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Machine Learning in Empirical Asset Pricing and Risk Premia Forecasting

https://github.com/zliu2019/ML-APRP-Forecasting

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Date: 12/10/2020

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Motivation

- Problems in Empirical Asset pricing and Risk Premia forecasting:
  - premia predicting
    - conditional expectation of a future realized return
    - market efficiency - returns driven by unpredictable news
  - variable/factor selection (large pool, correlated)
  - functional form (ambiguity, hidden pattern and relations)
- Machine learning can help in empirical asset pricing with:
  - a diverse collection of high-dimensional models for complex uncertainty
  - regularization techs for factor selection and avoid overfitting
  - efficient nonlinear modeling
- Two canonical research agendas:
  - cross-sectional (across one asset class, predictive signals)
  - **time-series** (directly forecasting)

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Our goal:

- Explore the predictive power of cutting-edge Machine Learning models for time series forecasting on financial industry

Outlines:

- Identify powerful models in various industries
- Apply them on ***financial time series*** and make predictions
- Evaluate them in two-fold:
    - high prediction accuracy: RMSE, MAPE, OWA
    - large economic gains for investors: portfolio Sharpe ratio, return, risk

Data

- 2005-2019, daily, 108 tickers from Yahoo Finance
- ETFs, mutual funds, real estates, commodities

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Next:

- **Models**
- **Python framework design**
- **Hyperparameter tuning**
- **Prediction accuracy**
- **Portfolio performance**
- **Conclusion**

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Models

- ESRNN
  - M4 Competition Winner, an international series of competition
- Telescope
  - improved from ESRNN

Similarities:

- Hybrid of traditional time series models and Machine Learning techniques
- Both have been proved to have excellent predict power in time series
  - Firstly, extracted patterns (trend, seasonality, etc)
  - Train Machine Learning models on resulting series
  - Make predictions
  - Add patterns back

Model 1: ESRNN[1]

- Mixes Exponential Smoothing with dilated LSTM network
- Main elements:
  - Deseasonality - ES
  - Generation of forecast - NN
  - Ensembling - average top N models

