A Study on the Use of Artificial Intelligence for Learning Characteristics of Funds' Behavior (Summary Report)

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Abstract

This document is a summary of a report on research commissioned in October 2018 by Japan's Government Pension Investment Fund (hereinafter called "GPIF") to Sony Computer Science Laboratories, Inc. (hereinafter called "Sony CSL") on "A Study on the Use of Artificial Intelligence for Learning Characteristics of Funds' Behavior".[1]

Implications:

- Artificial intelligence (hereinafter called "AI") that could identify key differentiators among funds and ensure uniformity in the assessment of existing and candidate funds would make it possible to select funds without depending on individual experience and ability of GPIF personnel.
- AI can detect changes in investment behavior of candidate funds. An ongoing process to verify these changes would make it possible to have greater confidence in the reliability of AI.

Case Study

Fund selection:"What is the key difference between existing Fund A and candidate Fund B(Japanese equity funds)?"

AI was used to map the funds by the stock holding ratio in targeted equities, and a methodology of Explainable AI (hereinafter called "XAI") optimized for fund selection interpreted the features by which the AI differentiated them. Across a limited sample analysis concluded that AI characterizes candidate Fund B's preference for equities in a certain sector as the key differentiator between it and existing Fund A. This case study implies that the output of AI analysis coincides with the output of conventional analysis of equity holdings.

Fund selection:"Assessment of investment behavior change by candidate Fund C (Japanese equity fund)"

Using a relatively coarse data set (monthly trading data), AI was able to detect that candidate Fund C's investment behavior underwent a major change, and it was confirmed that this coincided with a change of the portfolio manager in charge. Use of this AI approach made it possible to verify the change in investment behavior before and after the change of the portfolio manager in charge.

Monitoring of existing funds:"Why did existing Fund D exhibit change in its investment behavior during the 'Coronavirus shock' equity market?(foreign equity fund)"

Between February and April 2020, amid the 'Corona shock' market, the AI detected changes to Fund D's investment behavior. Our initial hypothesis was that this drift was caused by

[1] Project members: Hiroaki Kitano, Dr. (President and Director), Takao Tajiri (Project Leader), Takahiro Sasaki, Dr. (Researcher), Masanori Hashido, Dr. (Visiting Researcher), Takumi Morita (ditto), Tomonari Murakami (ditto), Takahiro Ishikawa (ditto) and research assistants.

emergent countermeasures against the highly volatile market, etc. However, consultation with Fund D confirmed that the cause was actually an operational change of a risk control mode in accordance with a longstanding policy. Therefore it was not classed as a serious incident. It is challenging for AI to specifically detect serious incidents with the current model, however it may become possible to capture them once a sufficient number of cases have been accumulated by detecting changes of investment behavior through ongoing monitoring of existing funds.

Future research

GPIF's fourth Medium-Term Plan calls for active deployment of new technologies including AI and RPA in order to enhance operational capabilities and efficiency. From the beginning, a high priority for this research has been to move forward in developing AI-based adjunct solutions for GPIF's concerns that the selection and assessment of candidates based on qualitative criteria could lead to accusations of "arbitrariness" and "subjectivity." For the future, it will be important to pursue a model that is sufficiently robust for operational deployment by focusing on the following three criteria: "building up a set of cases to validate fund selection," "expanding trial implementations to assess a larger pool of candidate funds," and "determining AI's role and its ultimate objective in the fund selection process."

This research derived from GPIF's proactive pursuit of AI's potential for fund selection and monitoring has yielded awards from EQ Derivatives and Asian Investor magazines and has drawn attention from asset owners/managers and global media because of the unique viewpoint provided by implementing AI in operations.We would like to express sincere appreciation to GPIF for its long-term approach, which fosters understanding of the importance of allocating sufficient time and resources to pursue this research opportunity.

1 Research progress

This research project had three phases:

- 1st Phase:"A Study on the Use of Artificial Intelligence within Government Pension Investment Fund's Investment Management Practices" (2017-2018) [1, 2]

  Under this research study, a proof-of concept prototype system called Style Detector Array (SDA) based on deep learning [3] was developed. The prototype, based on a small universe of 100 Japanese equities, was developed to search for a model which would detect some aspect of funds' investment behavior. We chose as that aspect similarity to well-known investment styles (value, momentum, etc.) in order to make it easy to explain to GPIF and others in the financial industry.

- 2nd Phase pre-interim report: "A Study on the Use of Artificial Intelligence for Learning Characteristics of Funds' Behavior" (October 2018-October 2019)

  Building on the 1st phase prototype, we developed a system called "Resembler" as an extension and an application of SDA in the research program. Resembler provided quantitative metrics for a type of information about the characteristic behavior of fund management firms such as investment strategy and asset management process that previously was only qualitative. Experimental implementation of Resembler in GPIF operations validated that the system can capture a characteristic investment style of each fund manager, and changes to it over time, that may not be captured by characterizing it in terms of well-known reference styles. Additionally, results suggested that Resembler could uncover similarities among existing and candidate funds, which would assist GPIF in maintaining a diversified manager structure and selecting suitable candidate funds. This research was released as an interim report in December 2019 [4, 5].

- 2nd Phase post-interim report: "A Study on the Use of Artificial Intelligence for Learning Characteristics of Funds' Behavior" (January 2020-June 2020)

  Building on the result of the experimental implementation of Resembler noted above, it was developed into two applications:

  - "Mutual-resemblance": assessment of similarities among funds, primarily for fund selection.
  - "Self-resemblance": detection of characteristic investment behavior, applied to both selecting among candidate funds and monitoring of existing funds.

This summary report discusses the following case studies:

- Fund selection:
  - "What is the key differentiator between existing Fund A and candidate Fund B?(Japanese equity funds)" (An experimental implementation of Mutual-resemblance)
  - "Detection of change in portfolio manager at candidate Fund C(Japanese equity fund)" (An experimental implementation of Self-resemblance)
- Monitoring of existing funds:

  - “Why did existing Fund D exhibit change in its investment behavior during the ‘Coronavirus shock’ ?(foreign equity fund)” (An experimental implementation of Self-resemblance)

This is a summary report covering a part of the material discussed in the full final report.

