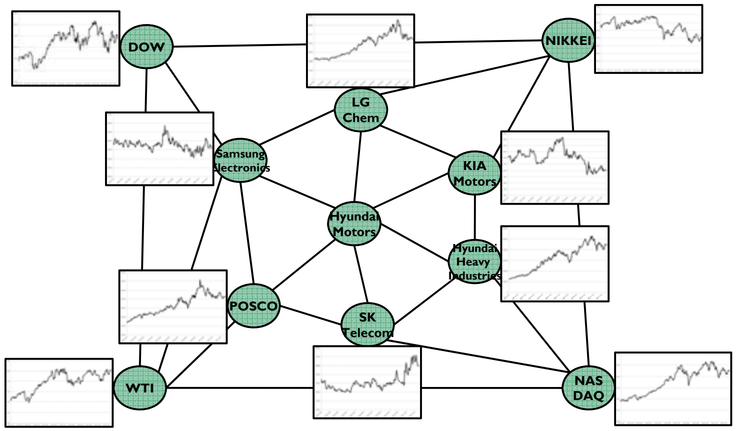


Method: Technical Indicators Transformation

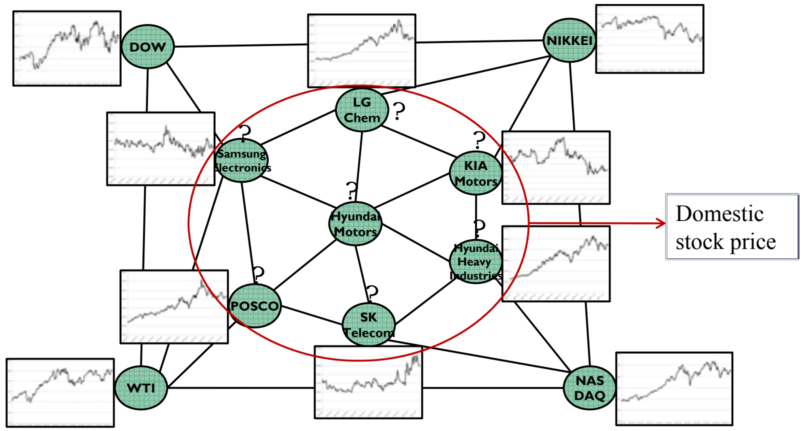


Method: Original Structure

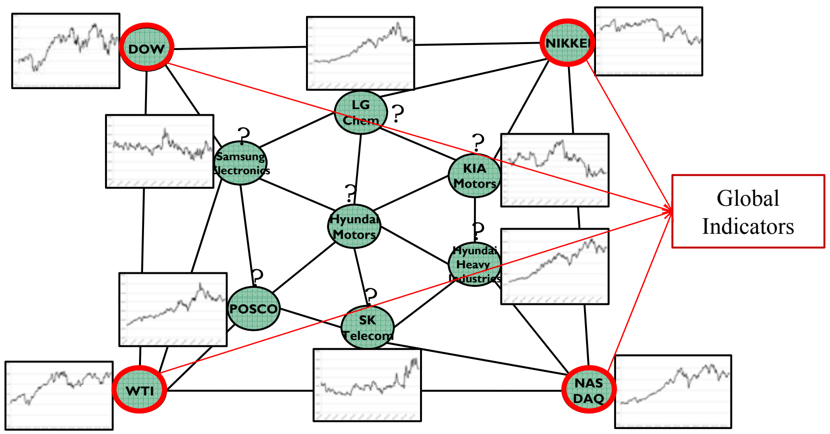




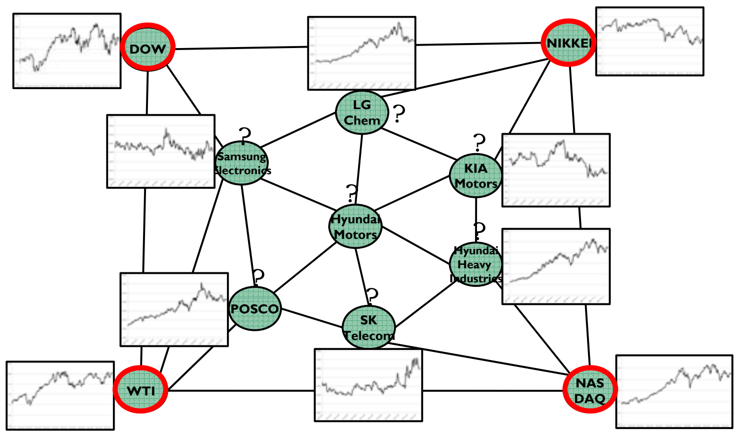
It is necessary to get some information from the stock prices of subject company like POSCO, SK Telecom, and so on for predicting that of Hyundai Motors.



But it shows some practical difficulties for getting such information because the information in real-time of these company is varied simultaneously.

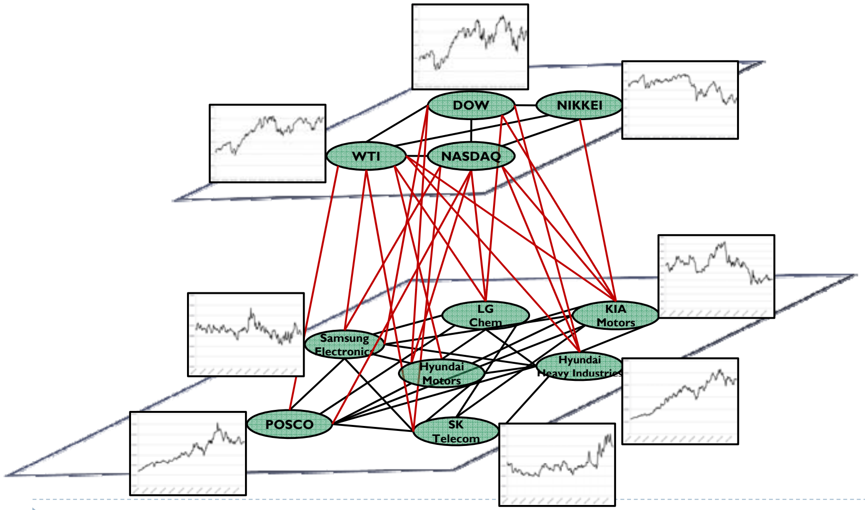


Therefore, the information of Hyundai Motors is to be carried out using some indexes, which can be obtained such as Dow, Nikkei, and WTI.

