A Novel Approach to Align Forecasts to Competing Operational Business Outcomes

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ABSTRACT

We research and develop an approach and tool that quantities credit union branch cash-on-hand forecasts and identifies the set of predictions among a set of competing models that balances competing KPIs among the Chief Membership Engagement Officer (CMEO) and Chief Financial Officer (CFO). This research project extends the **2021 Crossroads Classic Analytics Challenge** among Butler University, Indiana University, University of Notre Dame, and Purdue University where the student authors won first place in the undergraduate division. We show 1) how our ensembled forecast aligns to a couple custom and changeable business KPIs agreed upon among the CMEO and CFO, 2) how any model forecast could be evaluated from these business perspective metrics prior to deployment, and 3) we develop a tool that the credit union's Business Intelligence team can use in practice.

INTRODUCTION

The motivation for our study is that if a business tries to identify a model with the lowest prediction error, the "best" forecast could be different based on the error metric used. Furthermore, even using the same error metric, demand forecasts that have the same overall statistical performance will likely not yield the same business performance. For example, consider among a pair of predictive models having the same statistical performance, one model consistently over forecasts while the other consistently under forecasts. The under-forecasted model would likely lead to the common operational problem of more stockouts. In our case, customers not able to withdraw cash when they need it. While the other over-forecasted model would yield the operational issue of having too much inventory, which in our case could mean not gaining interest on available cash on hand or the credit union being charged additional transfer fees. The example forecasts below (Over-, Under-, and Balanced-) all have the same SMAPE of 75.

Figure 1: Actual v.s. Forecast Weekly Total Cash Used (SMAPE)

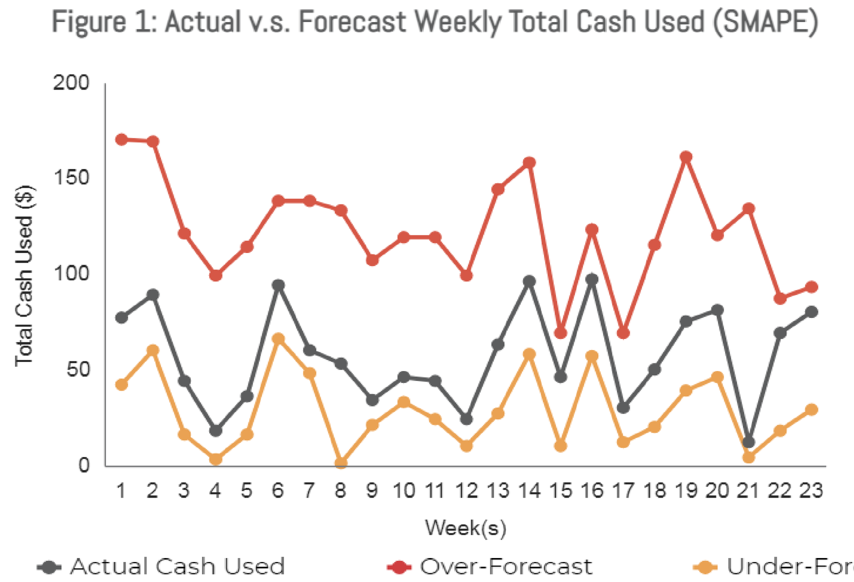
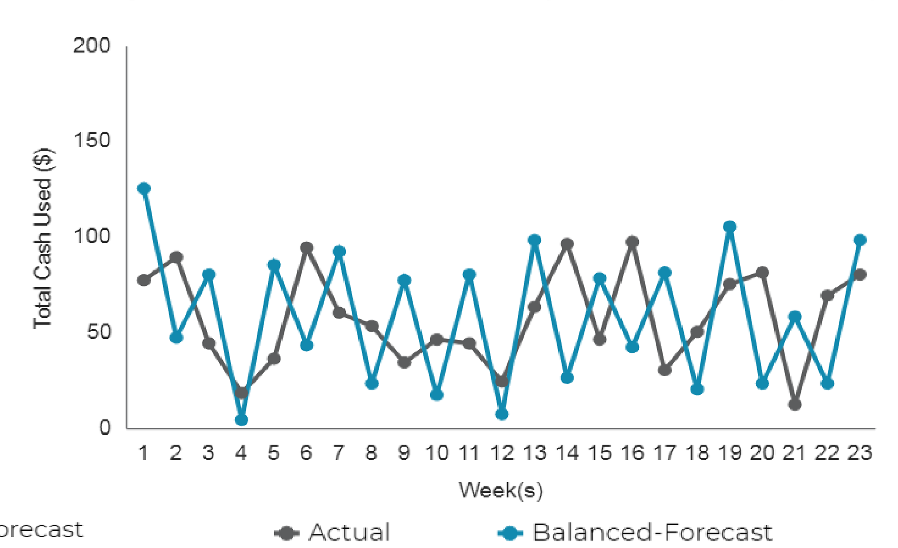


