Rules or Intuition: Analysis of Signal from Monetary Policy Decision

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Abstract

Not Now

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1 Introduction

The recent Fed's decision on federal funds against hiking inflation rate has sparked interest in the future course of monetary policy. As the upward trend of inflation is getting weaker, there are also debate regarding when the Fed turns nose of the airplane. Since 1994, FOMC has issued policy statement right after the meeting with quarterly projection of the economy. And this post-meeting statements provide greater transparency to fed's monetary policy decision. Currently, under the forward guidance principle since 2012, the Fed's monetary policy statement has provided some insight into the direction of the policy rate.

Other central banks also provided policy guidance via public communication for the future policy direction as well as the Fed. Specifically after the Global Financial Crisis, when many of developed countries suffered from constraint by the effective lower bound of interest rate, this practice became more prevalent. And this indicates that the qualitative expression in the statement has been as important as the quantitative decision as a part of the monetary policy. The words and nuances of the statement are very carefully crafted to provide an indication of the current Board's monetary policy stance, as well as the direction of the policy rate in the future. Therefore, the wording of the statement before the rate hike and the rate drop could be substantially different for the Fed to give an intentional signal to the market.

Bank of Korea(BOK) also has posted the statement after the Monetary Policy Board (MPB) meeting regarding the policy decision as well as the market expectation. Though there were no explicit forward guidance like Fed, BOK has communicated by giving a minute[1] and press conference after the MPB meeting. MPB meeting was held in every month until 2016 but now 8 times per year to follow global standards. Monthly meeting had provided more frequent signal to the market but decision could be affected by more volatile monthly indicators.

Motivation of this paper -

Effectiveness of Text analysis to know the policy in advance

Decision is affected by other factor?

[1] Currently, a minute is released two weeks after the meeting

If so, how much this difference is estimated based on TR.

Literature Text mining techniques are one of the methodologies for performing quantitative analysis based on frequent words in the document. Previous studies have presented objective indicators, diagrammed relationship, and drawn meaningful conclusions based on indicators through quantitative analysis of text data on various social issues.

다음 논문들 정리하기

- Amy Handlan 2020
- Pongsak Luangaram1 Warapong Wongwachara 2016
- Andrea Pavelkova 2022
- Taeyoung Doh, Dongho Song, and Shu-Kuei Yang 2022
- (Korea) Young Joon Lee† Soohyon Kim‡ Ki Young Park§ 2019

This paper analyzes whether it is possible to predict policy rate changes and identify factors that affect policy rate changes based on relevant prior research. While previous studies utilized text mining techniques to detect monetary policy changes and summarized the results, this study directly applied data mining techniques used for prediction to summarize the features of monetary policy resolutions to make actual predictions and evaluate their predictive power. in the sense that it is different. This paper is organized as follows.

Insert 'Summary of result'

In Chapter 2, we briefly review the previous studies and discuss the differences and contributions of this study, and in Chapter 3, we summarize the data mining analysis methodology for evaluating the predictive power. Chapter 4 discusses the results of the analysis and interprets the implications for monetary policy, and Chapter 5 concludes with policy implications based on the results.