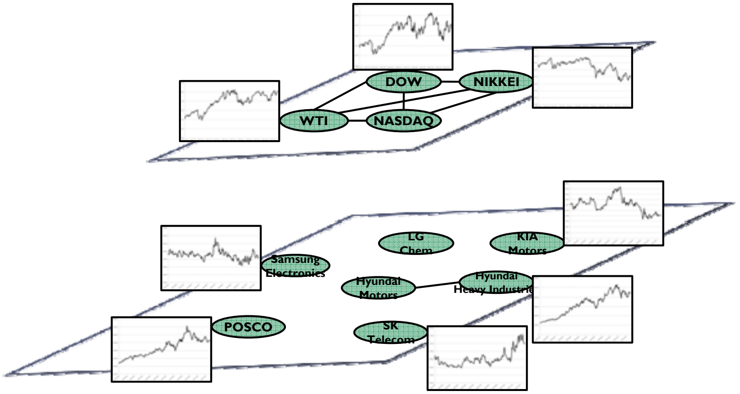


But such nodes like Dow and Nikkei in a planar structure make difficult to influence on Hyundai Motors directly.

Method: Hierarchical Structure

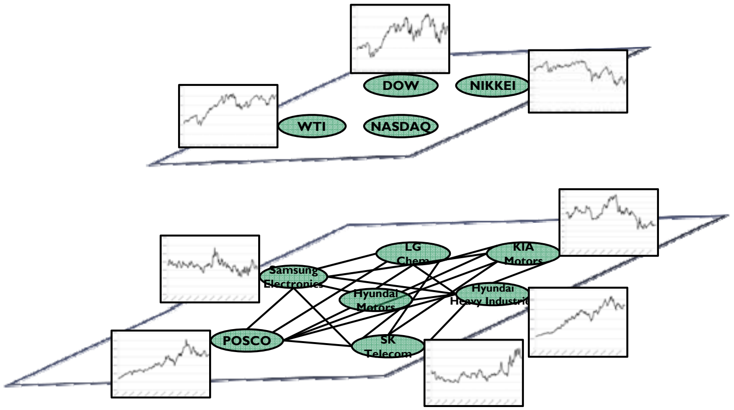


Method: Hierarchical Structure



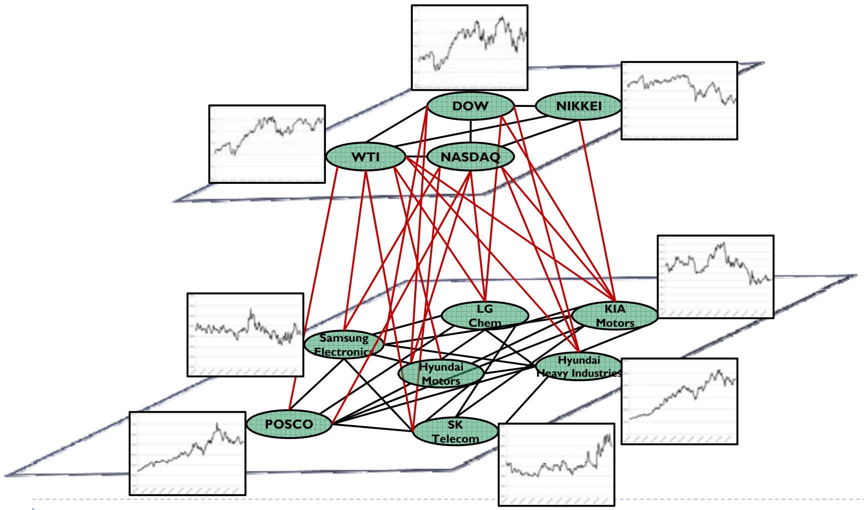
In a upper layer, consist of national and economy indexes which are DOW, NASDAQ, NIKKEI, WTI and so on.

Method: Hierarchical Structure

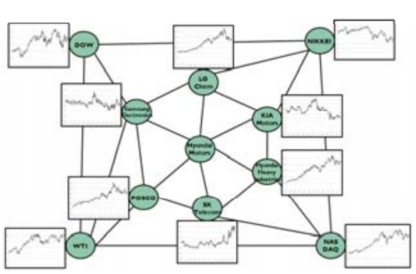


A lower layer consist of company indexes, which are POSCO, SK telecom and so on.

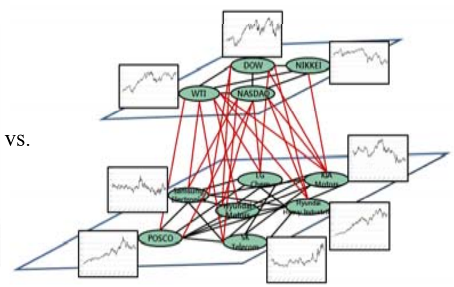
Method: Hierarchical Structure



Method: Original Structure vs. Hierarchical Structure



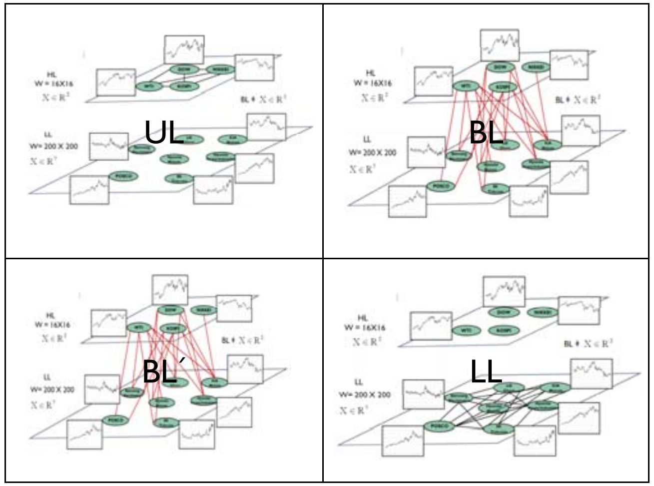
vs.



Original SSL structure did not directly incorporate relations between national, economic indexes and company indexes.

Hierarchical structure formulation can be directly affects nation and economy indexes to company indexes.