Figure 2: Actual v.s. Forecast Weekly Total Cash Used (SMAPE)



RESEARCH QUESTIONS

- How have others evaluated model forecasts with competing statistical metrics in the academic literature and do they consider business perspective metrics?
- Can we develop a new methodology to identify the "best" forecast as one that aligns competing statistical metrics and custom competing business KPIs?
- Could we develop a software tool that the credit union's Business Intelligence team can use to identify the best forecast to deploy in practice?

LITERATURE REVIEW

We compared our methodology with other similar studies and found a clear methodological gap in the academic literature in how to evaluate multiple statistical error considerations combined with decision-makers KPIs.

		Forecasting models			Evaluation criteria				Decision maker metrics	
Reference	Evaluation & Selection Method	Time-Series	Regression	Classification	SMAPE	MAPE	RMSE	MAE	CFO KPI	CMEO KPI
(Xu & Ouenniche, 2012)	ELECTRE, PROMETHEE	✔	✔			✔		✔		
(Mehdiyev, et. al., 2016)	PROMETHEE		✔				✔	✔		
(Rautray & Dash, 2018)	TOPSIS			✔						
(Petropoulos et. al., 2018)	Judgmental Selection	✔				✔		✔		
(Badulescu & Cheikhrouhou, 2021)	ANP-TOPSIS	✔				✔	✔	✔		
Our Study	Modified AHP-TOPSIS	✔	✔		✔	✔	✔	✔	✔	✔

METHODOLOGY

MODEL DEVELOPMENT

Explanatory Data Analysis
- Broke down data by branches
- Explore white noise, trend and seasonality
- Calculate residuals and ACF

Data Preprocessing
- Data Cleaning
- Data Reduction
- Categorical Feature Transformation

Cross Validation
- 5-Fold Cross Validation
- Training data: 80%
- Testing data: 20%

Model Selection
- TBATS
- ARIMA
- PROPHET
- Neural Network
- XG Boost
- Stacked Ensembles

Model Formation
- Generate models in R studio to predict daily "TotalCashUsed" for each branch.

ANALYTICAL HIERARCHY PROCESS (AHP)

Six Potential Models:

S Stacked Ensemble (H_2O)
P Prophet
X XGBoost
N nnetar (Neural Network)
T TBATS
A ARIMA

Criteria for Model Comparisons:

- MAE
- RMSE
- MAPE
- SMAPE (1)
- SMAPE (2)
- Decision Maker Metrics ($)

STEP 1: Pairwise Comparison Matrix

Use a pairwise comparison, meaning two alternatives are compared according to a criterion and one is preferred.

STEP 2: Normalize to Synthesize

- Normalize the matrices.
- Prioritize the decision alternatives within each criterion.

STEP 3: Criteria Preference Matrix

Combine preference vectors:

	Criteria					
Model	MAE	RMSE	MAPE	SMAPE1	SMAPE2	Cost
S	0.139106	0.151247	0.178751	0.144988	0.090705	0.134144
P	0.157563	0.15985	0.199547	0.15429	0.177825	0.163961
X	0.208461	0.193085	0.105645	0.214831	0.234595	0.194808
N	0.141732	0.155605	0.152923	0.154205	0.207922	0.160665
T	0.175623	0.17018	0.177489	0.165697	0.08575	0.177354
A	0.177515	0.170034	0.185646	0.165989	0.203203	0.169067

STEP 4: Rank Criteria

Rank the criteria based on its relative importance to the decision makers.

STEP 5: Normalize Ranked Criteria

Normalize the criteria matrix from step 4.

STEP 6: Preference Vector for the Criteria

Calculate the preference vector for the criteria:

Criteria	MAE	RMSE	MAPE	SMAPE1	SMAPE2	Cost
Preference Vector	0.034274	0.034274	0.073628	0.140313	0.462549	0.254963

STEP 7: Overall Scores and Overall Ranking

Overall Scores

Model	Overall Score
S	0.1547
P	0.1590
X	0.2010
N	0.1523
T	0.1653
A	0.1678
Total:	1.0000

Overall Ranking

Ranking	Model:
1	nnetar
2	Stacked Ensemble
3	Prophet
4	TBATS
5	ARIMA
6	XGBoost

STUDY IMPLICATIONS

- We developed a Shiny App in R which can be utilized directly by the credit union to identify the best forecast to deploy for their business.
- The business could customize backorder cost and interest rate parameters based on how decision-makers KPIs may change.