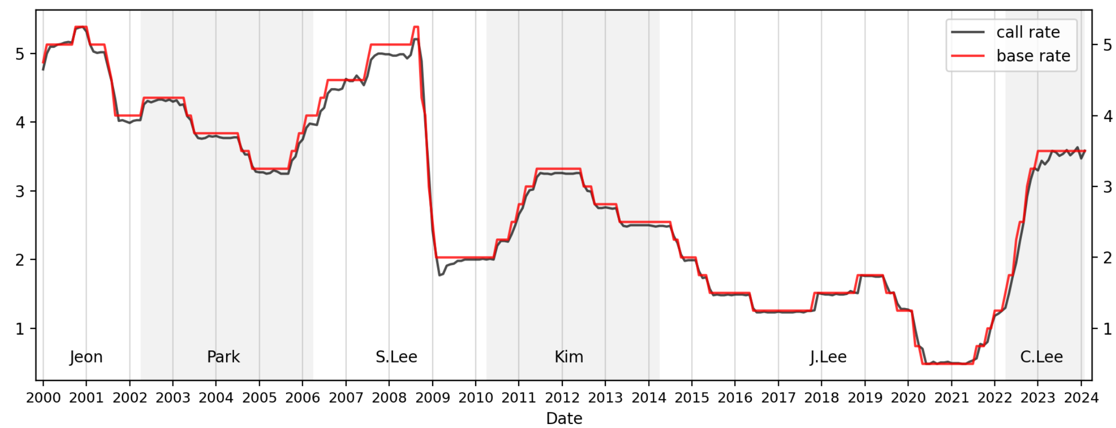
2 Text Analysis

2.1 MPB Statement

Monetary Policy Board(MPB) is the authority to determine the monetary policy of Korea resided in the Bank of Korea. The Governor of Bank of Korea holds the chairman of the board and the deputy governor also participates as ex officio member. Rest five members are recommended by the Ministry of Strategy and Finance, the Governor of Bank of Korea, the Chairman of the Financial Services Commission, the Chairman of the Korea Chamber of Commerce and Industry, and the Chairman of the National Bank Federation, and all of them are appointed by the President of the Republic of Korea. A meeting shall be resolved with the attendance of at least five members and the approval of a majority of the members present. MPB meeting, which determines the base rate, was held monthly until 2016, but it was held eight times a year from 2017. Before 1998, the chairman of the board was the minister of finance and the monetary policy was highly influenced by the government. After overcoming the Asian Financial Crisis, MPB has been operated more independently than before. Therefore, our target MPB statement starts from April 2002 when the independence of monetary authority had been strengthened and new Governor Park was appointed. There have been five governors until the end of 2023 and 233 statement during the periods. Figure 1 shows the base rate, which is the policy rate of Korea and the call rate[2] which corresponds to effective federal funds rate, by the governor.

[2] overnight loan rates between financial intermediaries

Figure 1: Base rate and call rate of Korea



* Notes:

Table 1: MPB's decision by governor

Governor	Term	Total	Raise	Cut	Keep
Park	Apr. 2002-Mar.2006	48	4	4	40
S. Lee	Apr. 2006-Mar.2010	48	5	5	38
Kim	Apr. 2010-Mar.2014	47	5	3	39
J. Lee	Apr. 2014-Mar.2022	76	5	9	62
C. Lee	Apr. 2022-	14	7	0	7
Total	Apr.2002-Dec.2023	233	26	21	186

* Notes: Most of MPB's decision during the sample period is made in 25 basis points change.

In this paper, we first analyzed the frequency of words appearing in each policy statement to understand their characteristics. We used the text of the "Monetary Policy Direction"(1) section from the policy statements announced by the Bank of Korea as the subject of analysis. We analyzed policy statements from the initial announcement date up to the May 2023 statement. We created word lists for each policy statement and conducted a Word Count analysis based on them to examine overall characteristics. Additionally, we checked the frequently used words for each statement. We used the Okt(Open Korean Text) Korean language processor from the KoNLPy package to extract words corresponding to nouns, verbs, adjectives, adverbs, determiners, and conjunctions. For Chinese characters, we first converted them to Korean and then extracted the words. We selected only words corresponding to the Korean language, excluding numbers and alphabets. We created a document-word matrix using the refined words and evaluated the similarity between adjacent statements based on this matrix.

2.2 Similarity

$$\text{Similarity} = \frac{\mathbf{x} \cdot \mathbf{y}}{\|\mathbf{x}\|\|\mathbf{y}\|} = \frac{\sum x_i y_i}{\sqrt{\sum x_i^2}\sqrt{\sum y_i^2}} \tag{1}$$

(In data mining techniques such as cluster analysis, the distance between two objects is typically used as a criterion for determining the similarity between observations and forming clusters.) In this paper, we also decided to measure the similarity between policy statements using the concept of distance. This is because, to capture changes in the tone of policy statements, we need to find points where the similarity between two adjacent statements drops sharply, i.e., when the distance becomes large. To apply the concept of distance, we chose to use the cosine similarity measure, which is deemed appropriate for comparing the similarity of documents. To examine whether the actual policy interest rate changes can be accurately predicted, we transformed the similarity measure. In the case where the similarity measure based on the frequently used words of the two documents is the highest, i.e., perfectly matched, it is considered as 1, and the similarity measure is subtracted from 1 to derive a dissimilarity measure. This is because if the dissimilarity between two adjacent documents increases sharply, it can be judged that this implies a change in the policy stance. In this study, we used the dissimilarity measures from periods t-1 to t-6 as input variables along with additional variables for the model, and the presence or absence(2) of interest rate changes at period t as the output variable.

Similarity formula

2.3 Forecasting Model

2.3.1 Benchmark

$$
\begin{aligned}
y_t = {} & \beta_1 \pi_t - 1 + \beta_2 (TR_t - 1 - Base_t - 1) + \beta_3 (\pi_t - \pi_t^*) \\
& + \gamma_1 \dot{s}imil_{t,t-1} + ... + \gamma_6 \dot{s}imil_{t,t-6} + \varepsilon_t
\end{aligned}
\tag{2}
$$

2.3.2 Decision Tree

Decision trees are models that predict output values for given input values, and they can be divided into classification trees for categorical outputs and regression trees for continuous outputs. In this paper, we selected the Classification and Regression Trees (CART) algorithm to analyze the relationship between the dissimilarity between monetary policy statements and the presence or absence of interest rate policy changes. CART is a non-parametric method that does not require assumptions about the model. In other words, it is a non-parametric method that does not require prerequisites such as which probability distribution the observed values follow, or assumptions like linearity or homoscedasticity in parametric models. Data is split in the order of variables with the highest explanatory power. In decision trees, this is expressed as branches splitting. When the data is divided, a criterion is needed to group similar target variable values. For this purpose, impurity functions such as the Gini index are used. That is, branches are divided in a way that reduces impurity. Decision tree models provide a basis for classification or prediction by generating easy-to-understand If-then rules. This makes the interpretation of the final tree structure straightforward. Additionally, even if there are an unnecessarily large number of input variables, the method can be usefully applied in variable selection since it automatically discards variables that are not effective in reducing impurity.

