Realvo

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Introduction and Purpose

Real estate investment trusts (REITs) represent over 1.5 trillion dollars in equity market capitalization in the United States and represent one of many present forces in humanity's current desire to ascertain increasing levels of capital dominance. Within this space, corporate and small-family REITs differ significantly in structure, risk, and sensitivity to economic trends.

Forecasting their returns remains a challenge due to the complex interplay of factors, including:

- Consumer Price Index (CPI)
- Debt-to-Equity Ratio (DER)
- Market capitalization
- Capitalization rate
- Funds from operations (FFO) growth

To address this, we developed **Realvo**—an analytical study of REIT feature relationships using Temporal Fusion Transformers (TFT) and Extreme Gradient Boosting (XG-Boost). Our approach attempts to extend the of understanding of feature representations of REITs.

Dataset and Experimental Setup

We utilized the SPG and INVH REIT datasets for our analysis. Key variables included date, total shareholder equity, debt-to-equity ratio, gross profit, revenue, total liabilities, EPS, cash on hand, NOI, assets, EBITDA, net income, cap rate, V1, long-term debt, and CPI. The data was collected, cleaned, normalized, and merged into a unified dataset. The date was indexed starting from '1' in 2014 and incremented sequentially as more data was gathered. With this comprehensive dataset and engineered features, we trained predictive models to analyze financial trends and forecast REIT performance.

References

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Model

TFT Architecture: The Temporal Fusion Transformer (TFT) is used to forecast sequential financial indicators using static metadata and time-varying past and future inputs. The architecture consists of:

- Gating Residual Networks (GRN)
- Variable Selection Networks
- Static Covariate Encoders
- Temporal Processing comprised of a seq-to-seq layer and a multi-headed attention block

We suspect that the GRN and static covariate encoder are not optimized, so we propose modifying the GRN's dense Feed Forward Networks (FFN) and static covariate encoder with a Mixture of Experts (MOE) layer that routes each token's hidden representation to a subset of expert FFNs using a learned gating network based on the established TIME MOE architecture. Ideally, the changes to the GRN and static covariate encoder will lower the computational barrier, learn richer representations of the data, and provide insight into the functionality of the gating mechanism. XGBoost is one of many popular models we intend to train for benchmarking against the modified TFT.

