Discussion of

“Machine Learning Mutual Fund Flows”

by Fausch, Frigg, Ruenzi, and Weigert.

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2025 FMA Consortium on Asset Management

Overview of the paper

Goal: Forecasting fund flows based on observable characteristics $\mathbf{z}_{i,t}$:

$$\widehat{\text{flow}}_{i,t+h} = \mathbf{z}_{i,t}'\widehat{\boldsymbol{\theta}}$$

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$\hookrightarrow$ Liquidity management (e.g., optimize your cash reserves, reduce needs for costly credit lines).

$\hookrightarrow$ Capital efficiency (e.g., timing investments around expected inflows).

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↪ Liquidity management (e.g., optimize your cash reserves, reduce needs for costly credit lines).

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Issues:

↪ $\mathbf{z}_{i,t}$ can be large (variable selection, risk of overfitting).

↪ Is $\mathbf{z}_{i,t}'\widehat{\boldsymbol{\theta}}$, i.e., linearity, a reasonable assumption?

Overview of the paper

Main idea: the investors' decision process might be non-linear, i.e.,

$$\widehat{\text{flow}}_{i,t+h} = \cancel{\mathbf{z}'_{i,t}\widehat{\boldsymbol{\theta}}} \quad \widehat{f(\mathbf{z}_{i,t})}$$

$\hookrightarrow$ A non-linear $\widehat{f(\mathbf{z}_{i,t})}$ produces more accurate $\widehat{\text{flow}}_{i,t+h}$.

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Focus on interpretability, i.e., $\forall j = 1, \ldots, p$

$$\frac{\partial\ \widehat{\text{flow}}_{i,t+h}}{\partial\ \widehat{f(z_{ij,t})}}$$

How the expected flow $\widehat{\text{flow}}_{i,t+h}$ changes as a function of $z_{ij,t}$?

My comments:

Comments/observations:

#1: Opening the black box (SHAP values).

#2: Economic evaluation (funds sorting strategy).

Comment #1: Opening the black box.

SHAP values and interpretability

Originally introduced as a game-theoretic tool to assign credit to players in cooperative games by considering:

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- ↪ Calculate the marginal/additional contribution each player brings for a given coalition.
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Key principles:

- ↪ Look at every possible coalition of ~~players~~ predictors.
- ↪ Calculate the marginal/additional contribution each ~~player~~ predictor brings for a given ~~coalition~~ forecast.
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- ↪ Single predictors: $\{ER\}$, $\{TNA\}$ $\Longrightarrow$ $R^2(\{ER\}), R^2(\{TNA\})$
- ↪ Full set: $\{ER, TNA\}$ $\Longrightarrow$ $R^2(\{ER, TNA\})$

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The average marginal contribution (SHAP value) for ER and TNA are:

$$\phi_{ER} = \frac{1}{2}\left[R^2(\{ER\}) - R^2(\{\})\right] + \frac{1}{2}\left[R^2(\{ER, TNA\}) - R^2(\{TNA\})\right]$$

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$$\phi_{TNA} = \frac{1}{2}\left[R^2(\{TNA\}) - R^2(\{\})\right] + \frac{1}{2}\left[R^2(\{ER, TNA\}) - R^2(\{ER\})\right]$$

SHAP values and interpretability

Consider two predictors: Expense ratio (ER) and total net assets (TNA).

Each predictor combination gives a performance (e.g., R^2, MSE),

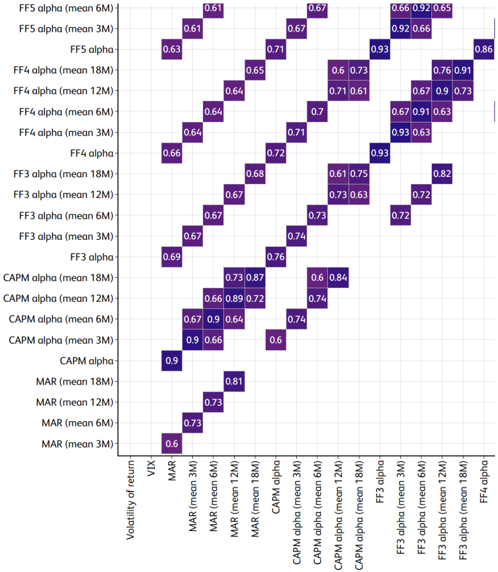
- $\hookrightarrow$ Empty set: $\{\}$ $\Longrightarrow$ 0.01
- $\hookrightarrow$ Single predictors: $\{ER\}$, $\{TNA\}$ $\Longrightarrow$ $0.03, 0.04$
- $\hookrightarrow$ Full set: $\{ER, TNA\}$ $\Longrightarrow$ 0.05

The average marginal contribution (SHAP value) for ER and TNA are:

$$\phi_{ER} = \frac{1}{2}[0.03 - 0.01] + \frac{1}{2}[0.05 - 0.04] = 0.015$$

$$\phi_{TNA} = \frac{1}{2}[0.04 - 0.01] + \frac{1}{2}[0.05 - 0.03] = 0.025 \qquad \phi_{TNA} > \phi_{ER}$$

Comment #1a: SHAP and correlated predictors



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When predictors are correlated, their SHAP values become more ambiguous

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Recall that, for e.g.,:

$$\phi_{ER} = \frac{1}{2}[R^2(\{ER\}) - R^2(\{\})] + \frac{1}{2}[R^2(\{ER, TNA\}) - R^2(\{TNA\})]$$

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↪ Assume ER and TNA are positively correlated.

↪ $R^2(\{ER, TNA\}) < R^2(\{ER\}) + R^2(\{TNA\})$ (redundant information).