2 Fund Selection

Case study in fund selection: "What is the key differentiator between existing Fund A and candidate Fund B?(Japanese equity funds)" (An experimental implementation of Mutual-resemblance)

GPIF's decision making process for fund selection is based on analysis by GPIF personnel of funds' past quantitative performance and various qualitative criteria including investment strategy, operating processes, team/human resources, etc [6]. Because such a wide range of information is involved, the evaluation process tends to be complex and time consuming. AI could potentially provide a unified and intuitive overview of the data that would help increase efficiency. Use of AI could also contribute to resolving concerns that have been raised by the GPIF Board of Governors that qualitative evaluation could be susceptible to complaints of "arbitrariness" and "subjectivity" by third parties [7]. AI mapped all existing and seven candidate active funds(Japanese equity funds) based on portfolio holding weight data (Fig.1). The results can be summarized as follows:

- Mapping of existing funds (gray lines) based on investment style exhibits three clusters as shown circled in red, blue and green.
- Overall, the mapping of the seven candidate funds (candidate Fund B shown in orange, others in pink) is centered on the area circled in red, suggesting they have investment styles similar to those existing funds.
- Four candidate funds are close only to the red cluster, however the other three candidates are relatively close to either blue or green.

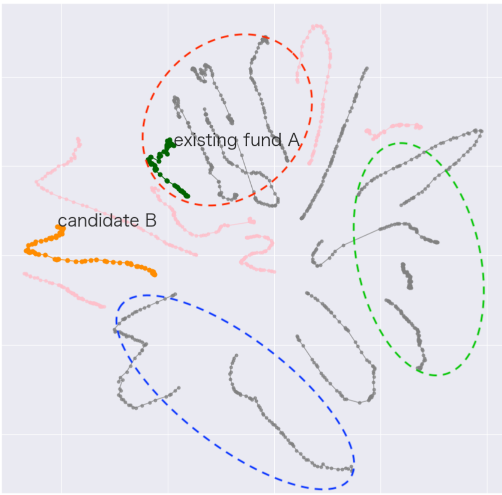


Figure 1: Map of existing funds and candidate funds(grey dots: existing funds, pink dots: candidate funds, green dots: existing fund A, orange dots: candidate fund B)

We undertook a sample case study trying to discover the key differentiator that AI identified between existing Fund A and candidate Fund B, which is described below. In Fig.2, Fig.3 and Fig.4 the AI visualizes how each equity affects the mapping of each fund. This reveals that both Individual Issue ① and Individual Issue ② characterize the mapping of candidate Fund B. Fig.5 applies the same type of visualization to Sector ③, to which both Individual Issue ① and Individual Issue ② belong. This suggests that Fund B shows strong preference toward Sector ③.

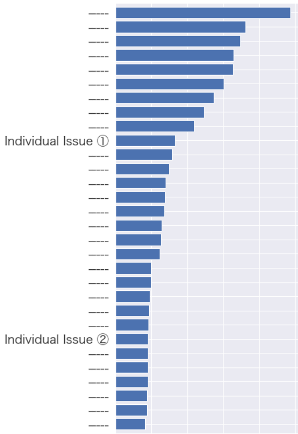


Figure 2: Importance of individual stocks

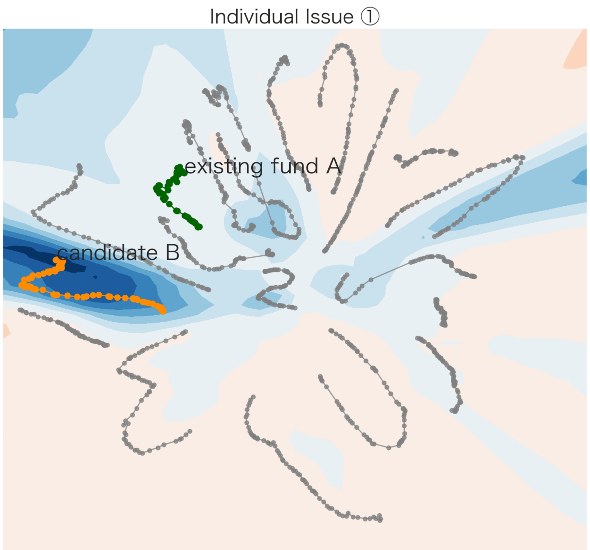


Figure 3: Preference toward Individual Issue ① (Blue area: Strong preference, Orange area: Weak preference)

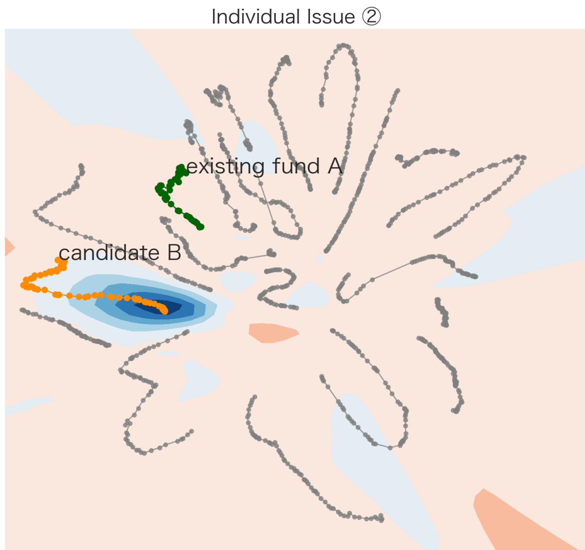


Figure 4: Preference toward Individual Issue ② (Blue: Strong/Orange: Weak)

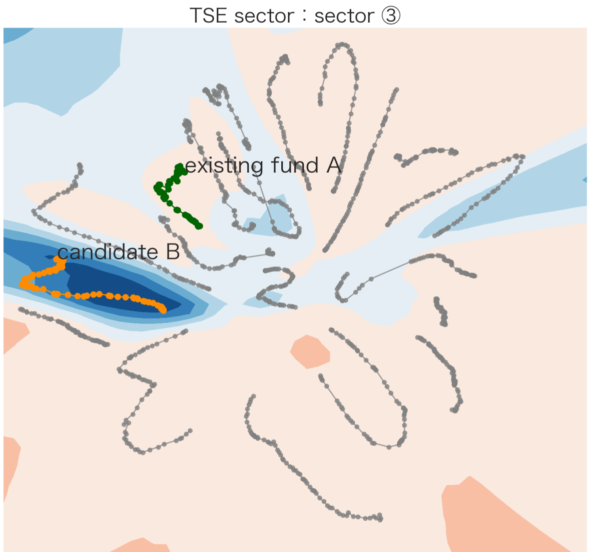


Figure 5: Preference toward sector ③ (Blue: Strong/Orange: Weak)