2.3.3 Neural Network

Neural networks are a data mining technique that models network structures consisting of nodes and links, mimicking the structure of the human brain. Like decision trees, they involve a repetitive learning process using collected historical data to uncover inherent patterns in the data. In a multilayer neural network composed of an input layer, hidden layer(s), and output layer, the hidden layer processes the linear combination of variable values transmitted from the input layer using a non-linear function and forwards them to another hidden layer or the output layer. The function that combines the input information is called a composition function, and the function responsible for transmission is referred to as an activation function or transfer function. To fit a neural network model, it is common to scale all input and output variable values between 0 and 1. For categorical variables, if there is an order, they can be appropriately transformed into values between 0 and 1. If the order has no significance, dummy variables can be created and used. One of the advantages of neural network models is their wide range of applicability, as they can handle both categorical and continuous input/output variables, although some variable transformations may be needed. In addition, since output results are derived from the nonlinear combinations of input variables, neural networks generally possess excellent predictive power. However, there are some limitations to neural network models. Despite their strong predictive capabilities, they may not provide a clear explanation or rationale for the output results. Moreover, building a neural network model can be time-consuming due to the complex learning processes involved.

2.3.4 Random Forest

Random Forest, proposed by Breiman (2001), is an ensemble method that utilizes bootstrap sampling to create variations in data and incorporates randomness in tree structure formation. Using various bootstrap samples, multiple decision trees are generated, and the final prediction is obtained by aggregating the predictions from these trees for new observations. This method benefits from enhanced predictive power due to the diversity and randomness incorporated in the model compared to single models. It is known that using the largest tree, without pruning, can result in better predictive power. Skipping the pruning step saves computational time, reducing the burden of creating multiple trees. However, there are limitations to using a Random Forest compared to a single tree model. One of these limitations is that it cannot be represented singularly or visualized due to the aggregation of multiple tree models.

3 Empirical Results

From the start of the Bank of Korea's monetary policy decision announcements in January 2004 to May 2023, a total of 229 decision statements that were released were used for analysis. During this period, interest rates changed a total of 47 times. For all models - decision tree, artificial neural network, and random forest - the input variables are the dissimilarity between adjacent decision statements over the past six occurrences and the difference between BOK's base rate and the FFR. The target variable for prediction was whether the policy interest rate changed or not, assigning 1 if a change occurred and 0 if the existing rate was maintained.