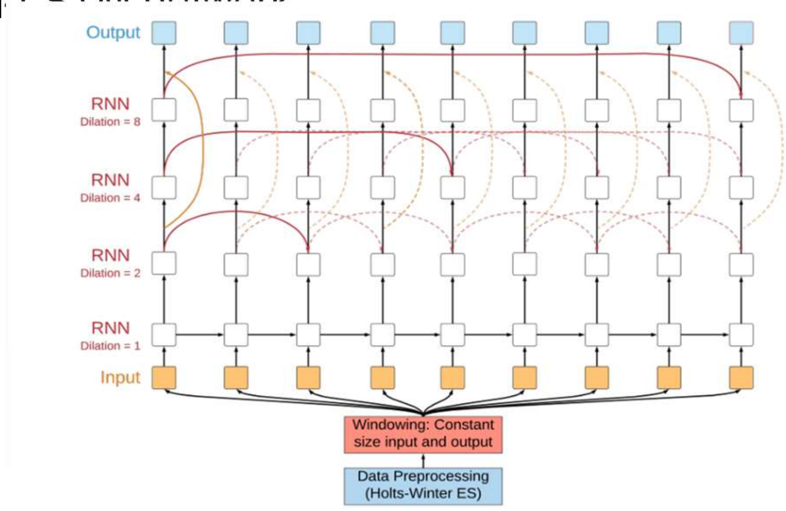
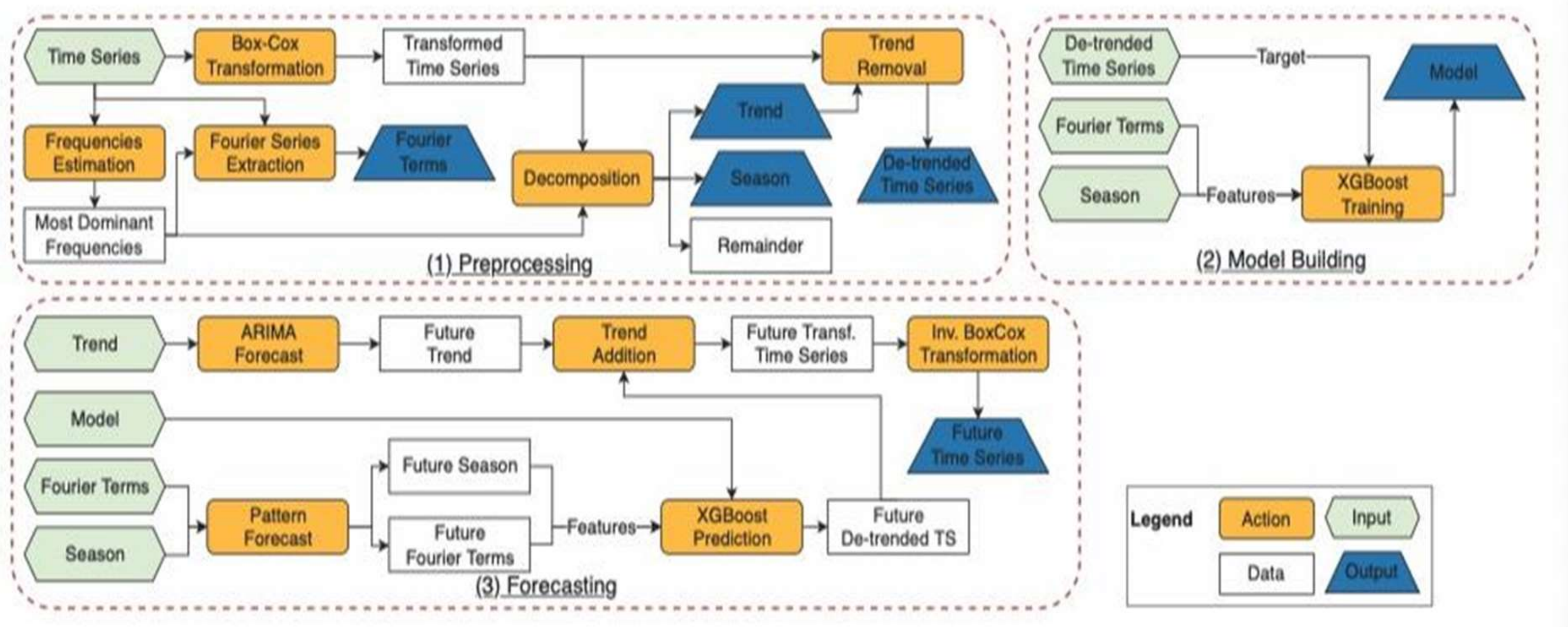