Fig.6 explains the preference for Individual Issue ④ and Sector ⑤ by existing Fund A, while candidate Fund B has a weaker preference toward that sector, but the equity and the sector are less decisive than Individual Issue ①, Individual Issue ② and Sector ③. These analyses conclude that AI characterized Sector ③ as the key differentiator between existing Fund A and candidate Fund B. This implication coincides with conventional analysis based on trends in sector weight. The next step should be to explore the reasoning and future expectations, valuation, etc. behind this sector preference. This case study implies that AI can add insight to the results of conventional analysis tools with easily-understood visualizations.

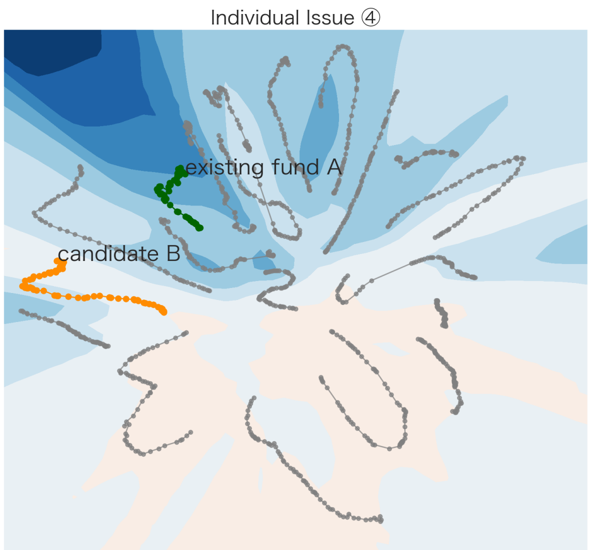


Figure 6: Preference toward Individual Issue ④ (Blue: Strong/Orange: Weak)

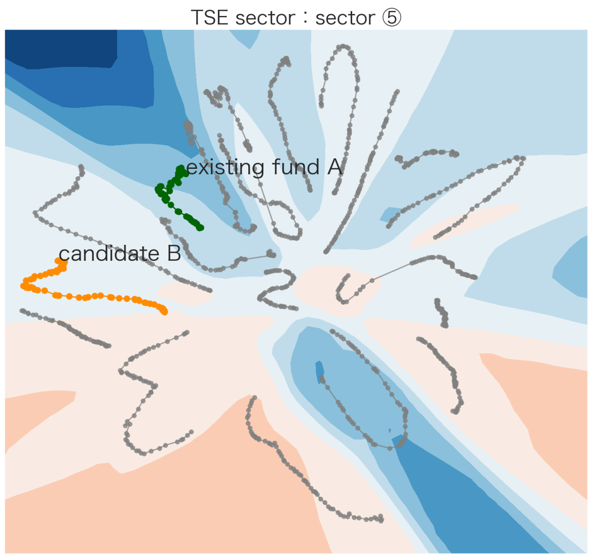


Figure 7: Preference toward sector ⑤ (Blue: Strong/Orange: Weak)

Methodology

The "Mutual-resemblance" model was developed to apply deep learning technology to evaluate the similarity among existing and candidate funds for fund selection purposes. The model incorporates a Variational Autoencoder (VAE) [8, 9, 10, 11, 12], which consists of an encoder for embedding high-dimensional data into low-dimensional data and a decoder for reproducing high-dimensional data from low-dimensional data. This is combined with a methodology of Explainable AI (XAI) [13, 14, 15, 16, 17, 18, 19, 20, 21] called Shapley Additive Explanation Value (SHAP) which makes it possible to explain the features on which the AI focused. (See Fig.8)

Reasons for employing VAE:

- The encoder and decoder are capable of integrating and visualizing the data.
- In comparison to the latest algorithms such as GAN (Generative Adversarial Network) [22], VAE is a relatively simplified model, which makes its behavior more readily interpretable and means it has a low learning cost.
- It is extendable to accommodate bigger data sets in the future, because the architecture can be adapted to a broad range of cases by making the network structure more complex.
- The combination of SHAP and decoder functionality enhances explainability, thus addressing the "black box problem" that will be of growing significance for AI.
- VAE gives stable results in generating inferences from relatively coarse historical data sets, in this case monthly portfolio weight.

The encoder takes the holding weight in each equity as input and maps this as two-dimensional data. A map is created from the embedded data to intuitively represent the similarity among funds. "Projector" has a function that assists in understanding the map created by the encoder by visualizing the decoder's output to show features such as equities, industries, and risk factors on the map. Another way to think of it is that Projector serves as a lens to explore the map from various points of view; in fact, a set of lenses that the user can switch between to highlight implicit and explicit information about each fund. SHAP provides a significance indicator to guide the choice of lens to facilitate efficiently perceiving the features on which the AI is focused. Picture data for image recognition is understandable mere by SHAP, however, since in the case of investment fund analysis, what can be intuitively inferred about funds based on numerical data, lists of equity holdings in the portfolio, etc. is limited, so we developed this novel implementation that combines SHAP and VAE for better interpretation.