Method: Hierarchical Structure Similarity Matrix



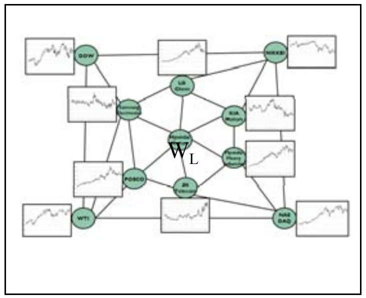
Method: Hierarchical Structure Similarity Matrix

$$\alpha_{HL}\begin{bmatrix} W_{UL} \\ 16 \text{ X } 16 & 0 \\ 0 & 0 \end{bmatrix} + \alpha_{BL}\begin{bmatrix} 0 & W_{BL} \\ W_{BL}' & 0 \end{bmatrix} + \alpha_{LL}\begin{bmatrix} 0 & 0 \\ 0 & W_{BL} \end{bmatrix}$$

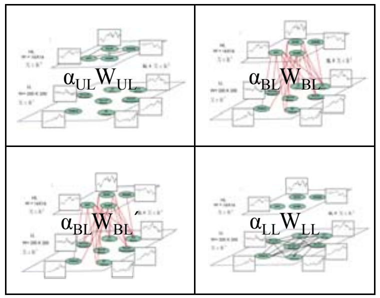
$$= \begin{bmatrix} \alpha_{UL}W_{UL} & \alpha_{BL}W_{BL} \\ \alpha_{BL}W_{BL}' & \alpha_{LL}W_{LL} \end{bmatrix}$$

Method: Original Similarity Matrix vs. Hierarchical Structure Similarity Matrix

- Plain Similarity Matrix vs. Hierarchical Similarity Matrix



vs.



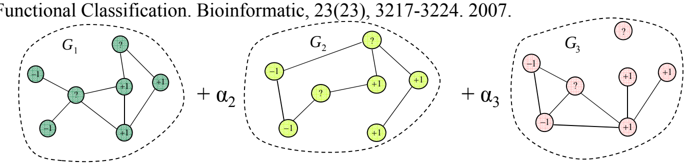
- Not consider the hierarchical structure
- Considers the hierarchical structure using Global Indicators

Method: Implementation of Hierarchical Structure

➢ Graph Combination

<Reference>

•Shin, H., et al.,. Graph Sharpening plus Graph Integration: A Synergy that Improves Protein Functional Classification. Bioinformatic, 23(23), 3217-3224. 2007.

$L(\alpha) = \alpha_1$  $+ \alpha_2 \quad + \alpha_3$

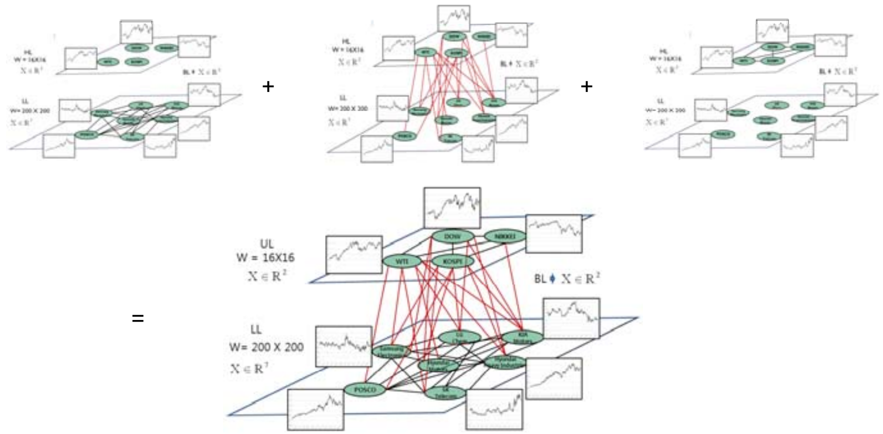
$$\min_{\alpha} \; y^T (I + \sum_{k=1}^{m} \alpha_k L_k)^{-1} y$$

$$f = (I + \sum_{k=1}^{m} \alpha_k L_k)^{-1} y \qquad (1)$$

m : Number of graphs

L_k: Graph Laplacian

Method: Implementation of Hierarchical Structure



The hierarchical structure attempts optimization for each layer by letting the similarity between company and between nation.

Method: Implementation of Hierarchical Structure

$\alpha_{LL} L_{LL} \quad + \quad \alpha_{BL} L_{BL} \quad + \quad \alpha_{UL} L_{UL}$

$$\min_{\alpha, f} \; (f - y)^T (f - y) + \sum_{k \in \{LL, BL, UL\}} \alpha_k f^T L_k f$$

$$f = (I + \sum_{k \in \{LL, BL, UL\}} \alpha_k L_k)^{-1} y \qquad (2)$$

f : company price up / down

Method: Implementation of Hierarchical Structure

- The dual problem then leads to

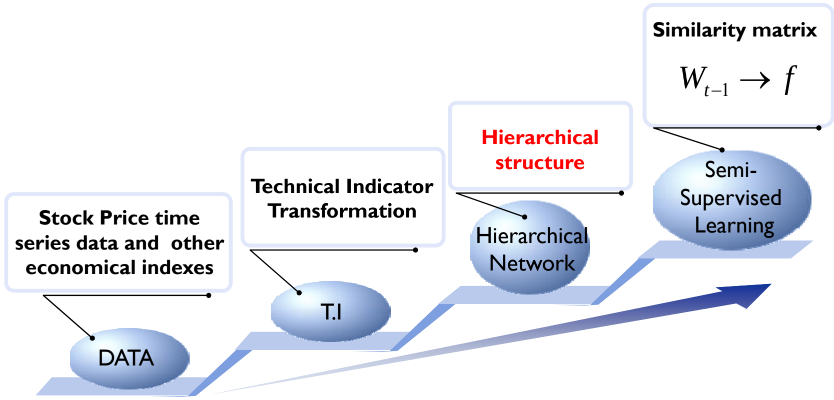
$$\min_{\alpha} y^T (I + \sum_{k=\{LL,BL,UL\}} \alpha_k f^T L_k f)^{-1} y \equiv d(\alpha)$$

$$0 \le \alpha_k \le c_2, \quad \sum_{k=\{LL,BL,UL\}} \alpha_k \le c_1 \qquad (2)$$

<Reference>

• Shin, H., et al.,. Graph Sharpening plus Graph Integration: A Synergy that Improves Protein Functional Classification. Bioinformatic, 23(23), 3217-3224. 2007.

Methods: Procedure



<Reference>

- Shin, H., et al.,. Graph Sharpening plus Graph Integration: A Synergy that Improves Protein Functional Classification. Bioinformatic, 23(23), 3217-3224. 2007.
- Shin, H., et al., Oil Price Prediction From Influence Propagation. Proc. of Annual Meeting of Institute for operations Research and the Management Sciences(INFOMS 2009), pp.370, San Diego, USA, 2009.