Figure 2: BOK's base rate and Federal Funds Rate

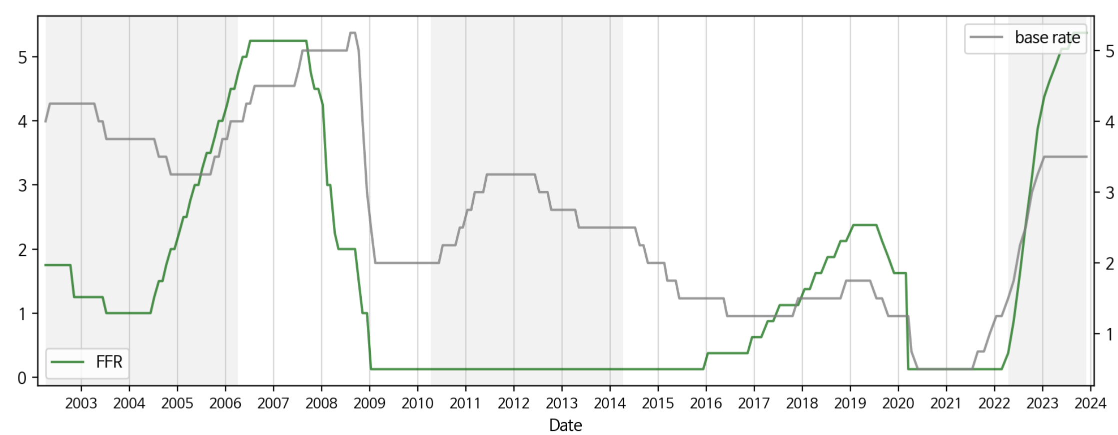


Figure 3: Korea-US interest gap

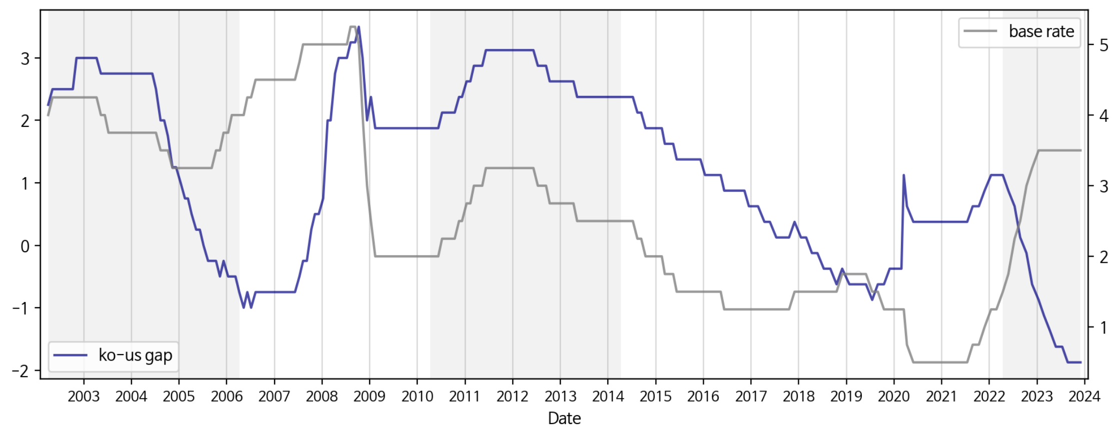


그림 2는 그림 3과 통합될 예정

Figure 4: [비유사도, 기준금리]

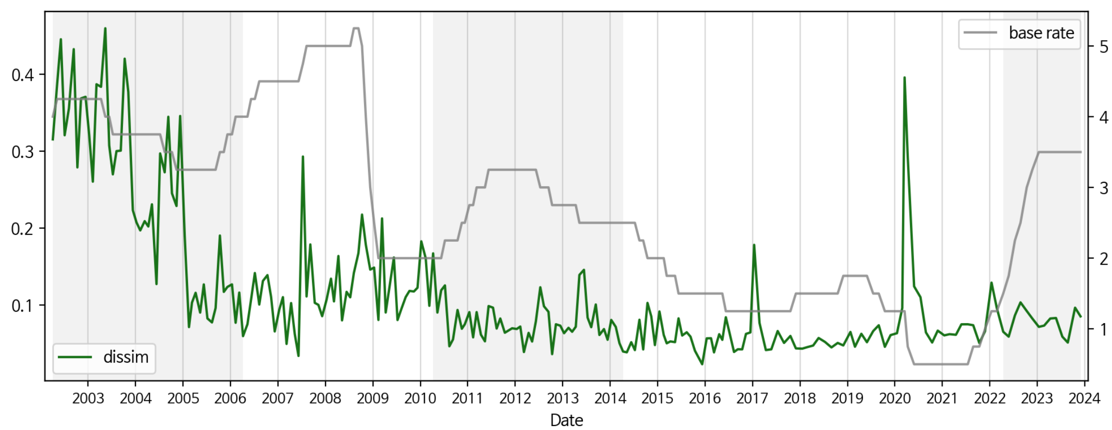


Figure 5: [TR1, 기준금리]

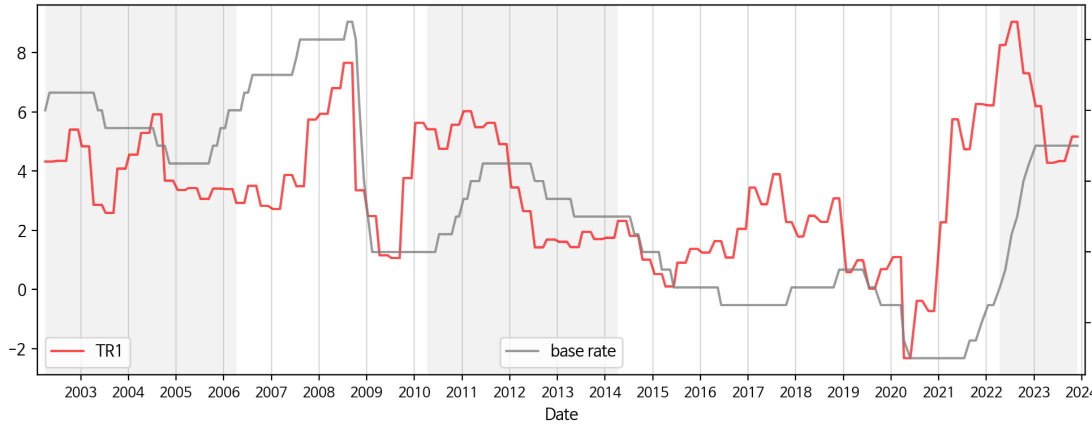
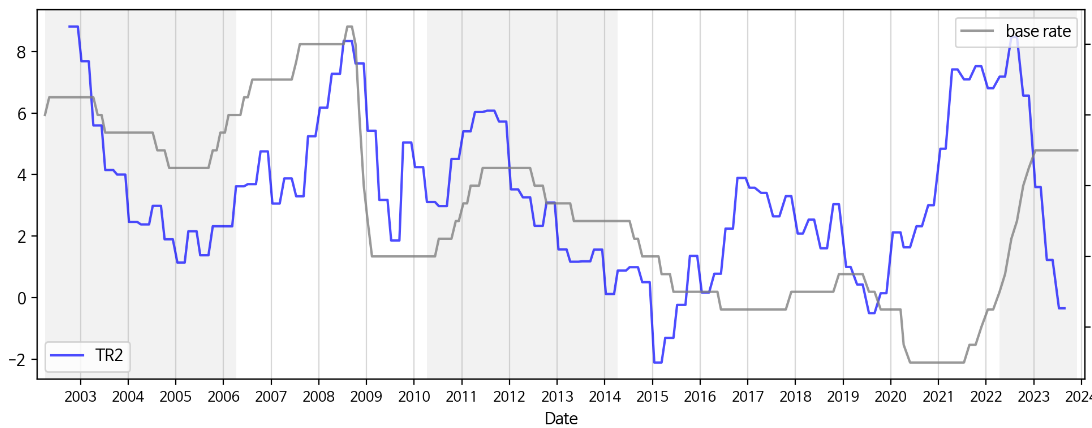