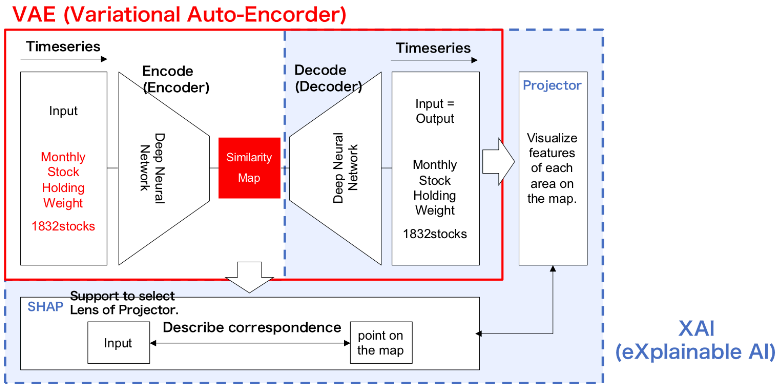


Figure 8: Overview of Mutual-resemblance model

Case Study: "Detection of change in portfolio manager at candidate Fund C(Japanese equity fund)" (An experimental implementation of Self-resemblance)

Fig.9 shows the investment behavior drift of candidate Fund C from 2016 to 2017[2]. We confirmed that there was a change of the portfolio manager at Fund C during the period. AI enables to understand the impact on investment style, transition period, etc. caused by the change in portfolio manager. This makes it possible to capture a sample of candidate fund behavior related to the fund's team and human resources strategy by facilitating more incisive and insightful dialogue with regard to the change's impact and transition period.

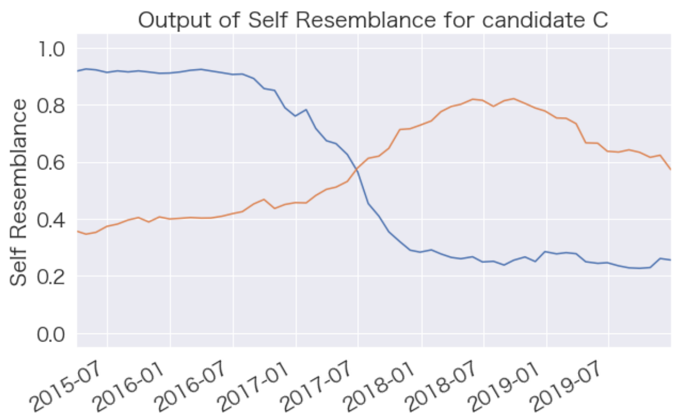


Figure 9: Output of Self-resemblance for candidate fund C(Blue line: training period 2015-01 ∼2017-04, Orange line: training period 2018-01∼2019-06)

Methodology

Detection is based on Self-resemblance, a property which assesses drift of characteristic investment behavior. It uses the same mechanism as the Resembler tool described in "An Interim Report on 'A Study on the Use of Artificial Intelligence for Learning Characteristics on Funds'

[2]High line graph shows adaptation of the inherent investment behavior. In case the line shows drift, it implies separation of the inherence.

Behavior',” released in December 2019 (See Fig.10). The main points of this methodology are as follows:

- Uses a relatively coarse data set (monthly trading data).
- Application of multiple models trained on different time series data in order to explore a variety of viewpoints for detecting change.
- Uses a deep neural network trained on trading and portfolio weighting data of GPIF and on market data by Factset and ICE Data Services, from 20 funds (including existing and candidate funds) to detect the characteristic (uniqueness) of each fund.

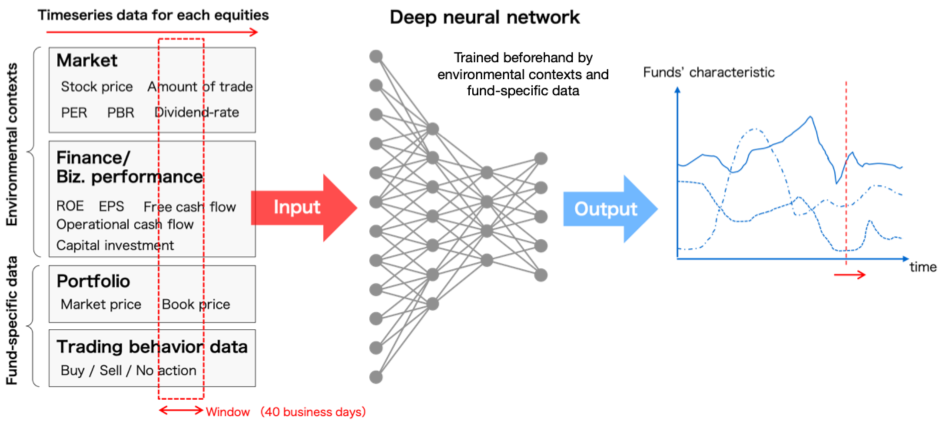


Figure 10: Overview of Self-resemblance

3 Monitoring of existing funds

Case study in fund monitoring: "Why did existing Fund D exhibit change in its investment behavior during the 'Coronavirus shock' equity market?(foreign equity fund)" (An experimental implementation of Self-resemblance)

Between February and April 2020, a drift away from characteristic investment behavior by some existing funds was detected amid the 'Coronavirus shock' equity market, although the majority of funds maintained consistent Self-resemblance. Fig.11 shows that Fund D, which is an actively traded foreign (non-Japanese) equities fund, exhibited a dip in Self-resemblance, detecting a drift of characteristic investment behavior by during the period. Additional investigation indicated this fund had taken some trading actions on a scale it had never done before. Our initial hypothesis was that the drift was caused by emergent countermeasures against the highly volatile market or initiating a pre-reported investment policy change sooner than planned. However, consultation with Fund D confirmed that the cause was actually an operational change of a "risk control mode" in accordance with a longstanding policy. The switch of risk control mode fell within its operational guidelines and therefore was not classed as a serious incident. The Corona shock had no significant impact on the investment policy of the fund. Longer-term time series data is needed to analyze how AI interpreted the Coronavirus shock.

In the past—although rare—there have been serious incidents with funds contracted to manage GPIF assets, for which GPIF has had to take measures. Given GPIF's limited resources and wide responsibilities, it is not feasible to monitor all the activities of every fund closely. It is challenging for AI to specifically detect serious incidents with the current model, however it may become possible to capture them once a sufficient number of cases have been accumulated by detecting changes of investment behavior through ongoing monitoring of existing funds.