Experiment

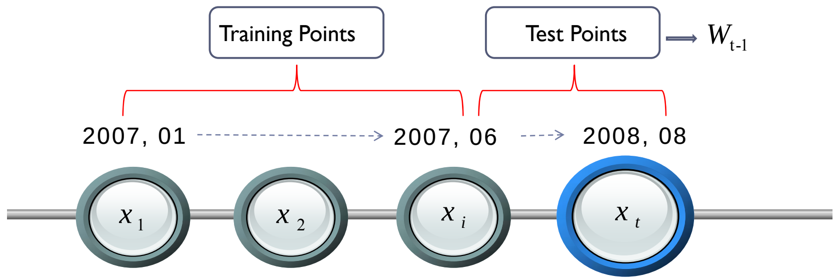
Experiment: Data

Upper Layer data(16)	DOW, NASDAQ, NIKKEI, HSI, SSE, TSEC, FTSE, DAX, CAC, BSE_SENSEX, IBOVESPA, AORD, KOSPI, Exchange_rate(KRW-USD), WTI, CD(Certificate of Deposit)
Low Layer data(200)	Kospi_200_company(POSCO, LG Chem, Samsung Electronics, Hyundai Motors, KIA Motors, Hyundai Heavy Industries, SK Telecom…)

Total all kinds data - 216

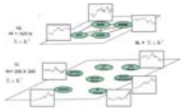
Period: 2007.01 ~ 2008.08
Number of time point: Daily data point- 403

Experiment: Time Setting

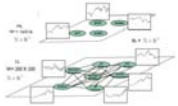


Experiment: Variables

- Upper Layer: Closing Price, Trading Volume.



- Lower Layer: Closing Price, Trading Volume, Trading Value, PER, Dividend Yield, Capital stock, Listed shares.



- Between Layer: Closing Price, Trading Volume.

Experiment: Variables

- Input variable :

  Similarity Matrix calculated by TIs of Closing Price, Trading Volume, Trading Value, PER, Dividend Yield, Capital stock and Listed shares.

	Hyunda i motors	POSCO	LG Chem	SK Telecom	…
Hyundai motors	-	-	-	-	-
POSCO	-	-	-	-	-
LG Chem	-	-	-	-	-
SK Telecom	-	-	-	-	-
…	-	-	-	-	-

- Output variable :

  Label of **Closing Price**

  calculated by $X_t = sign(X_t - MA_5(X_t))$ ⇒ $X_t =$ up(+1)/down(-1)

Experiment: Variables

➢ Variables Definition

- PER(price-to-earnings ratio): $PER = \frac{\text{Price per Share}}{\text{Annual Earnings per Share}}$
- Closing Price: Price of the last transaction of a particular stock completed during a day's trading session on an exchange.
- Trading Volume: This is the daily number of shares of a security that change hands between a buyer and a seller. Also known as volume traded. Also see Up volume and Down volume.
- Trading Value: Trading Volume X (open_price+close_price)/2

Experiment: Variables

➢ Variables Definition

- Dividend Yield: The dividend yield or the dividend-price ratio on a company stock is the company's annual dividend payments divided by its market cap, or the dividend per share divided by the price per share. It is often expressed as a percentage. Its reciprocal is the Price/Dividend ratio.
- Capital Stock Listed: Money or Financial capital.
- Listed Shares: Listed stocks number

Experiment: Model Comparison

SSL$_{_HR}$: Hierarchical Structure(Relation) Semi-Supervised Learning

SSL : Plain Semi-Supervised Learning

ANN : Artificial Neural Network

SVM : Support Vector Machine (RBF)

Experiment: Parameter Selection

- Hierarchical graph combination model parameter selection
  K={3, 4, 5, 6, 7, 8, 9, 10, 15, 20}, μ(c1)={0.01, 0.05, 0.07, 0.1, 0.5, 0.75, 1, 10, 100},
  c_{2ratio} ={0.35, 0.5, 0.75, 1}
  - Best parameter combination K={15}, μ(c_1)={0.01}, $c_2 = c_1$ X c_{2ratio},

- Semi-Supervised Learning(SSL) model parameter selection
  K={3, 4, 5, 6, 7, 8, 9, 10, 15, 20} , μ(c1)={0.01, 0.05, 0.07, 0.1, 0.5, 0.75, 1, 10, 100}
  - Best parameter combination K={15}, μ={0.01}

- Support Vector Machine(SVM) model parameter selection
  Gamma= {0.01, 0.1, 1, 10, 100, 1000}
  - Best parameter combination Gamma= {0.1}

- Artificial Neural Network(ANN) model parameter selection
  Hidden node= {1, 2, 3, 4, 5, 6, 7}
  - Best parameter combination Hidden node= {4}

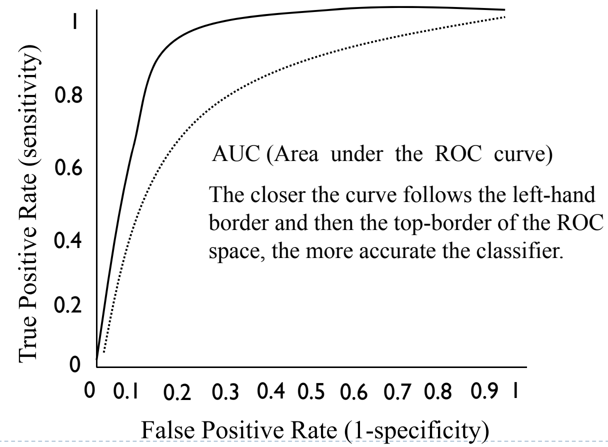
Experiment: Measurement

- Comparison of Accuracy(AUC: Area under curve)

- Comparison of Profit: ROI(Return On Investment)

Experiment: Measurement(AUC)

- Comparison of Accuracy(AUC: Area under curve)



Experiment: Measurement(ROI)

- Comparison of Profit: ROI(Return On Investment)

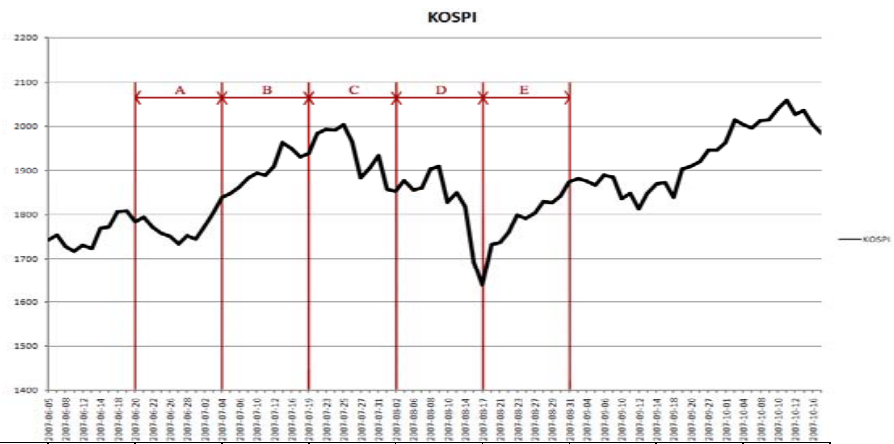
$$\frac{sell\ order\ \ price - buy\ order\ \ price}{buy\ order\ \ price}$$