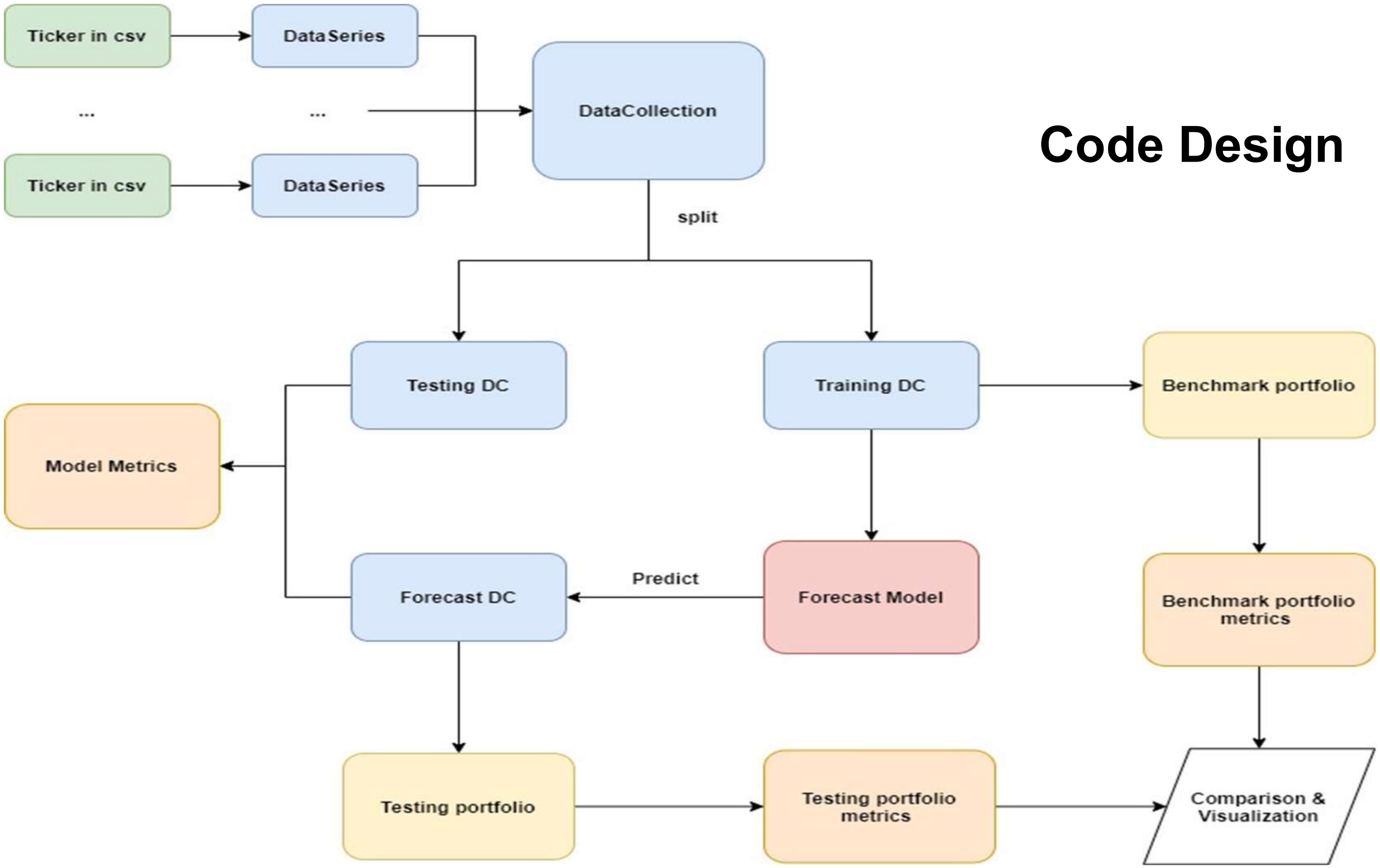
Figure 1: NN Architecture by Smyl et al. (2018)

Model 2: Telescope[2]

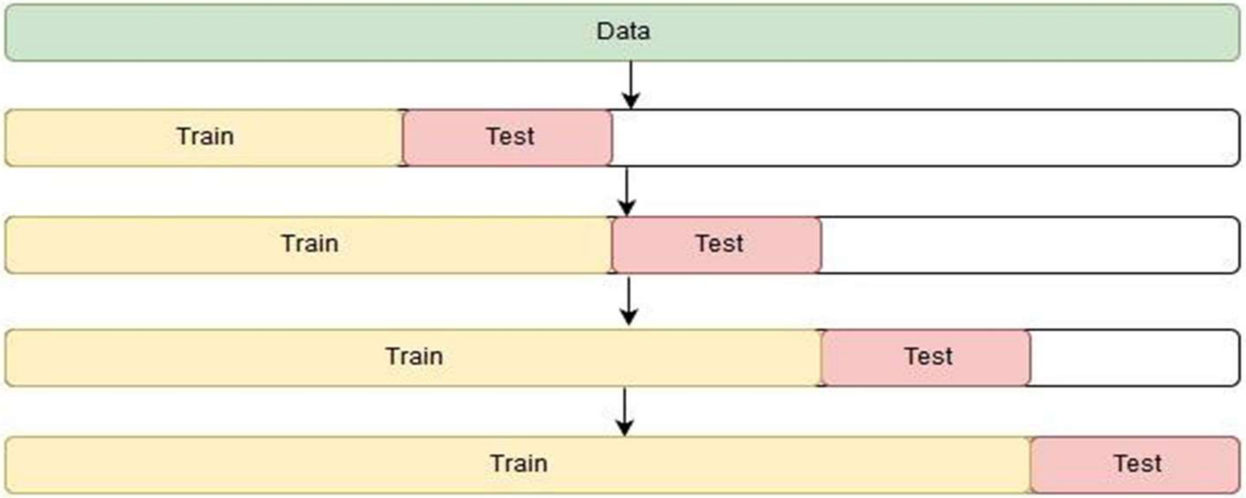
Hybrid multi-step-ahead forecasting approach based on time series decomposition