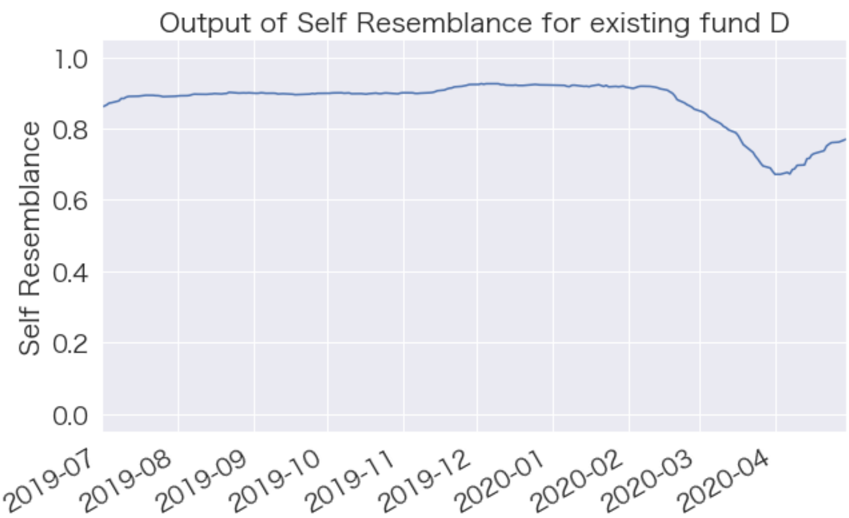


Figure 11: Output of Self-resemblance for existing fund D

4 Future research

GPIF's the fourth Medium-Term Plan calls for active deployment of new technologies including AI and RPA in order to enhance operational capabilities and efficiency. If GPIF were to choose to continue research into AI, the following three themes would merit detailed study:

- In order to reach the point of deploying AI operationally, it will be necessary to build up a set of cases spanning a certain number of years. However, in this research we only addressed one case covering approximately six months. Future research is needed to accumulate additional cases that will validate the performance of AI in supporting fund selection.
- This paper is a pilot study of AI at the final stage of fund selection. However to address the Board of Governors' mandate to select high-potential funds from the full universe of fund managers [23] at the initial stage, it is required to expand trial implementations to take advantage of AI's potential to deal with big data, for deploying it with a larger number of candidate funds to manage GPIF's assets.
- Determining AI's role and its ultimate objective in the fund selection process. We believe that, depending upon the role and objective assigned to AI, it offers a promising future prospect of ensuring uniformity (and excluding variation due to individual judgment) in the assessment of existing and candidate funds based on the output of a hybrid analysis that combines AI with GPIF's accumulated knowhow in fund selection using the judgment and insights of GPIF personnel acquired by years of experience.

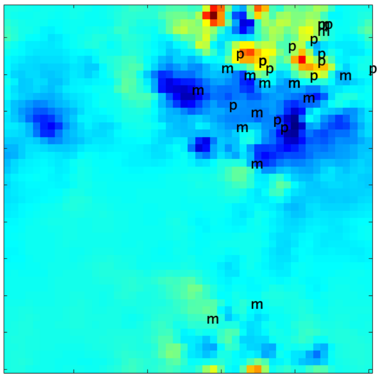
The shift among public asset owners towards spending more on new technologies and data resources has also been evolving. GPIF's proactive pursuit of AI's potential for fund selection and monitoring has yielded research praised by the industry. The published results have been recognized with awards two years in a row from EQ Derivatives, a special interest magazine serving the financial industry that caters to asset owners and hedge funds, and Asian Investor magazine, a special interest magazine for institutional investors in the Asia-Pacific region. It has drawn attention from asset owners/managers and global media because of the unique viewpoint provided by implementing AI in operations. The research described in this paper has further advanced the leading edge of applying AI for the specific needs of asset owners by incorporating XAI in order to shed light on the "black box problem": that is, understanding what factors are contributing to an AI's output. This research project started with fundamental research and has been carried forward to experimental implementation. Many aspects of developing the fundamental research into applications have required substantial amounts of time. We would like to express sincere appreciation to GPIF for its long-term approach, which fosters understanding of the importance of allocating sufficient time and resources to pursue this research opportunity.

Exploratory study on fund behavior prediction

We are now working toward experimental implementation of an AI tool called "Replicator" that predicts how funds will behave in response to particular market conditions. We anticipate the following use cases:

- Refining risk scenarios:
  - In contrast to conventional risk analysis based on estimations of loss that would occur to the current portfolio in the event of a particular market risk eventuating, Replicator can analyze more sophisticated scenarios by making it possible to estimate loss while taking into account how funds would react to market risks.
  - Replicator can predict the robustness of the diversification in the manager structure by assessing whether outsourced funds would exhibit convergent behavior in response to a market environment change.
- Fund selection:
  - Asset owners must work with more limited quality and quantity of information when selecting candidate funds, as compared with existing funds. Replicator develops new inferences from candidate funds' investment behavior about how they would react to various market environments.

Past portfolio replication models had issues with accuracy caused by sensitivity to price variation noise. By focusing on predicting funds' behavior, the new approach implemented by Replicator avoids this problem.
Replicator makes use of a type of manifold learning algorithm called a self organizing map (SOM) [24, 25]. The model input consists of active weight data of GPIF (to characterize fund features) and factor return [26, 27]/value (to characterize market scenarios) by Factset and ICE Data Services. The output consists of the predicted active weight, representing investment behavior, based on each market environment. The following figure is an example of investment behavior prediction output. Red and yellow areas on the map indicate where Replicator predicts an increase in weight, on while blue and light blue areas indicate a prediction of decrease in weight. The map shows that actual increases in weight (p) fall within red/yellow and actual decreases (m) fall within blue/light blue, indicating fairly good prediction accuracy. We are continuing with research and development to refine the model and expand the data set to generate more consistent results across a range of different funds types.