Result

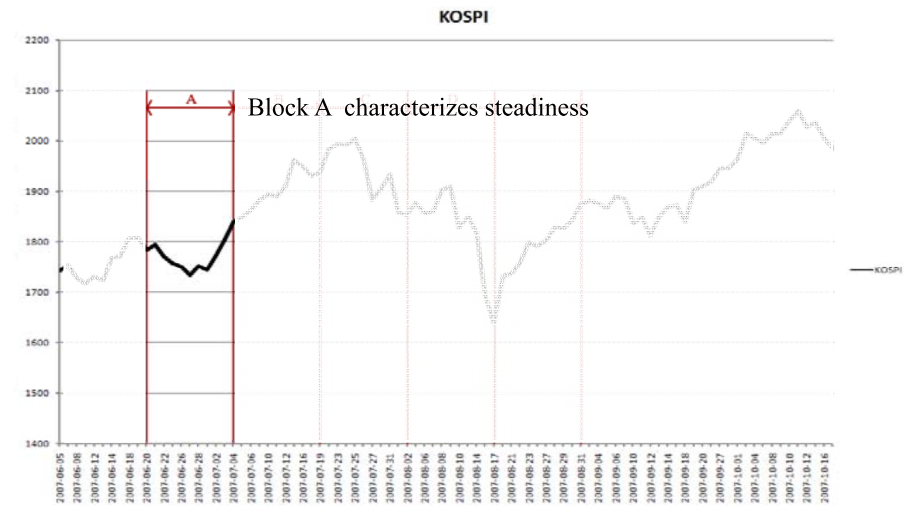
1. Accuracy based on AUC
2. Profit based on ROI

Result

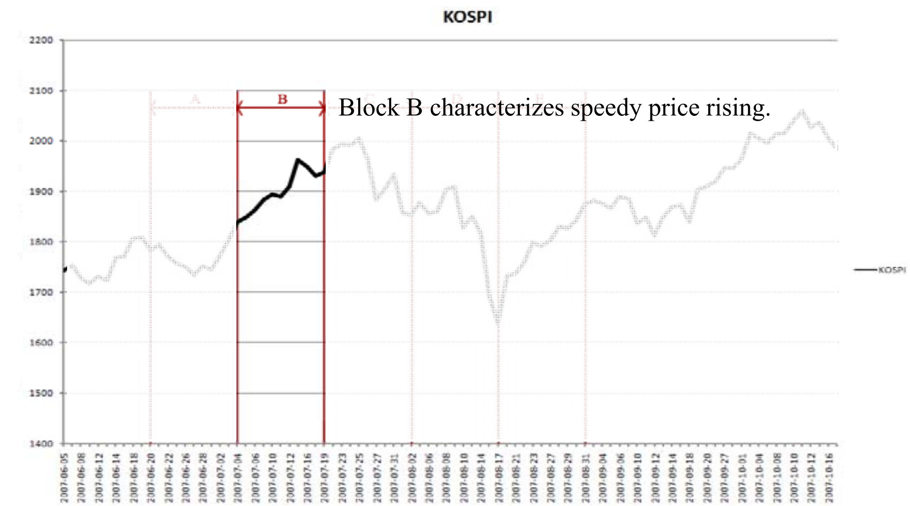
1. Accuracy based on AUC
2. Profit based on ROI



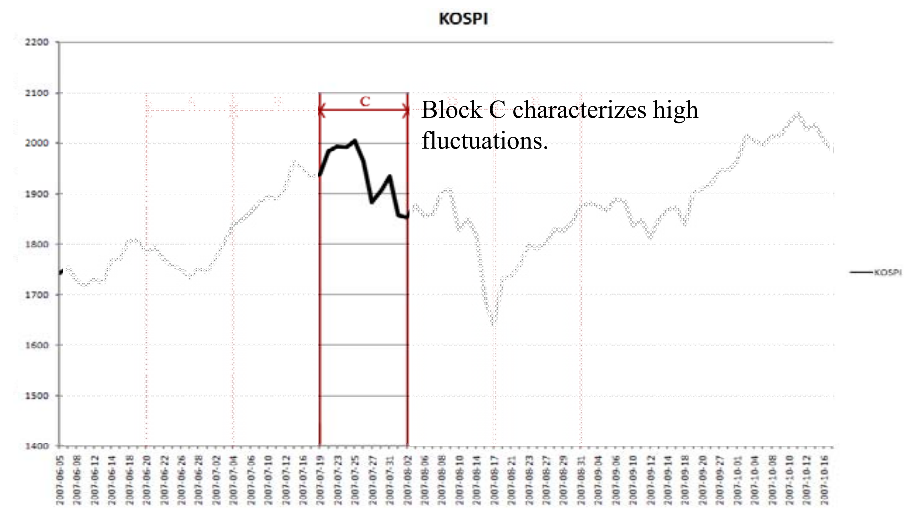
Time Point		07-06-05~ 07-06-19	07-06-20~ 07-07-03	07-07-04~ 07-07-18	07-07-19~ 07-08-01	07-08-02~ 07-08-16	07-08-17~ 07-08-30	07-08-31~ 07-09-13	07-09-14~ 07-10-02	07-10-04~ 07-10-17
SSL_HR	AUC	**0.7300**	**0.7580**	**0.7673**	**0.7714**	**0.7844**	**0.8377**	**0.8396**	**0.7441**	**0.8080**
SSL_Sum	AUC	0.7144	0.7304	0.7055	0.7202	0.6959	0.7925	0.7890	0.7261	0.7926
SVM	AUC	0.5444	0.5469	0.5214	0.5164	0.5380	0.8161	0.5403	0.6229	0.6303
ANN	AUC	0.5030	0.5063	0.5007	0.5012	0.5012	0.5204	0.5030	0.5039	0.5224



