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# Augmenting Transferred Representations for Stock Classification

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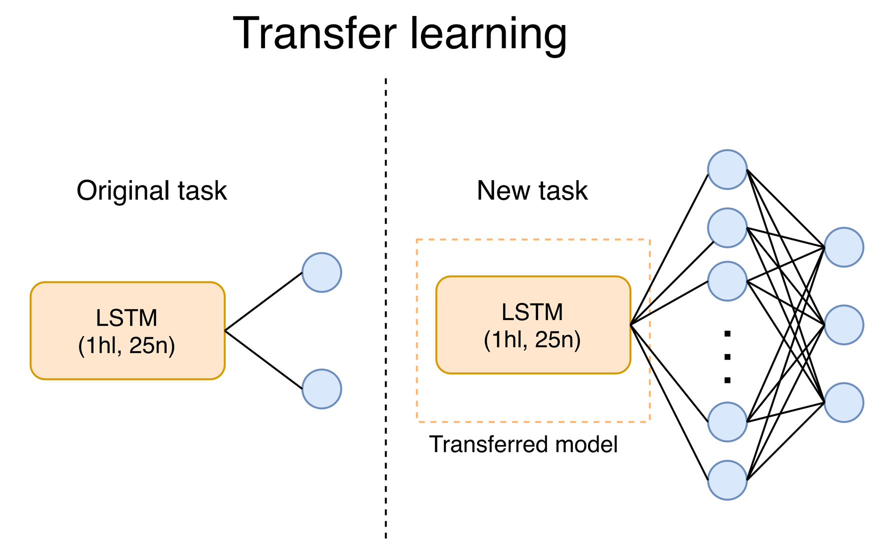
## Introduction

Stock classification is a challenging task due to high levels of noise and volatility of stocks returns.

- We show that using transfer learning can help, by pre-training a model to extract universal features on the full universe of stocks of the S&P500 index and then transferring it to another model to directly learn a trading rule.
- We propose the use of data augmentation on the feature space defined as the output of a pre-trained model (i.e., augmenting the aggregated time-series representation) and compare this approach the standard augmentation in the input space.
- We test our model by building the learned trading rule and calculate profitability considering transaction fees.
- Transferred models present more than double the risk-adjusted returns than their counterparts and augmentation methods on the feature space leads to 20% increase in risk-adjusted return compared to a transferred model without augmentation.