Rebalance prediction by Replicator

Appendix:Supplementary Data

Fund Selection

Case study:"What is the key difference between existing Fund A and candidate Fund B?(Japanese equity funds)"

Output of Projector

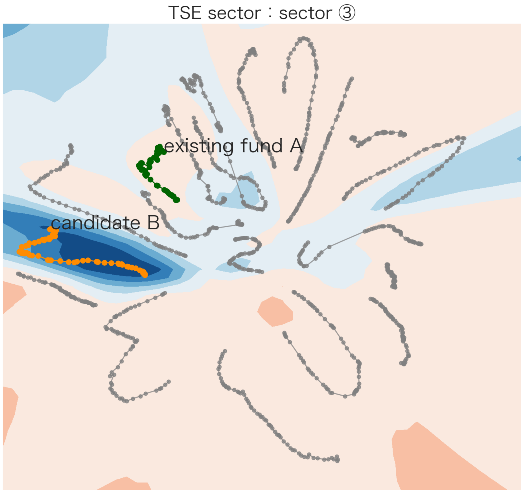


Figure 12: Preference toward sector ③ (Blue: Strong/Orange: Weak)

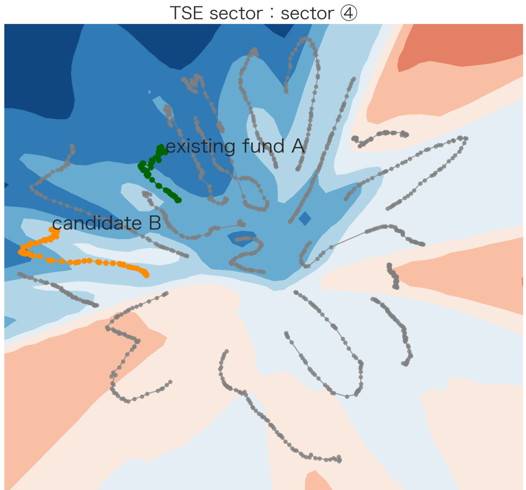


Figure 13: Preference toward sector ④ (Blue: Strong/Orange: Weak)

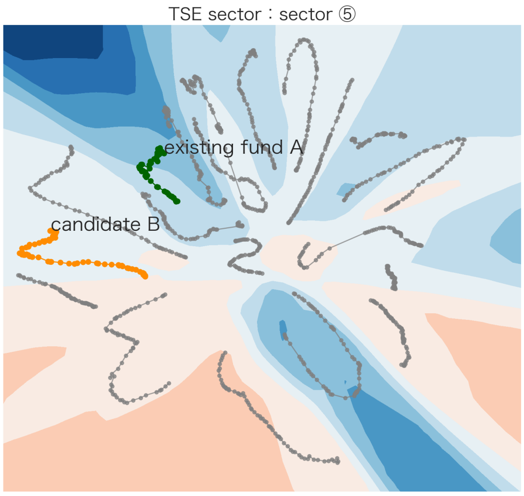


Figure 14: Preference toward sector ⑤ (Blue: Strong/Orange: Weak)

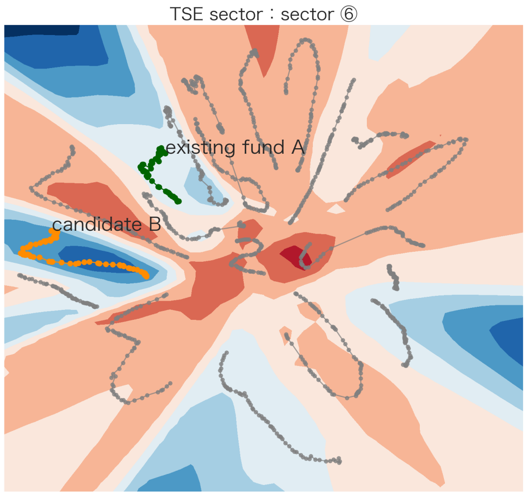


Figure 15: Preference toward sector ⑥ (Blue: Strong/Orange: Weak)

Case Study:“Detection of change in portfolio manager at candidate Fund C(Japanese equity fund)”

Output of Self-resemblance by monthly dataset

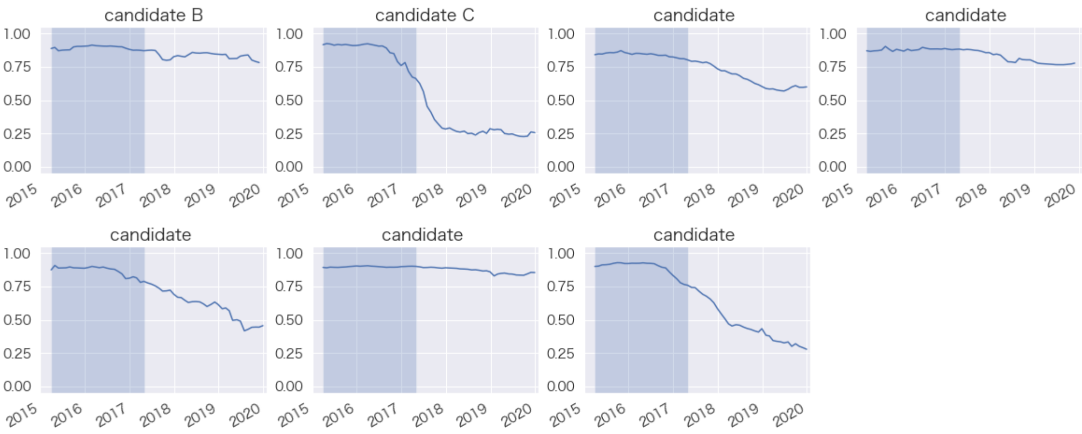


Figure 16: Output of Self-resemblance for candidates (training period:2015-02〜2017-04)

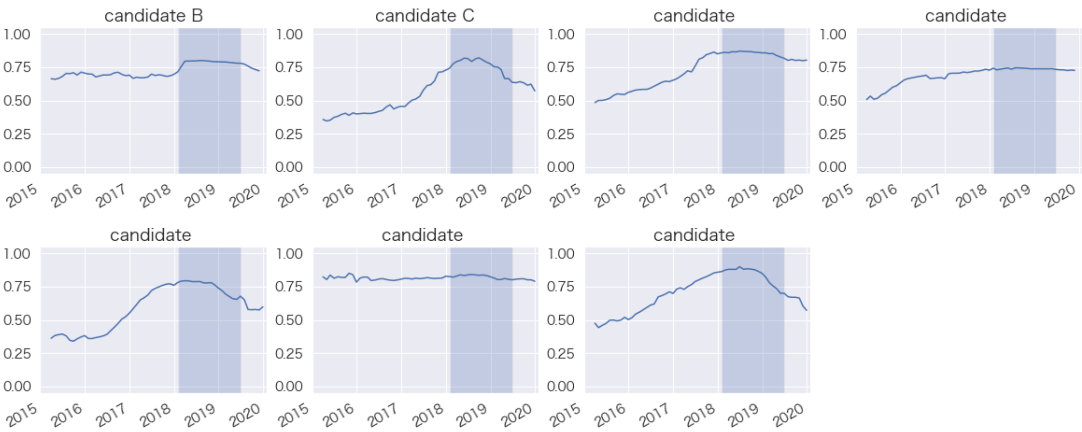


Figure 17: Output of Self-resemblance for candidates (training period:2018-01〜2019-06)