Figure 6: [TR2, 기준금리]



3.1 Word Counts

The 총재 임기 기간과 의결문 개수, 비유사도 평균 표 represents statistics for each governor's tenure, the number of decision texts announced, and the average dissimilarity. Excluding Governor Rhee Changyong, other governors saw interest rate changes in approximately 15 20Looking at the frequent words in the decision texts by each governor results in something like the 총재별 word count 상위 10개 표. After conducting a Word Count for words extracted through the KoNLPy library by each governor, we removed meaningless words such as '등' and '이다', and organized the top 10 words and their frequencies. [총재별 빈출단어에 대한 해석, 주요 시기별 비유사도에 대한 해석 등을 작성하는 위치]

Table 2: Word Counts in MPB Statement by Governor

Rank	Chulwhan		Seung		Sungtae		Joongsoo		Juyeol		Changyong	
	Word	Count	Word	Count	Word	Count	Word	Count	Word	Count	Word	Count
1	금리	134	유지	87	금융시장	82	경제	256	경제	398	둔화	75
2	금융시장	91	물가	73	가격	76	지속	213	성장	341	물가	62
3	상승	90	금리	67	유지	75	가격	153	회복	286	경제	58
4	물가	80	가격	61	지속	75	성장	142	지속	266	성장	58
5	안정	76	경제	58	물가	66	유지	140	상승	259	지속	56
6	기업	72	안정	55	경기	63	물가	135	증가	242	금리	52
7	자금	65	목표	53	증가	60	상승	128	물가	234	높다	51
8	경제	65	증가	52	소비자	48	위험	126	가격	230	영향	49
9	유지	61	콜	51	부동산	48	하락	114	영향	216	인상	46
10	지속	61	수출	50	수출	47	회복	113	하락	204	경기	42

* Notes:

Table 3: Statistics of Similarity within Each of Governor's Term

Governor	Start	End	N	N change	Mean	Std
Seung	2002-04-01	2006-03-31	48	8	0.248	0.115
Sungtae	2006-04-01	2010-03-31	48	10	0.122	0.047
Joongsoo	2010-04-01	2014-03-31	47	8	0.080	0.027
Juyeol	2014-04-01	2022-03-31	76	14	0.070	0.052
Changyong	2022-04-01	-	14	7	0.078	0.015

* Notes:

3.2 Forecasting

3.2.1 Decision Tree

A decision tree model was fitted using the dissimilarity, the Korea-US interest rate spread, and the rule-based rate from the past six terms as input variables, and whether there was an actual change in interest rate policy at time t as the target variable. The tree model based on the CART algorithm was used using Python's Scikit-Learn library. Pre-pruning limited max˙depth to 3. Analysis was conducted on a total of 229 decision texts from April 2002 to May 2023, divided into overall periods and periods for each governor. The dissimilarity of decision texts was calculated by subtracting cosine similarity between previous decision texts from one. In the model using TR2, six missing values occurred during Governor Park Seung's term due to lack of data. The Tree 평가점수+분할표 are fitting results for each model. Accuracy and AUC scores were derived by generating 50 bootstrap datasets based on relevant training data and applying models to them. [모형 적합 결과에 대한 해석을 작성하는 위치] The feature importance heatmap 그래프 visualizes the feature importance values of each decision tree model. Feature importance is an indicator that shows how much each independent variable has influenced the prediction of the dependent variable. If it's close to 1, it means that it had a significant impact, and if it's 0, it corresponds to variables not used in the model fitting process. [feature importance 결과에 대한 해석을 작성하는 위치]

Table 4: [의사결정나무 평가점수+분할표 전체, 총재별]

Governor	TR	Change-T	Change-F	Stay-T	Stay-F	BT Accuray	BT AUC Score
전체	1	16	31	183	3	0.88	0.6829
	2	11	35	179	2	0.74	0.8090
박승	1	4	4	40	0	0.94	0.8125
	2	4	3	35	0	0.88	0.9314
이성태	1	8	2	38	0	0.96	0.9975
	2	8	2	38	0	0.96	0.9975
김중수	1	4	4	39	0	0.92	0.9137
	2	4	4	39	0	0.92	0.9137
이주열	1	3	3	12	61	0.86	0.7547
	2	6	5	10	61	0.86	0.7398
이창용	1	7	0	7	0	1.00	1.0000
	2	7	0	5	0	1.00	1.0000

* Notes:

3.2.2 Neural Network

For the neural network model, the same input and output variables as the decision tree model were used for fitting. The Scikit-Learn library was used, and the Adam