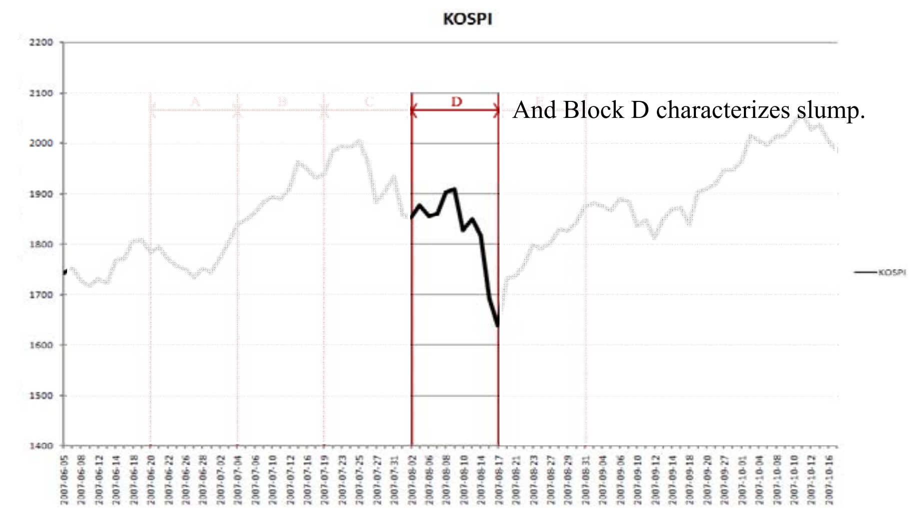
SSL_HR	AUC	**0.7580**
SSL	AUC	0.7304
SVM	AUC	0.5469
ANN	AUC	0.5063



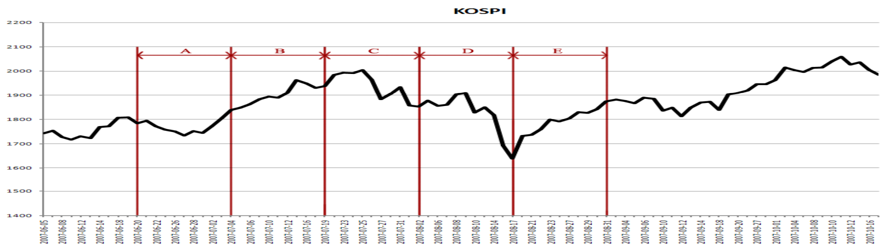
SSL_HR	AUC	**0.7673**
SSL	AUC	0.7055
SVM	AUC	0.5214
ANN	AUC	0.5007



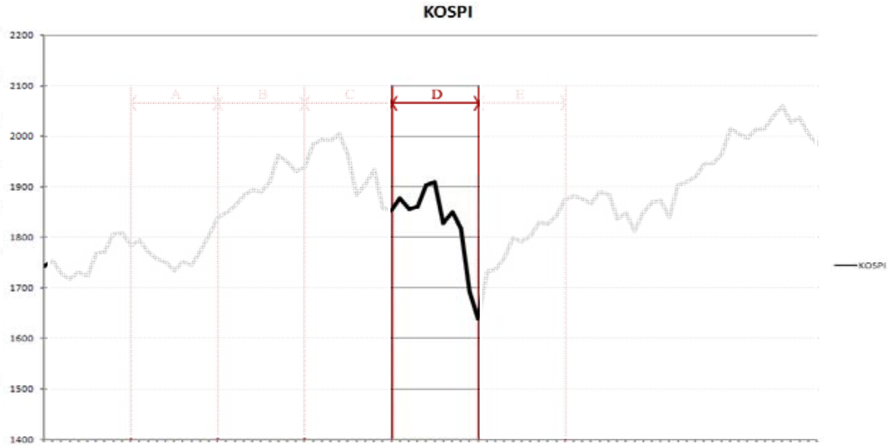
SSL_HR	AUC	**0.7714**
SSL	AUC	0.7202
SVM	AUC	0.5164
ANN	AUC	0.5012



SSL_HR	AUC	**0.7844**
SSL	AUC	0.6959
SVM	AUC	0.5380
ANN	AUC	0.5012



Time Point		07-06-05~ 07-06-19	07-06-20~ 07-07-03	07-07-04~ 07-07-18	07-07-19~ 07-08-01	07-08-02~ 07-08-16	07-08-17~ 07-08-30	07-08-31~ 07-09-13	07-09-14~ 07-10-02	07-10-04~ 07-10-17
SSL_HR	AUC	**0.7300**	**0.7580**	**0.7673**	**0.7714**	**0.7844**	**0.8377**	**0.8396**	**0.7441**	**0.8080**
SSL	AUC	0.7144	0.7304	0.7055	0.7202	0.6959	0.7925	0.7890	0.7261	0.7926
SVM	AUC	0.5444	0.5469	0.5214	0.5164	0.5380	0.8161	0.5403	0.6229	0.6303
ANN	AUC	0.5030	0.5063	0.5007	0.5012	0.5012	0.5204	0.5030	0.5039	0.5224

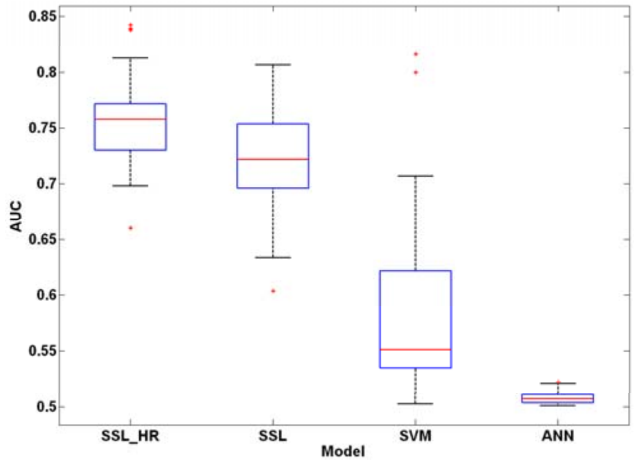


AUC: Block D

SSL_HR	**0.7844**
SSL	0.6959
SVM	0.5380
ANN	0.5012

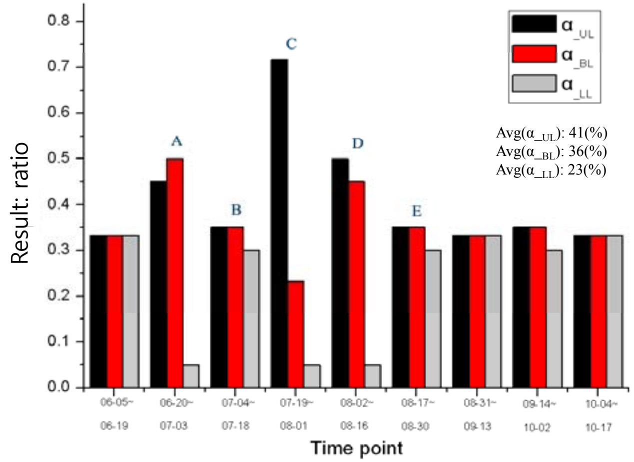
In particular, block D represented a sudden falling down as the crisis of pre-warning subprime mortgage loan.
The AUC at that time represented an excellent prediction of the hierarchical SSL relatively compared to other models