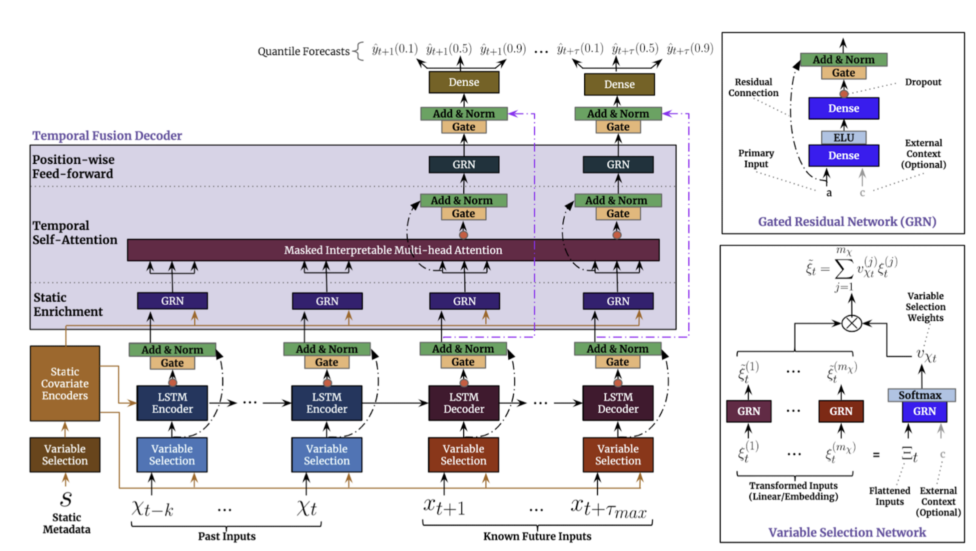

Figure 1. Temporal Fusion Transformer (TFT) Model

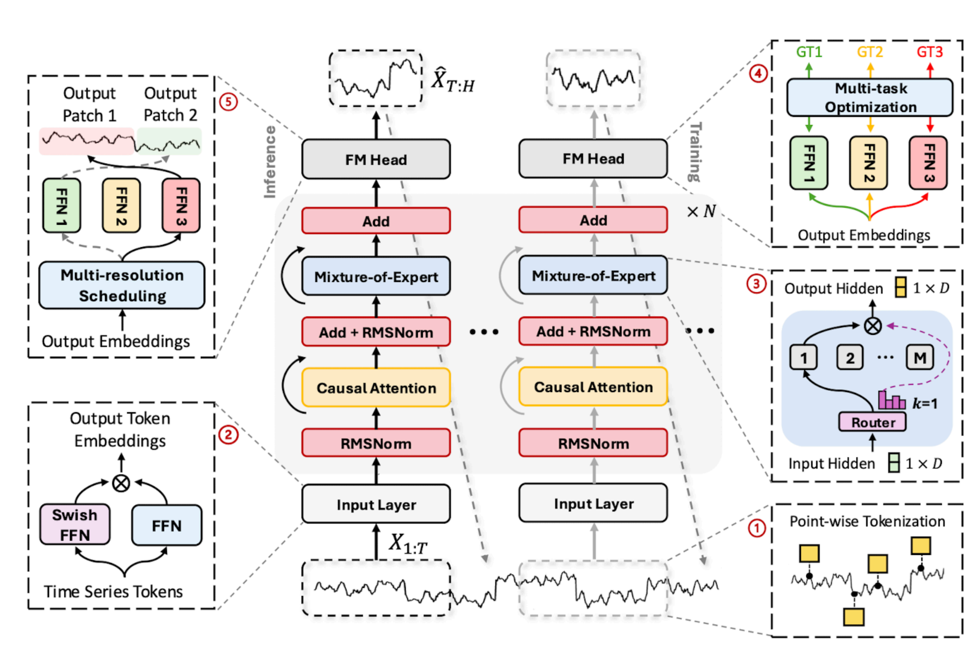

Figure 2. TIME-MOE Model Architectures

Results and Analysis

Model Training. A vanilla, unmodified TFT was trained on 3,200 SPG data points and validated on 800 held-out points. A Bayesian grid search (72 runs over 48 hrs) yielded a validation SMAPE of 10.223

SMAPE Loss. We use Symmetric Mean Absolute Percentage Error:

$$\text{SMAPE} = \frac{100\%}{T}\sum_{t=1}^{T}\frac{|y_t - \hat{y}_t|}{(|y_t| + |\hat{y}_t|)/2}$$

where y_t is the true value and $\hat{y}_t$ the TFT prediction at time t.

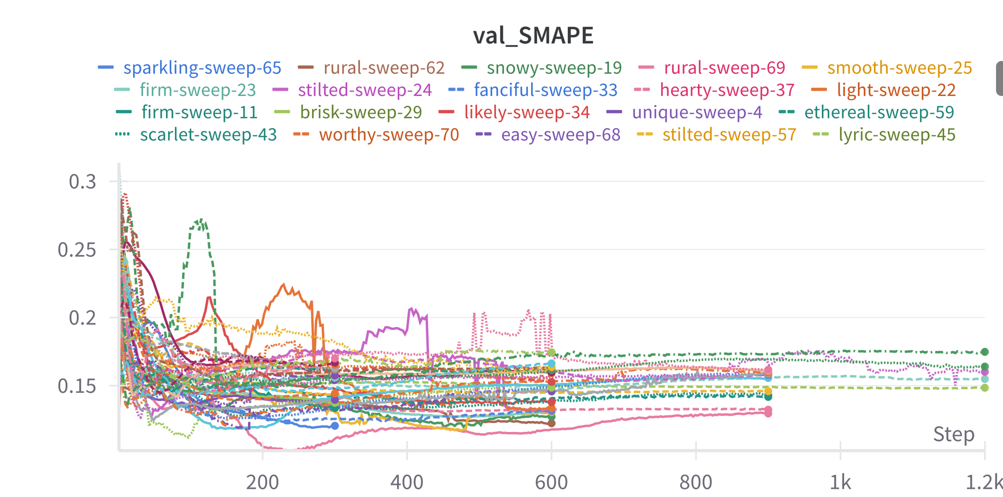

Figure 3. Validation Loss Minimization Search

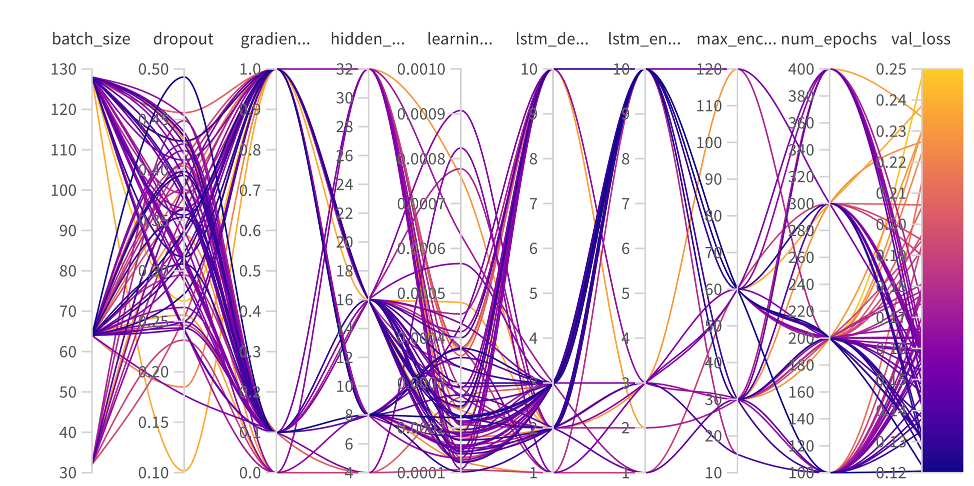

Figure 4. Hyper Parameter Parallel Coordinates

Loss convergence and Generalization. The exploding validation SMAPEs and the extremely low training SMAPEs indicate the model has a tendency to overfit, and the Bayesian grid search needs more training time to converge. The large minimum SMAPE loss score of 10.223 percent indicates that the model on average predicts 10.223 percent away from the true values.

Conclusion

We observed moderate to low accuracy in the TFT's predictions. We plan to optimize the model training by rewriting the complex py-torch TFT with a straightforward tensorflow implementation, and modify the GRN and static co-variate encoder with TIME-MOE implementation.