Case study:"Why did existing Fund D exhibit change in its investment behavior during the 'Coronavirus shock' equity market?(foreign equity fund)"

Output of Self-resemblance for domestic equity funds during the period of corona shock market

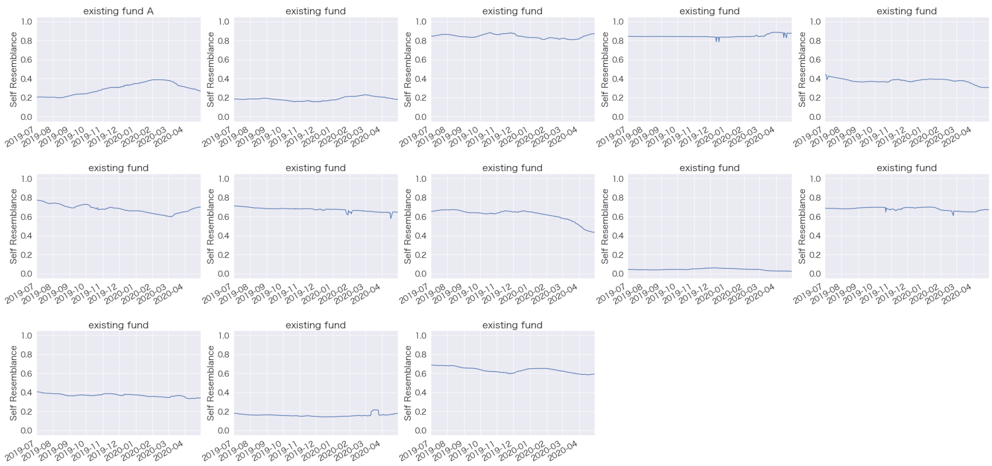


Figure 18: Output of Self-resemblance for domestic equity funds (training period:2015-01～2017-04)

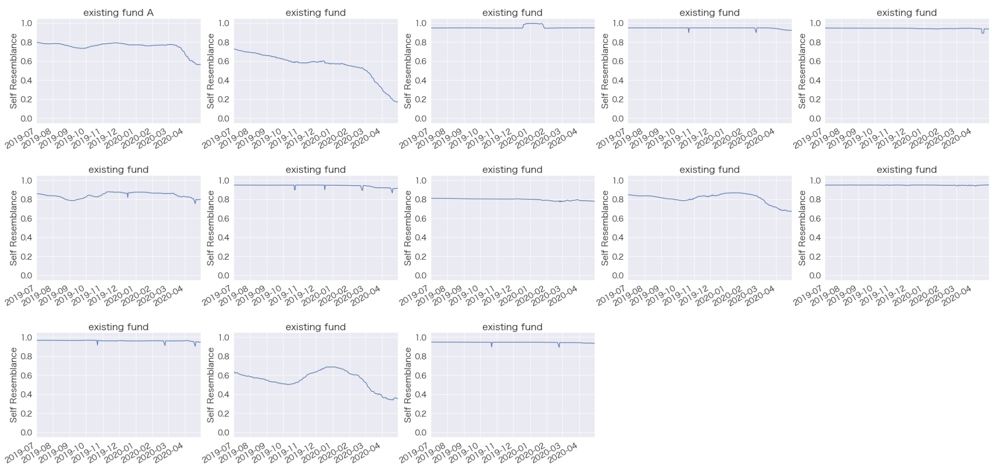


Figure 19: Output of Self-resemblance for domestic equity funds (training period:2018-01～2019-06)

Output of Self-resemblance for foreign equity funds during the period of corona shock market

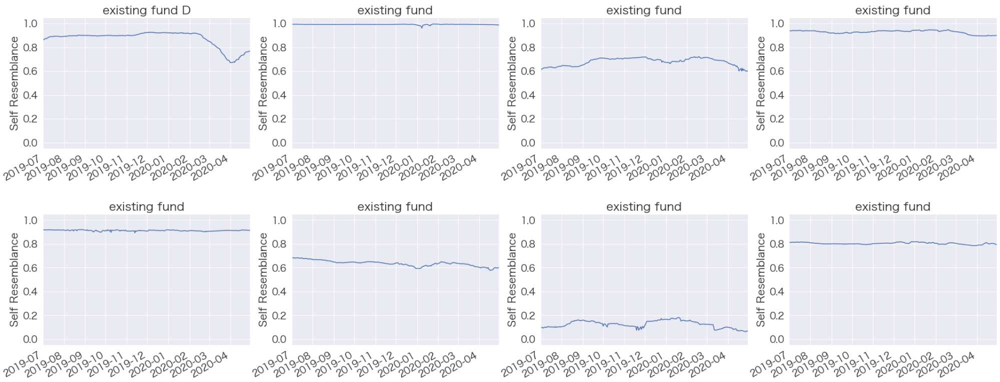


Figure 20: Output of Self-resemblance for foreign equity funds (training period:2015-01〜2017-04)