Code Design


Ticker in csv
DataSeries
...
...
Ticker in csv
DataSeries
DataCollection
split
Testing DC
Training DC
Benchmark portfolio
Model Metrics
Forecast DC
Predict
Forecast Model
Benchmark portfolio metrics
Testing portfolio
Testing portfolio metrics
Comparison & Visualization

Hyperparameters Tuning (Forward-Chaining Nested CV)



Empirical Evaluation:

- Model Performance
- Portfolio Performance

Figure 5: Data split for empirical analysis

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Model Performance - Metrics

- **overall weighted average (OWA)**
  - created by M4
  - compare with a benchmark model
  - the weighted average of
    - symmetric mean absolute percentage error (sMAPE)
      - uses percentage errors that are scale-independent and intuitive to understand
      - but it is always equal to two for a zero actual value, regardless of the forecast that is used
    - mean absolute scaled error (MASE)
      - fix problems of sMAPE
      - provide an alternative with better mathematical properties such as a defined mean and a finite variance
- **root mean squared error (RMSE)**
  - a popular absolute measure of fit

$$OWA = \frac{1}{2}\left(\frac{Model\ sMAPE}{Benchmark\ sMAPE} + \frac{Model\ MASE}{Benchmark\ MASE}\right)$$

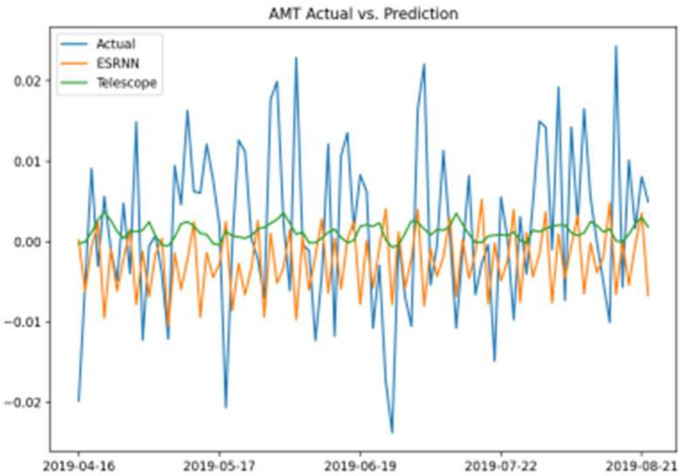
Model Performance - Results

- Both models beat benchmark on average (based on OWA)

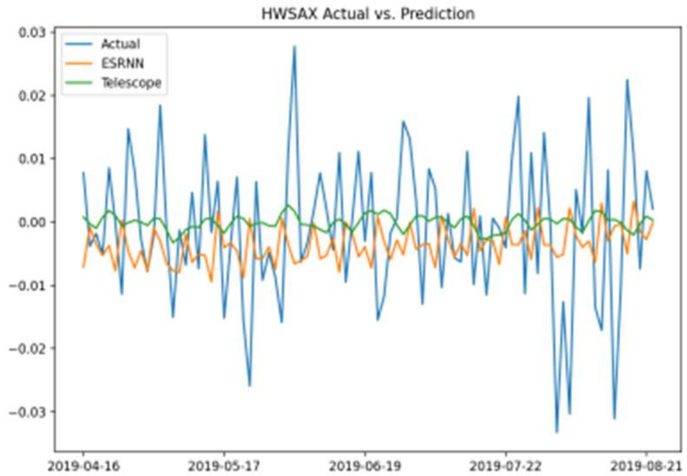
	ESRNN	Telescope
RMSE	0.015	0.012
MASE	0.657	0.473
MAPE	0.009	0.007
OWA	0.946	0.689

Model Performance - Visualization

- Outperforming benchmark does not mean great accuracy



(a) AMT actual vs. predictions



(b) HWSAX actual vs. predictions

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Portfolio Performance - Construction