Result: Accuracy based on AUC



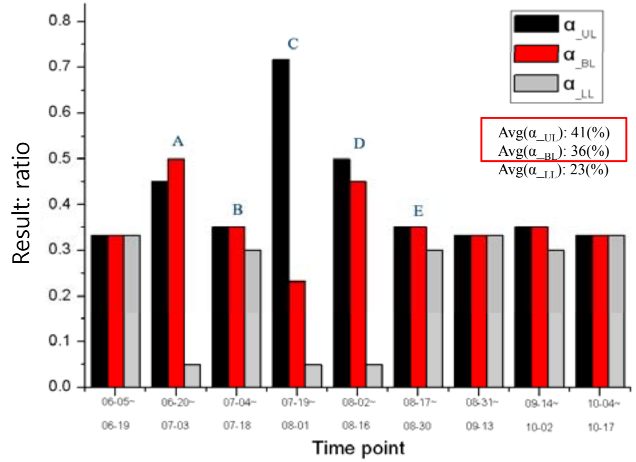
The proposed method-SSL$_{_HR}$ outperforms other models for most of time point.

Result: Significance of Layer weights(UL, BL, LL)



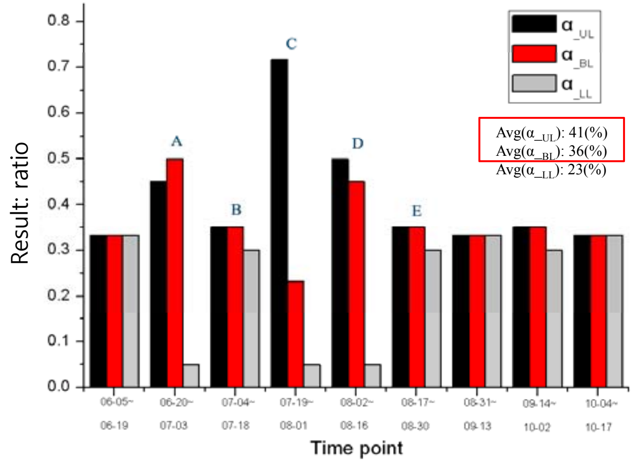
The coefficient values for each layer and how important they are.

Result: Significance of Layer weights(UL, BL, LL)



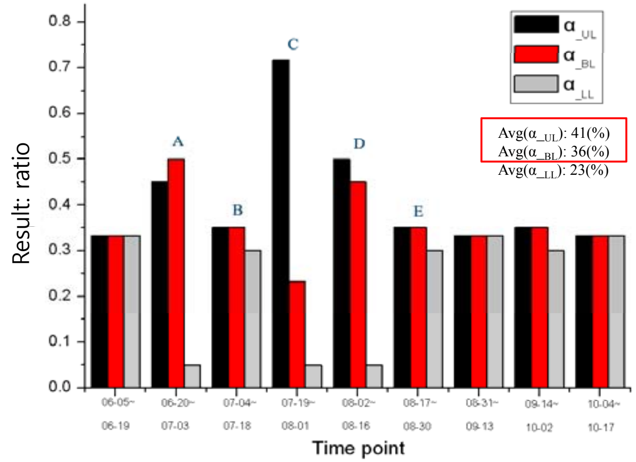
The Influences black bar and red bar represent a higher level.

Result: Significance of Layer weights(UL, BL, LL)



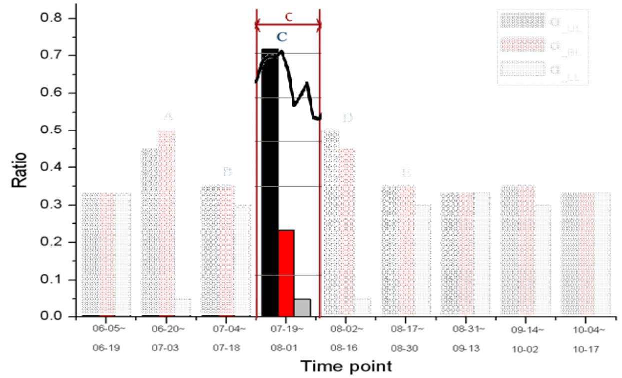
It means that in the prediction of the company's stock prices as mentioned the influence between nations throughout the world shows a higher level on the prices than that of between company.

Result: Significance of Layer weights(UL, BL, LL)



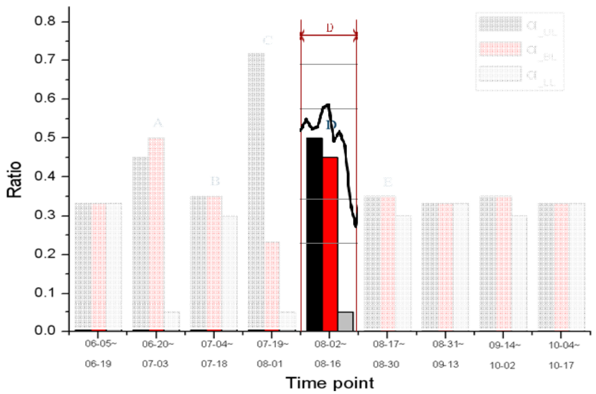
Specially, the upper layer and between layer are highly influenced in the block where the stock price has the tendency to fall.

Result: Significance of Layer weights(UL, BL, LL)



When the price show significant fluctuation as in block "C" and "D", the influence of upper layer(α_{UL}) and from upper layer to lower layer(α_{BL}) plays a critical role of prediction.

Result: Significance of Layer weights(UL, BL, LL)

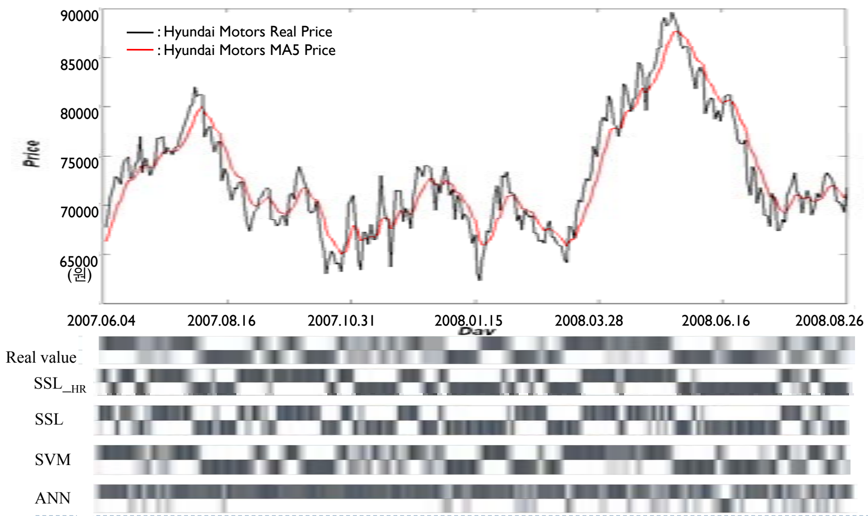


When the price show significant fluctuation as in black "C" and "D", the influence of upper layer(α_{UL}) and from upper layer to lower layer(α_{BL}) plays a critical role of prediction.