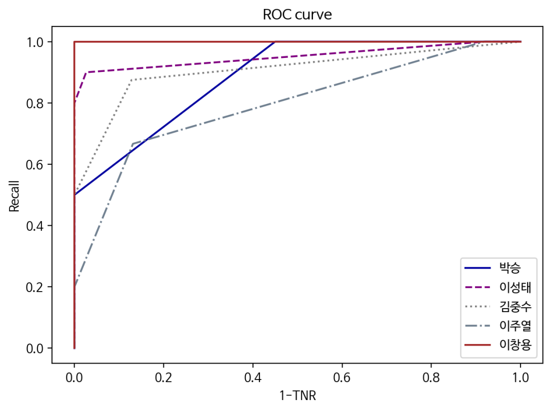


Figure 7: [의사결정나무 ROC - TR1]

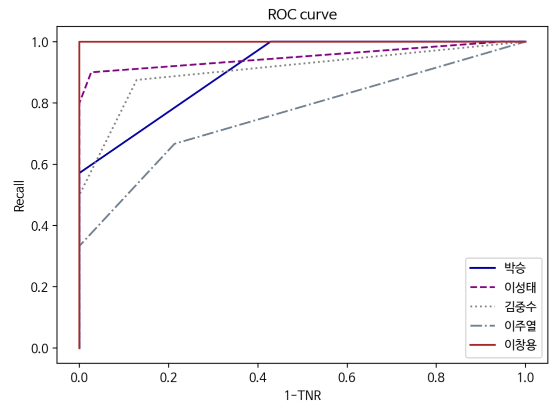


Figure 8: [의사결정나무 ROC - TR2]

optimizer was employed with a fixed random state of 0. As the number of input variables increased, the size of hidden layers was set to 9, 10, and 8 respectively. [모형 적합 결과에 대한 해석을 작성하는 위치]

Table 5: [신경망모형 평가점수+분할표 전체, 총재별]

Governor	TR	Change-T	Change-F	Stay-T	Stay-F	BT Accuray	BT AUC Score
전체	1	8	39	186	0	0.82	0.6667
	2	4	42	177	4	0.68	0.6706
박승	1	0	8	40	0	0.92	0.6793
	2	7	0	35	0	1.00	1.0000
이성태	1	10	0	38	0	1.00	1.0000
	2	2	8	37	1	0.82	0.6300
김중수	1	0	8	39	0	0.84	0.5893
	2	0	8	39	0	0.84	0.5625
이주열	1	3	12	58	3	0.80	0.5989
	2	1	14	58	3	0.82	0.7832
이창용	1	7	0	7	0	1.00	1.0000
	2	7	0	5	0	1.00	1.0000

* Notes:

3.2.3 Random Forest

The random forest model was also fitted using the same input and output variables as the previous models. The Scikit-Learn library was used, and the model was defined

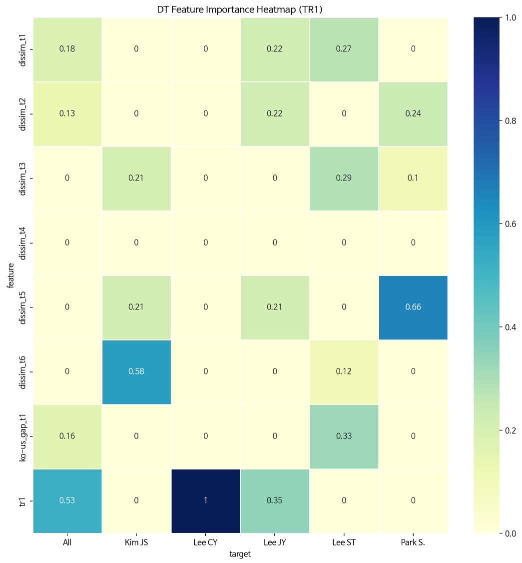


Figure 9: [DT Feature Importance - TR1]

Figure 10: [DT Feature Importance - TR2]

by limiting max depth to 3 with pre-pruning and setting n˙estimators to 20. Also, the fitting process was run with a fixed random state of 0. [모형 적합 결과에 대한 해석을 작성하는 위치]

4 Concluding Remarks

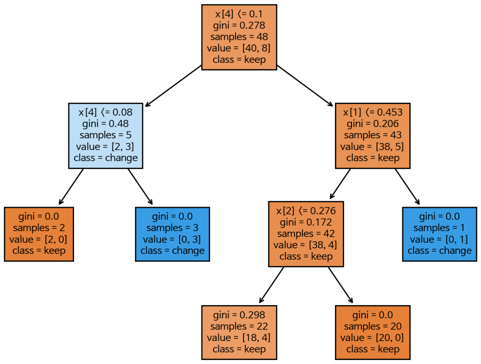


Figure 11: [박승 - TR1 (DT Tree Plot)]

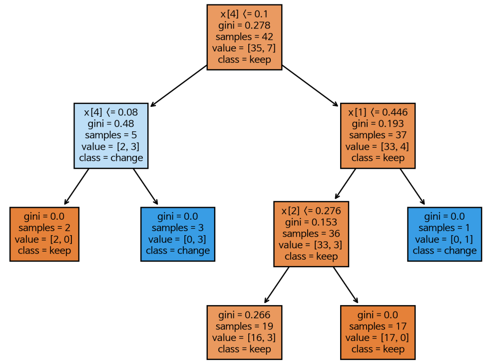


Figure 12: [박승 - TR2]