- minimum variance portfolio
    - a collection of assets combined to minimize the volatility of the overall portfolio
- efficient risk portfolio
    - a collection of assets combined to produce the highest possible returns at the given level of risk

For each type of construction, we compare an enhanced portfolio (predicted returns) with a benchmark portfolio (historical returns)

Portfolio Performance - Metrics

- high annualized return
- high Sharpe ratio
- small volatility
- small max drawdown

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Portfolio Performance - Results

	Minimum Variance Portfolio			Efficient Risk Portfolio (Vol=0.2)		
	Benchmark	ESRNN	Telescope	Benchmark	ESRNN	Telescope
Annu. Return	0.002	0.007	0.007	0.020	0.138	0.113
Annu. Volatility	0.010	0.018	0.102	0.016	0.132	0.200
Sharpe Ratio	-0.023	0.620	0.850	1.176	1.113	0.700
Max DrawDown	-0.005	-0.012	-0.050	-0.007	-0.065	-0.090

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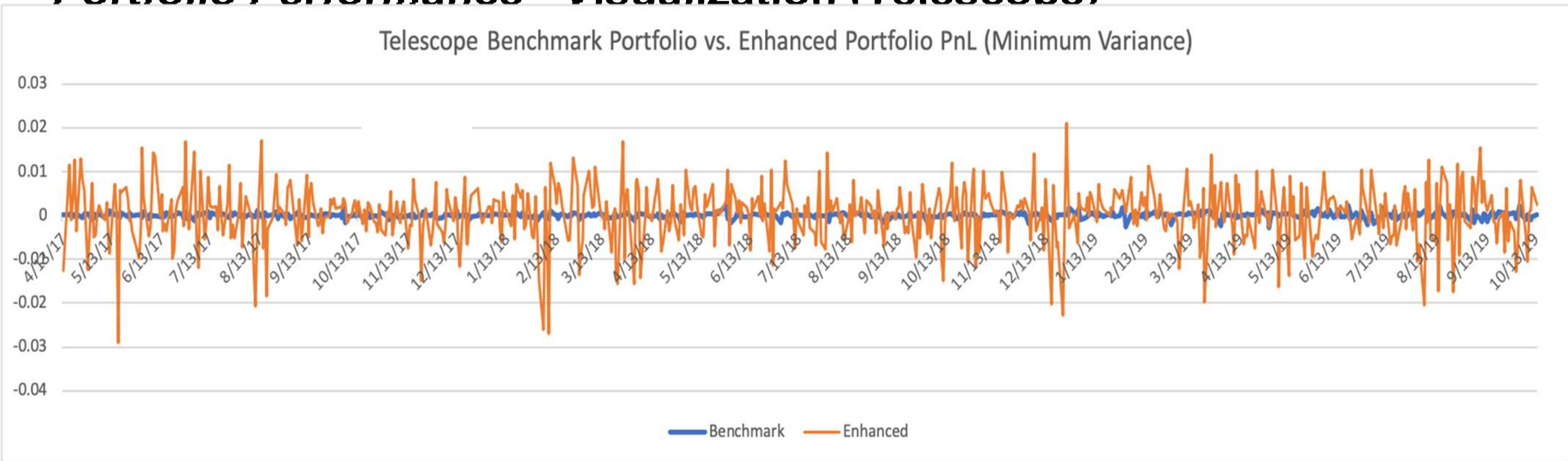
Portfolio Performance - Visualization (Telescope)