Result

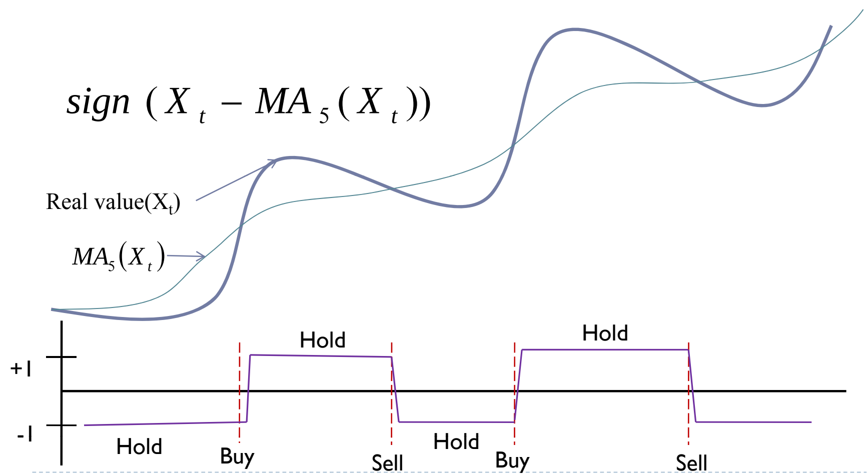
1. Accuracy based on AUC
2. Profit based on ROI

Result: Profit based on ROI

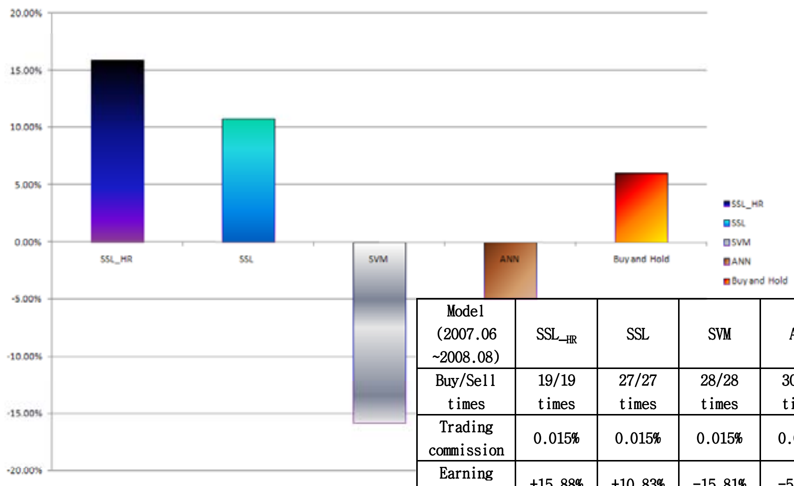


Result: Profit based on ROI

➢Buy and sell strategy



Result: Profit based on ROI



Model (2007.06 ~2008.08)	SSL_{-HR}	SSL	SVM	ANN	Buy and Hold
Buy/Sell times	19/19 times	27/27 times	28/28 times	30/30 times	--
Trading commission	0.015%	0.015%	0.015%	0.015%	0%
Earning Rate	+15.88%	+10.83%	-15.81%	-5.02%	+6.06%

Conclusion

Conclusion

- Interrelation between stock market.

  - Alteration factors in financial and other economy indexes have a network structure caused by a certain correlation between them.

- Advantages the hierarchical structure.

  - Hierarchical structure represent a simultaneous consideration for both the microscopic analysis of national and social figures and the analysis in and between hierarchies.

  - Hierarchical structure can perform more excellent prediction than the conventional methods due to the direct reflection of the relationship between countries and companys through the hierarchical structure

Conclusion

- Hierarchical structure SSL model showed a higher accuracy, profit than other models.

  - Stock price prediction model using hierarchical structure SSL was used to verify the proposed method, and the experiments showed promising results: 0.758 of the average AUC and the relatively excellent earning rate compared with other models.

- Hierarchical structure SSL model possible to apply it as a pre-warnin g system.

  - By introducing the hierarchical structure in a time series analysis, it is possible to consider the analysis between international and domestic markets and that makes possible to apply it as a pre-warning system for predicting international economy crises in case of need.

Future work

- **Trading strategy.**

  - The proposed method is necessary to increase the earning rates by introducing more various trading strategy.

- **Optimum portfolio composition.**

  - It can be expected that the safety and earning rate can be simultaneously improved by connecting the proposed model with an optimum portfolio composition method using various items.

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Appendix:Technical Indicator

- A transformation is needed to extract retrospective features from the time series data set

$$MA_z(X_t) = \frac{1}{z}(x_t) + \frac{z-1}{z} MA_z(X_{t-1}) \quad \textbf{Exponential Smoothing}$$

$$BIAS_z(X_t) = \frac{x_t - MA_z(X_t)}{MA_z(X_t)}$$

$$OSC_{j,z}(X_t) = \frac{MA_j(X_t) - MA_z(X_t)}{MA_z(X_t)}$$

$$ROC_z(X_t) = \frac{x_t - x_{t-z}}{X_t} \quad \textbf{The Relative Rate of Change for } x_t$$

between z consecutive trading days

Appendix:Technical Indicator

$$K_t^z = \frac{x_t - Min_{i=t-z-1}^{t}(x_i)}{Max_{i=t-z-1}^{t}(x_i) - Min_{i=t-z-1}^{t}(x_i)}$$

$$D_t^z = MA_3(K_t^z)$$

$$RSI_t^z = \frac{\sum_{i=t-z-1,\, x_i > x_{i-1}}^{t} \left(\left|x_i - x_{i-1}\right|\right)}{\sum_{i=t-z-1}^{t} \left(\left|x_i - x_{i-1}\right|\right)}$$

T.I were calculated under $z \in \{5\}, j \in \{20\}$