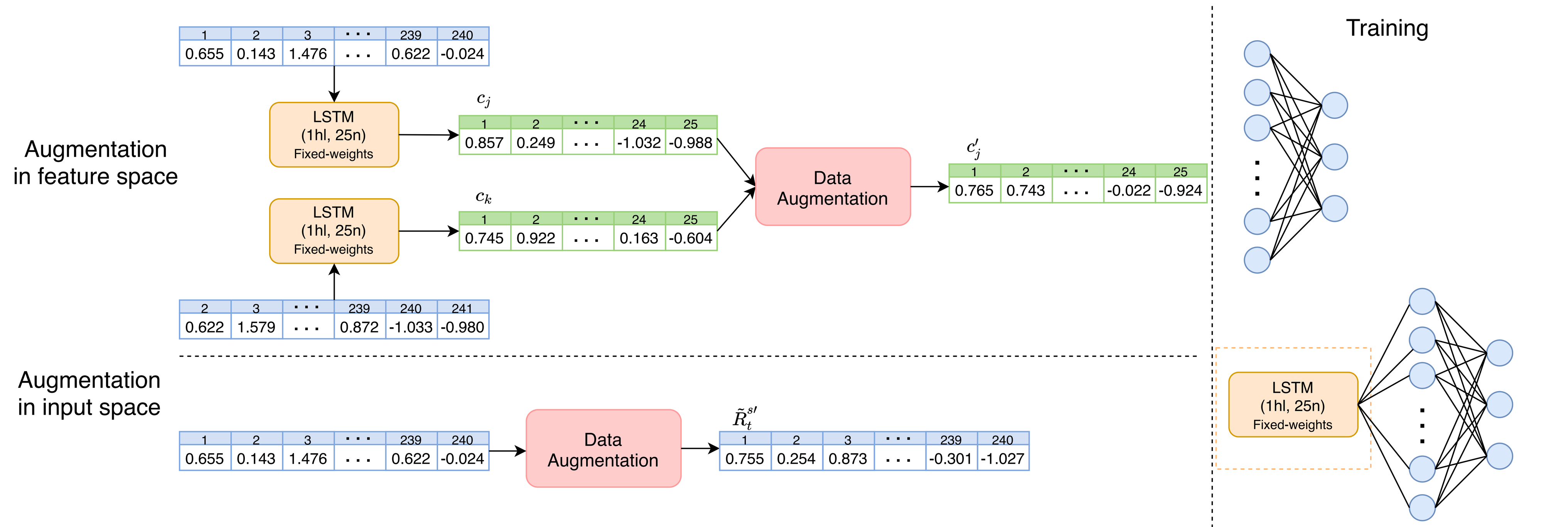
## Methodology



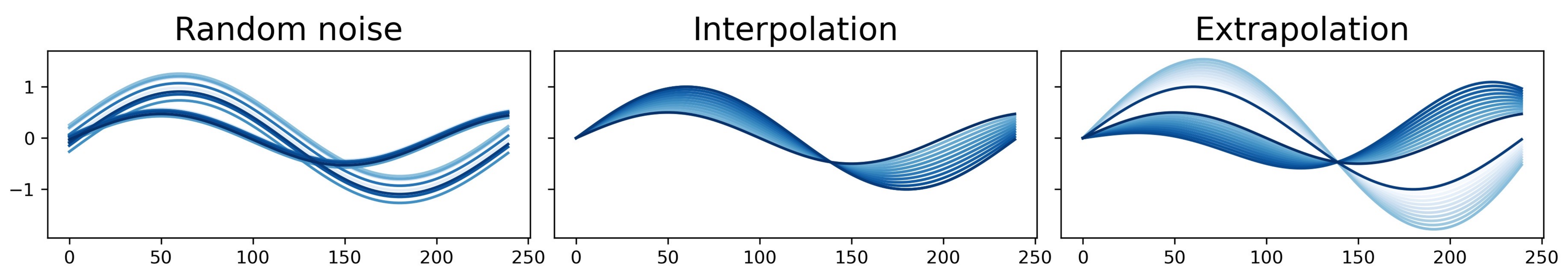

- Dataset: all constituent stocks of the S&P500 index, from1990 to 2018.
- Original task: binary classification, above daily median (trend up) or below (trend down). Network: single layer LSTM with 25n, and a fully connected two-neuron output.
- New task: trading rule with top $K$ stocks labelled *buy*, bottom $K$ stocks labelled *sell* and the rest as *do nothing*. Network: single layer LSTM (25n) fixed with a fully connected layer of {25,100} neurons and an output layer of 3.
- Loss: we used the cross-entropy loss and incorporated a loss term that optimizes the average return, as follows:

$$\mathcal{L}_{R+CE}(\Theta) = \mathcal{L}_{CE} + \alpha\mathcal{L}_{returns} = \mathcal{L}_{CE} + -\alpha\frac{1}{B}\sum R(i,t)$$

## Augmenting transferred representations




### Data augmentation in feature space:




- Interpolation [1]: for each sample, we find its $K$ intra-class nearest neighbors in feature space and for each pair a new vector is generated using:

$$\mathbf{c}'_j = (\mathbf{c}_k - \mathbf{c}_j)\lambda + \mathbf{c}_j$$

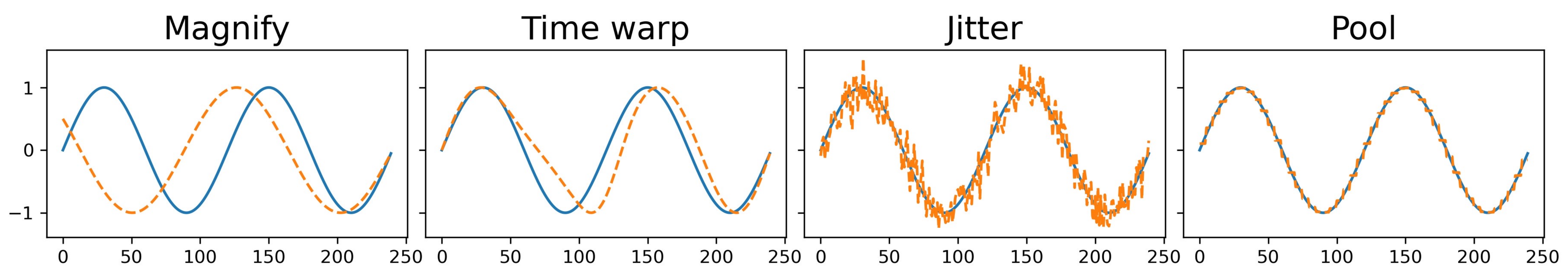
- Extrapolation: similarly, we apply extrapolation to the feature space vectors:

$$\mathbf{c}'_j = (\mathbf{c}_j - \mathbf{c}_k)\lambda + \mathbf{c}_j$$

- Noise: Gaussian noise is generated with zero mean and per-element standard deviation calculated across all transformed vectors in the dataset

$$\mathbf{c}'_i = \mathbf{c}_i + \gamma X, X \sim \mathcal{N}\{0, \sigma_i^2\}$$

### Data augmentation in input space:




- Magnify: a variation of window slicing [2], we randomly slice windows between 40% and 80% of the original time series, but always from the fixed end.
- Jitter: Gaussian noise with $\mu = 0$ and standard deviation $\sigma = 0.05$ is added [3].
- Pool: Reduces the temporal resolution without changing the length of the time series by averaging a pooling window.
- Time warp: time intervals between samples are distorted based on a random smooth warping curve by cubic spline with four knots at random magnitude [3].