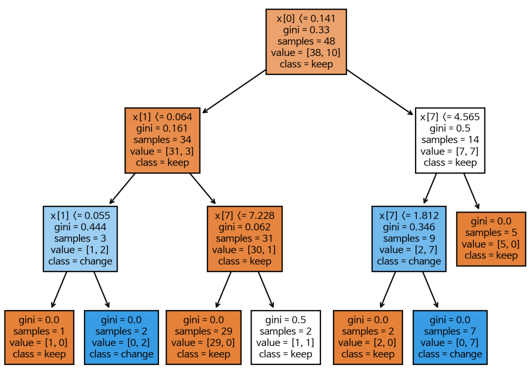


Figure 13: [이성태 - TR1]

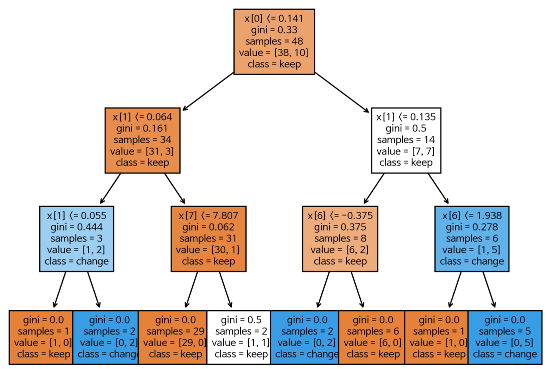


Figure 14: [이성태 - TR2]

References

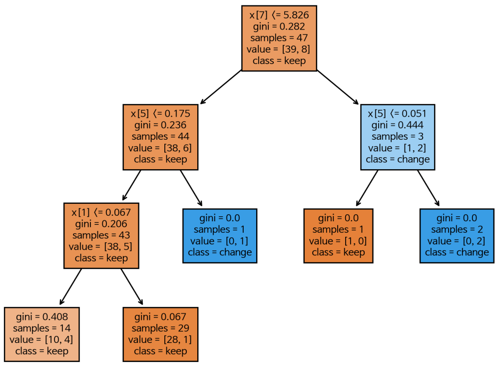


Figure 15: [김중수 - TR1]

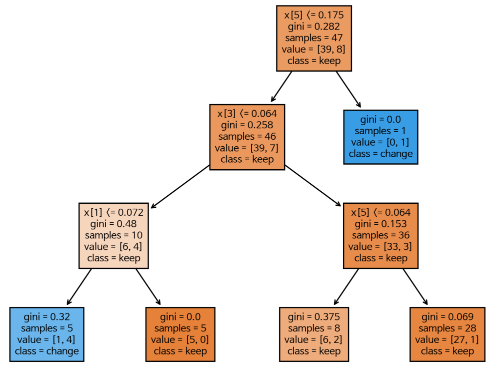


Figure 16: [김중수 - TR2]

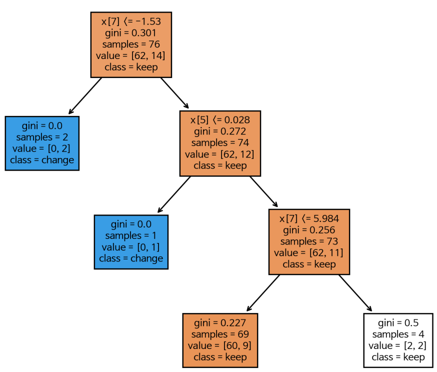


Figure 17: [이주열 - TR1]

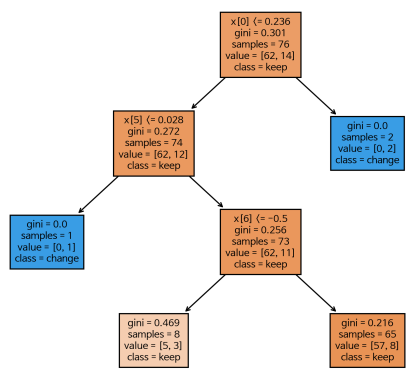


Figure 18: [이주열 - TR2]

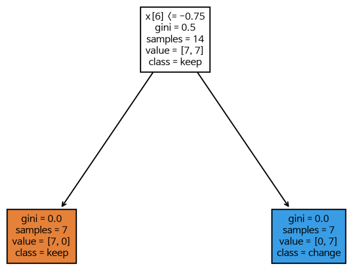


Figure 19: [이창용 - TR1]

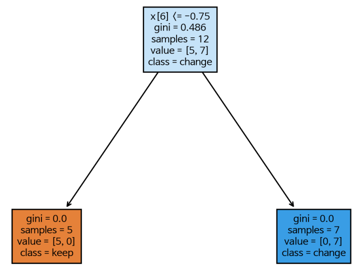


Figure 20: [이창용 - TR2]