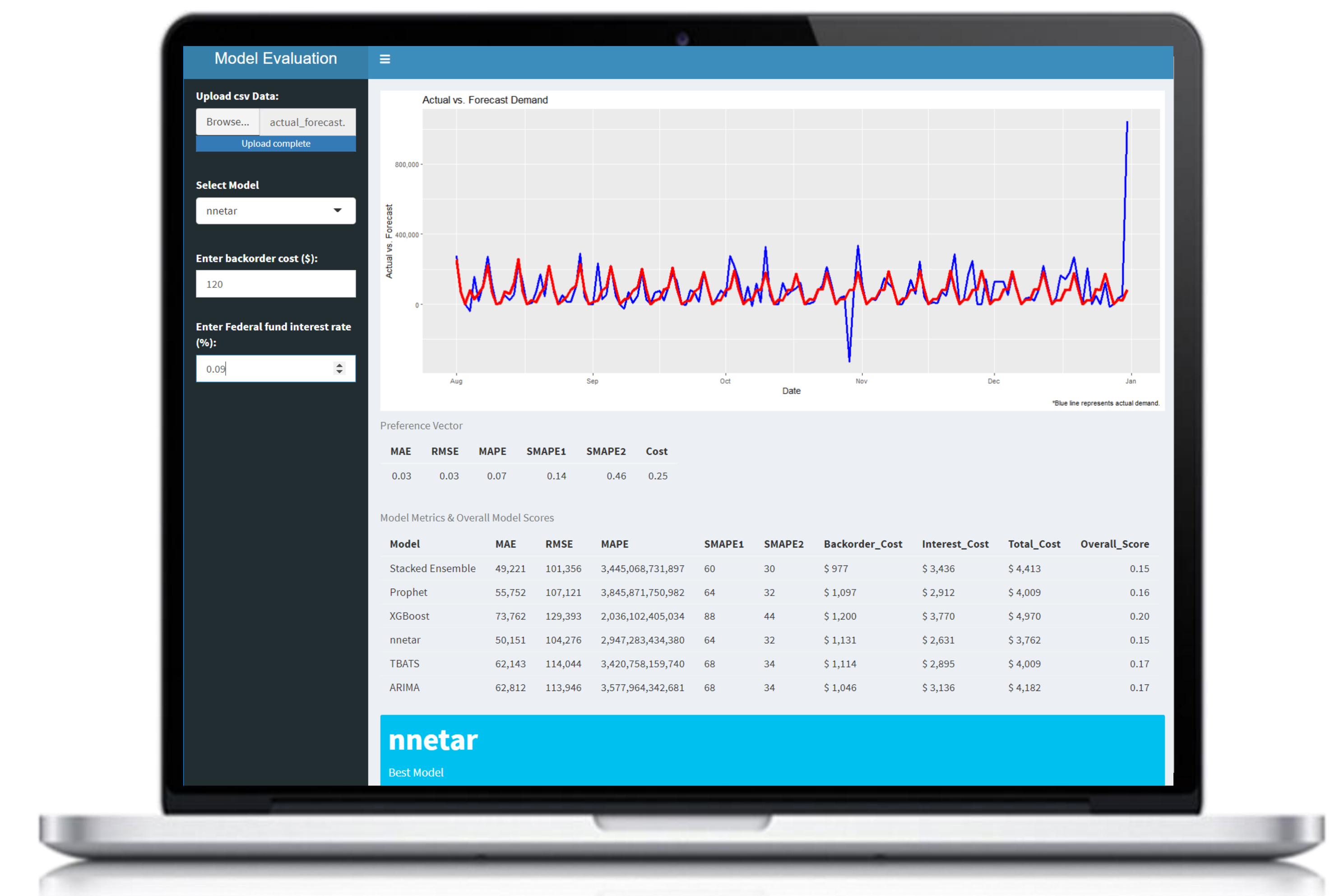


Figure 3. Model Evaluation Shiny App

By using our model evaluation App, the credit union can:

- Identify the best forecasting model among a set of competing models, even when statistical metrics might have conflicting suggestions.
- Lead to better business outcomes among competing decision makers.

CONCLUSIONS

- Our methodology, which is a combination of academic and real-world applications, can be widely used in other businesses in need of a model evaluation mechanism and is easy to implement.
- Through our research, we have successfully developed a practical tool for the credit union to evaluate different potential models in order to identify the "best" forecast for deployment.
- "Your brilliant problem-solving skills and critical thinking will enable TCU to reach targets, provide our team members with valuable resources, which will enable us to provide consistent WOW service to our members. Great work!"

--- Nicole Alcorn, CMEO of TCU

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