↪ The larger the correlation, the more ϕ_{ER} converges to ϕ_{TNA}.

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Model-agnostic?

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E.g., for a linear model $\Longrightarrow \widehat{\text{flow}}_{i,t+1} = \widehat{\beta}_{ER} ER_{i,t} + \widehat{\beta}_{TNA} TNA_{i,t}$,

$\hookrightarrow$ SHAP decompose the linear forecast $\widehat{\beta}_{ER} ER_{i,t} + \widehat{\beta}_{TNA} TNA_{i,t}$. Even if the true relationship is nonlinear.

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↪ Don’t capture true DGP ($R^2 << 1$).

↪ Vary across model choices.

What’s special about non-linear methods?

↪ It would be interesting to understand if non-linear methods pin down different predictors for fund flows.

Comment #2: Economic evaluation of forecasts.

2a) Sorting forecasts and long-short portfolios

To what extent are these performances really different from each other?

Panel A - top and bottom decile portfolios												
	Top 10%:				Bottom 10%:				Long-Short:			
	FF4	FF5	FF6	FF7	FF4	FF5	FF6	FF7	FF4	FF5	FF6	FF7
Equally weighted	-0.08*	-0.08*	-0.08*	-0.08*	-0.08*	-0.08*	-0.08*	-0.08*				
	(0.05)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)				
OLS - FF4	-0.03	0.02	0.02	-0.01	-0.19*	-0.17**	-0.17**	-0.18**	0.16	0.19*	0.19**	0.17*
	(0.05)	(0.08)	(0.06)	(0.07)	(0.10)	(0.08)	(0.08)	(0.08)	(0.11)	(0.10)	(0.08)	(0.09)
Elastic Net	-0.04	0.02	0.02	-0.02	-0.21*	-0.20**	-0.20**	-0.21***	0.17	0.22*	0.22**	0.17*
	(0.06)	(0.08)	(0.07)	(0.07)	(0.11)	(0.09)	(0.08)	(0.08)	(0.13)	(0.12)	(0.09)	(0.10)
Decision Tree	-0.05	-0.02	-0.02	-0.04	-0.12	-0.13**	-0.13**	-0.13**	0.07	0.11	0.11*	0.09
	(0.05)	(0.06)	(0.05)	(0.06)	(0.08)	(0.06)	(0.06)	(0.06)	(0.08)	(0.07)	(0.06)	(0.07)
Random Forest	0.00	0.01	0.01	0.01	-0.16*	-0.19***	-0.19***	-0.19***	0.12	0.16	0.16**	0.16**
	(0.05)	(0.06)	(0.06)	(0.05)	(0.09)	(0.07)	(0.07)	(0.06)	(0.10)	(0.09)	(0.08)	(0.07)
Gradient Boosting	0.00	0.02	0.02	0.00	-0.18*	-0.19***	-0.19***	-0.20***	0.18*	0.21**	0.21***	0.18**
	(0.05)	(0.06)	(0.06)	(0.06)	(0.10)	(0.07)	(0.07)	(0.06)	(0.11)	(0.09)	(0.08)	(0.08)
Neural Network (I)	-0.02	0.01	0.01	-0.02	-0.18*	-0.19***	-0.19***	-0.20***	0.16	0.20*	0.20**	0.16*
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2a) Sorting forecasts and long-short portfolios

Performance comes mainly from shorting the bottom 10%. To what extent can share classes of managed funds be shorted? How expensive is it?

	Panel A - top and bottom decile portfolios											
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Decision Tree	-0.05	-0.02	-0.02	-0.04	-0.12	-0.13**	-0.13**	-0.13**	0.07	0.11	0.11*	0.09
	(0.05)	(0.06)	(0.05)	(0.06)	(0.08)	(0.06)	(0.06)	(0.06)	(0.08)	(0.07)	(0.06)	(0.07)
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2b) Forecasting accuracy and fund performance

"If ML models can improve the accuracy of flow prediction for a given fund compared to more basic methods [...], then the liquidity management of that fund can potentially be improved by using ML methods."

	Long portfolio:					**Short portfolio:**					**Long-Short:**				
	CAPM	FF3	FF4	FF5	FF6	CAPM	FF3	FF4	FF5	FF6	CAPM	FF3	FF4	FF5	FF6
Mean	-0.017	-0.045	-0.050	-0.048	-0.048	-0.048	-0.072*	-0.072*	-0.078**	-0.078**	0.030*	0.028	0.021	0.030	0.030*
	(0.066)	(0.045)	(0.044)	(0.048)	(0.046)	(0.063)	(0.042)	(0.043)	(0.038)	(0.038)	(0.016)	(0.018)	(0.016)	(0.022)	(0.018)
OLS	-0.022	-0.049	-0.050	-0.048	-0.048	-0.050	-0.074*	-0.076*	-0.083**	-0.083**	0.030***	0.028***	0.028***	0.037***	0.037***
	(0.065)	(0.042)	(0.042)	(0.040)	(0.040)	(0.063)	(0.042)	(0.043)	(0.041)	(0.041)	(0.011)	(0.01)	(0.010)	(0.011)	(0.011)

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A negative alpha on the long leg? Value of forecast w.r.t to naive predictions?

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Perhaps one can look at the realized alphas based on predictability, i.e.,

i) Sort funds into quintiles based on R_j^2 each month.

ii) Compare average performance across quintiles.

iii) $Performance_{j,t+1} = \alpha + \beta R^2_{j,t} + \gamma \text{Controls}_{j,t} + \epsilon_{j,t+1}$.

Summary

Highly recommended reading! I learned a lot...