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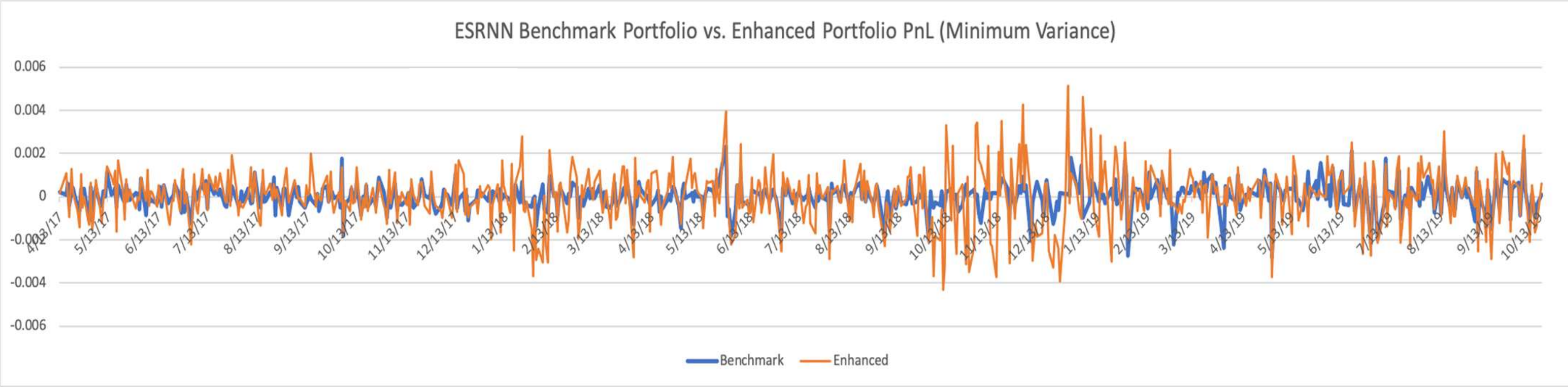
Portfolio Performance - Visualization (ESRNN)



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Conclusion

- **Volatile results:**
    - ML has its shortcomings as it cannot impose economic principles and hence cannot identify deep fundamental economic mechanisms along with a higher volatility in returns
    - Telescope is unable to recognize enough frequency terms to construct a tree-based model
- **Possible improvement:**
    - volatility modeling
    - add more features in Telescope
- **Future works:**
    - factor-based prediction models (LASSO)
    - predict factors’ time series instead of asset returns

References

[1] Bauer, Andre et al. "Telescope: An Automatic Feature Extraction and Transformation Approach For Time Series Forecasting on a Level-Playing Field". 2020 IEEE 36th International Conference on Data Engineering (ICDE).

[2] Smyl, Slawek. "A hybrid method of exponential smoothing and recurrent neural networks for time series forecasting." *International Journal of Forecasting* 36 (2020) 75-85.

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Questions?

Appendix:

input_size = 7
dilation = [[1,2],[4,8]]

Time Frame	Dilations	LSTM Size
Monthly	(1, 3), (6, 12)	50
Quarterly	(1, 2), (4, 8)	40
Yearly	(1, 2), (2, 6)	30

Table 1: Summary of network parameters

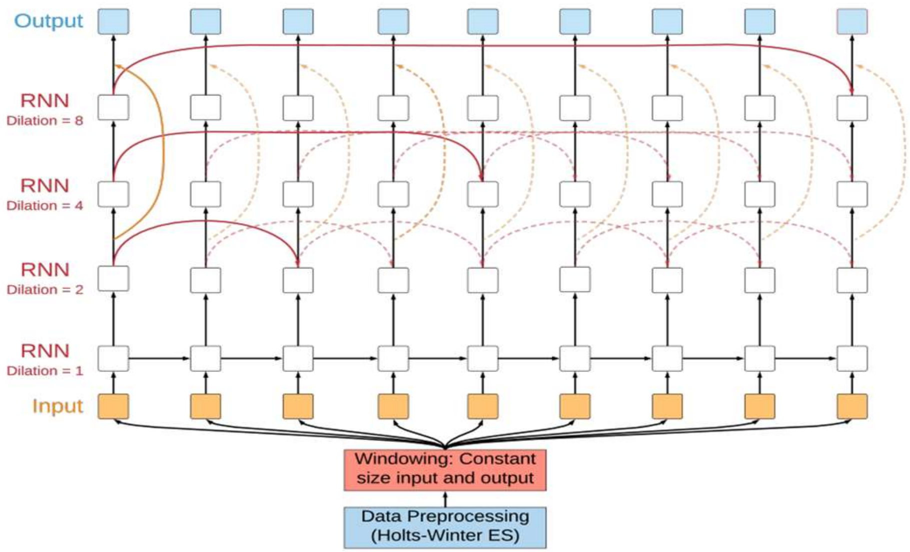

Figure 1: NN Architecture by Smyl et al. (2018)