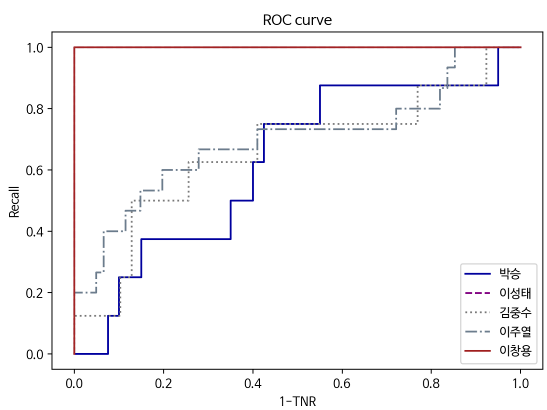


Figure 21: [신경망모형 ROC - TR1]

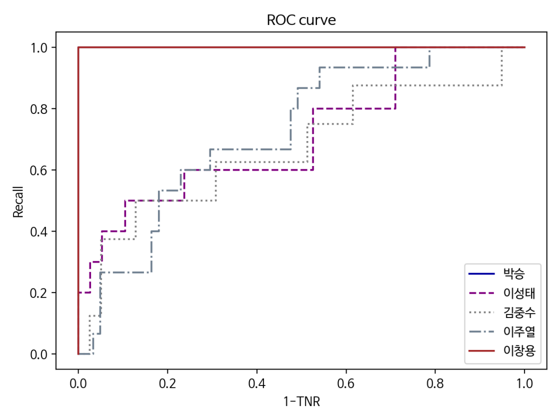


Figure 22: [신경망모형 ROC - TR2]

Table 6: [랜덤포레스트모형 평가점수+분할표 전체, 총재별]

Governor	TR	Change-T	Change-F	Stay-T	Stay-F	BT Accuracy	BT AUC Score
전체	1	6	41	186	0	0.82	0.8808
	2	2	44	181	0	0.62	0.9474
박승	1	3	5	40	0	0.92	0.8913
	2	3	4	35	0	0.86	1.0000
이성태	1	5	5	38	0	0.90	1.0000
	2	7	3	38	0	0.94	1.0000
김중수	1	5	3	39	0	0.94	0.9970
	2	5	3	39	0	0.94	1.0000
이주열	1	6	9	61	0	0.88	0.9810
	2	4	11	61	0	0.88	0.9837
이창용	1	7	0	7	0	1.00	1.0000
	2	7	0	5	0	1.00	1.0000

* Notes:

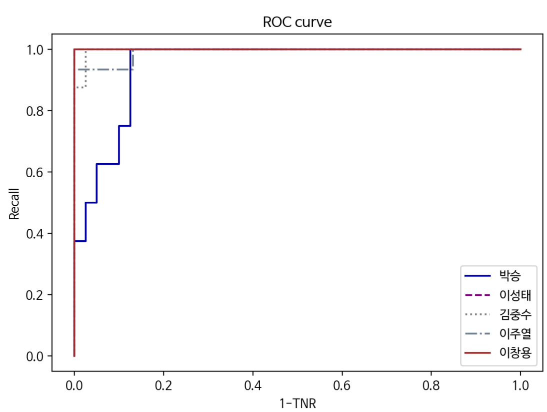


Figure 23: [랜덤포레스트 ROC - TR1]

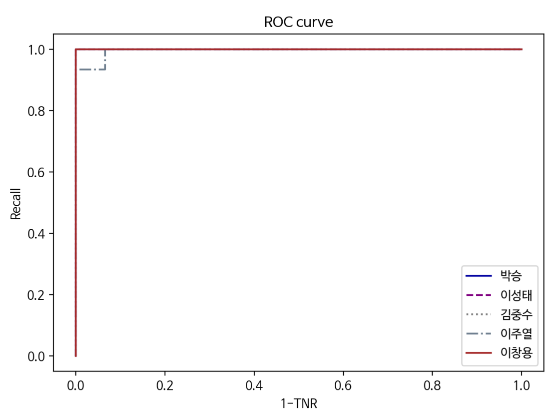


Figure 24: [랜덤포레스트 ROC - TR2]

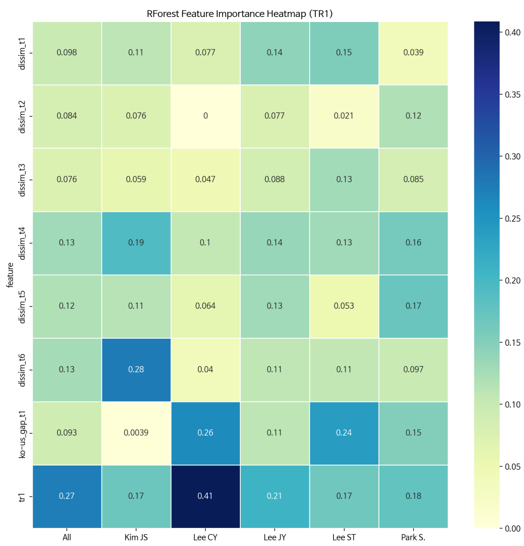


Figure 25: [RF Feature Importance - TR1]

Figure 26: [RF Feature Importance - TR2]