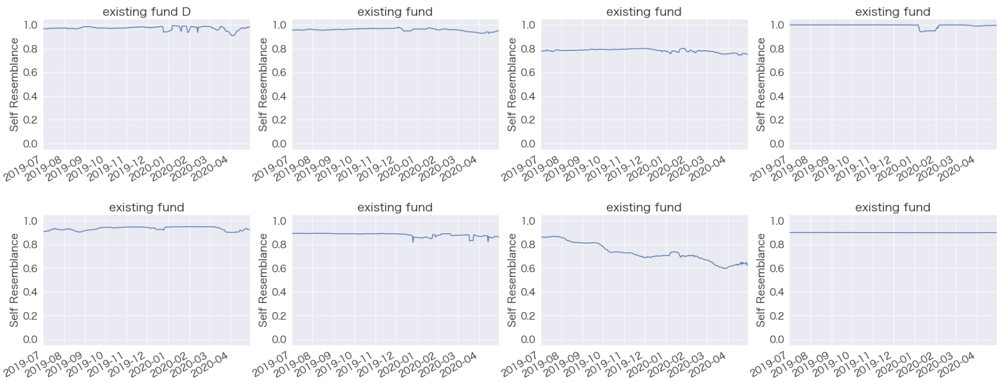


Figure 21: Output of Self-resemblance for foreign equity funds (training period:2018-01〜2019-06)

References

[1] Takahiro Sasaki, Hiroo Koizumi, Takao Tajiri, and Hiroaki Kitano. A study on the use of artificial intelligence within government pension investment fund's investment management practices (summary report). Tokyo, Japan: Government Pension Investment Fund, Mar 2018.

[2] A study on the use of artificial intelligence within government pension investment fund's investment management practices (summary report, Japanese Edition). Sony Computer Science Laboratories, Inc.

[3] G. E. Hinton and R. R. Salakhutdinov. Reducing the dimensionality of data with neural networks. *Science*, Vol. 313, No. 5786, pp. 504–507, 2006.

[4] Takao Tajiri, Takahiro Sasaki, and Hiroaki Kitano. A step toward a cybernetic whale: An interim report on "a study on the use of artificial intelligence for learning characteristics of funds' behavior". Tokyo, Japan: Government Pension Investment Fund, Dec 2019.

[5] An Interim Report on "A Study on the Use of Artificial Intelligence for Learning Characteristics of Funds' Behavior"(Japanese Edition). Sony Computer Science Laboratories, Inc., Dec 2019.

[6] Government Pension Investment Fund, Annual report fiscal year 2019 (Japanese Edition)

[7] Government Pension Investment Fund, Summary of the minute of the 3rd meeting of Board of Governors

[8] Diederik P Kingma and Max Welling. Auto-encoding variational bayes, 2013.

[9] Diederik P. Kingma, Danilo J. Rezende, Shakir Mohamed, and Max Welling. Semi-supervised learning with deep generative models, 2014.

[10] Carl Doersch. Tutorial on variational autoencoders, 2016.

[11] Danilo Jimenez Rezende, Shakir Mohamed, and Daan Wierstra. Stochastic backpropagation and approximate inference in deep generative models. In Eric P. Xing and Tony Jebara, editors, *Proceedings of the 31st International Conference on Machine Learning*, Vol. 32 of *Proceedings of Machine Learning Research*, pp. 1278–1286, Bejing, China, 22–24 Jun 2014. PMLR.

[12] Yoshua Bengio, Aaron Courville, and Pascal Vincent. Representation learning: A review and new perspectives. *IEEE transactions on pattern analysis and machine intelligence*, Vol. 35, No. 8, pp. 1798–1828, 2013.

[13] Scott M Lundberg and Su-In Lee. A unified approach to interpreting model predictions. In I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett, editors, *Advances in Neural Information Processing Systems 30*, pp. 4765–4774. Curran Associates, Inc., 2017.

[14] Marco Tulio Ribeiro, Sameer Singh, and Carlos Guestrin. "why should i trust you?": Explaining the predictions of any classifier, 2016.

[15] Scott M Lundberg, Gabriel Erion, Hugh Chen, Alex DeGrave, Jordan M Prutkin, Bala Nair, Ronit Katz, Jonathan Himmelfarb, Nisha Bansal, and Su-In Lee. From local explanations to global understanding with explainable ai for trees. *Nature machine intelligence*, Vol. 2, No. 1, pp. 2522–5839, 2020.

[16] Scott M Lundberg, Bala Nair, Monica S Vavilala, Mayumi Horibe, Michael J Eisses, Trevor Adams, David E Liston, Daniel King-Wai Low, Shu-Fang Newman, Jerry Kim, et al. Explainable machine-learning predictions for the prevention of hypoxaemia during surgery. *Nature biomedical engineering*, Vol. 2, No. 10, pp. 749–760, 2018.

[17] Erik trumbelj and Igor Kononenko. Explaining prediction models and individual predictions with feature contributions. *Knowledge and Information Systems*, Vol. 41, pp. 647–665, 2013.

[18] Avanti Shrikumar, Peyton Greenside, and Anshul Kundaje. Learning important features through propagating activation differences. 2017.

[19] A. Datta, S. Sen, and Y. Zick. Algorithmic transparency via quantitative input influence: Theory and experiments with learning systems. In *2016 IEEE Symposium on Security and Privacy (SP)*, pp. 598–617, 2016.

[20] Sebastian Bach, Alexander Binder, Grégoire Montavon, Frederick Klauschen, Klaus-Robert Müller, and Wojciech Samek. On pixel-wise explanations for non-linear classifier decisions by layer-wise relevance propagation. *PloS one*, Vol. 10, No. 7, p. e0130140, 2015.

[21] Stan Lipovetsky and Michael Conklin. Analysis of regression in game theory approach. *Applied Stochastic Models in Business and Industry*, Vol. 17, No. 4, pp. 319–330, 2001.

[22] Ian J. Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. Generative adversarial networks, 2014.

[23] Government Pension Investment Fund, Summary of the minute of the 4th meeting of Board of Governors

[24] T. Kohonen. *"Self-Organization and Associative Memory"*, Vol. 8. 1984.

[25] T. Kohonen. The self-organizing map. *Proceedings of the IEEE*, Vol. 78, No. 9, pp. 1464–1480, 1990.

[26] Eugene F. Fama and Kenneth R. French. Common risk factors in the returns on stocks and bonds. *Financial Ecomomics*, Vol. 33, No. 1, pp. 3–56, Feb 1993.

[27] Mark M. Carhart. On persistence in mutual fund performance. *The Journal of Finance*, Vol. 52, No. 1, pp. 57–82, Mar 1997.

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