## Results

- Ann ret and vol: annualized return and annualized volatility.
- Information Ratio (IR): ratio between excess return (portfolio returns minus benchmark returns) and tracking error (standard deviation of excess returns).
- Downside information ratio (DIR) ratio between excess return and the down-side risk (D. Risk: variability of under-performance below the benchmark), that differentiates harmful volatility from total overall volatility.

| Method | Ann ret | Ann vol | IR | D. Risk | DIR | Acc | Macro-F1 |
|---|---|---|---|---|---|---|---|
| LSTM [4] | 29.2 | **28.66** | 1.02 | 19.08 | 1.53 | — | — |
| No TL (25)+$\mathcal{L}_{CE}$ | 12.99 | 38.15 | 0.34 | 25.48 | 0.52 | 73.13±18.94 | **33.57 ± 6.5** |
| TL+FC(25)+$\mathcal{L}_{CE}$ | 32.25 | 30.29 | 1.06 | 19.6 | 1.65 | 68.34±16.5 | 31.79±5.12 |
| TL+FC(25)+$\mathcal{L}_{R+CE}$ | 34.62 | 30.20 | 1.15 | 19.59 | 1.77 | 64.79±16.86 | 30.72±5.28 |
| TL+FC(25) Extrapolation | **39.70** | 29.43 | **1.35** | 18.96 | **2.09** | 62.90±17.87 | 30.10±5.81 |
| TL+FC(25) Interpolation | 36.87 | 29.69 | 1.24 | **18.93** | 1.95 | 62.46±17.80 | 29.95±5.74 |
| TL+FC(25) Noise | 30.97 | 29.15 | 1.06 | 19.14 | 1.62 | 62.43±18.12 | 29.95±5.81 |
| TL+FC(25) Jitter-feat | 39.11 | 29.93 | 1.31 | 19.22 | 2.03 | 62.71±17.84 | 30.04±5.71 |
| TL+FC(25) Jitter-input | 29.74 | 39.94 | 0.96 | 20.12 | 1.48 | 68.23±16.62 | 31.75±5.06 |
| TL+FC(25) Magnify | 20.39 | 29.41 | 0.69 | 19.86 | 1.03 | 63.78±16.78 | 30.42±5.47 |
| TL+FC(25) Pool | 27.18 | 29.96 | 0.91 | 19.64 | 1.38 | 57.71±17.43 | 28.38±5.72 |
| TL+FC(25) Time Warp | 32.76 | 29.46 | 1.11 | 19.21 | 1.71 | 61.81±19.96 | 29.80±5.48 |

| Method | Ann ret | Ann vol | IR | D. Risk | DIR | Acc | Macro-F1 |
|---|---|---|---|---|---|---|---|
| LSTM [4] | 29.2 | 28.66 | 1.02 | 19.08 | 1.53 | — | — |
| No TL (100)+$\mathcal{L}_{R+CE}$ | 21.05 | 39.95 | 0.55 | 25.9 | 0.84 | 57.02±21.95 | 28.24±8.12 |
| TL+FC(100)+$\mathcal{L}_{CE}$ | 30.83 | 30.31 | 1.02 | 19.79 | 1.56 | 68.88±15.93 | 31.95±4.76 |
| TL+FC(100)+$\mathcal{L}_{R+CE}$ | 32.14 | 29.97 | 1.07 | 19.87 | 1.62 | 64.72±17.25 | 30.7±5.41 |
| TL+FC(100) Extrapolation | 27.38 | 29.33 | 0.93 | 19.42 | 1.41 | 62.74±17.73 | 30.05±5.81 |
| TL+FC(100) Interpolation | 30.84 | 29.72 | 1.04 | 19.38 | 1.59 | 62.49±17.35 | 30.01±5.63 |
| TL+FC(100) Noise | 29.02 | 29.44 | 0.99 | 19.2 | 1.51 | 62.2±17.82 | 29.87±5.73 |
| TL+FC(100) Jitter-feat | **37.14** | 29.31 | **1.27** | **18.92** | **1.96** | 61.84±17.89 | 29.75±5.75 |
| TL+FC(100) Jitter-input | 29.49 | 30.32 | 0.97 | 19.73 | 1.49 | 67.79±17.18 | 31.64±5.46 |
| TL+FC(100) Magnify | 22.11 | 30.36 | 0.73 | 20.21 | 1.09 | 67.12±16.68 | 30.34±5.27 |
| TL+FC(100) Pool | 27.64 | 29.50 | 0.94 | 18.98 | 1.46 | 57.64±17.89 | 28.37±5.89 |
| TL+FC(100) Time Warp | 26.64 | 29.65 | 0.90 | 19.49 | 1.37 | 65.55±18.03 | 29.69±5.89 |

## References

[1] Terrance DeVries and Graham W. Taylor, "Dataset augmentation in feature space", 2017.

[2] Arthur Le Guennec, Simon Malinowski, and Romain Tavenard, "Data augmentation for time series classification using convolutional neural networks", in *ECML/PKDD Workshop on Advanced Analytics and Learning on Temporal Data*, 2016.

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