Multi-Task Learning for Stock Selection

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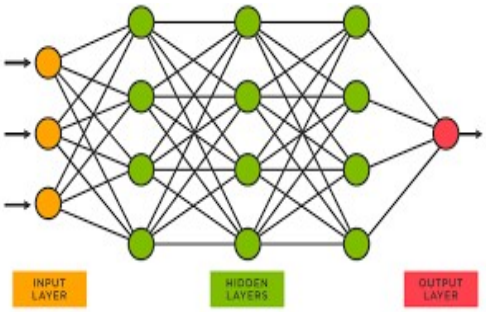
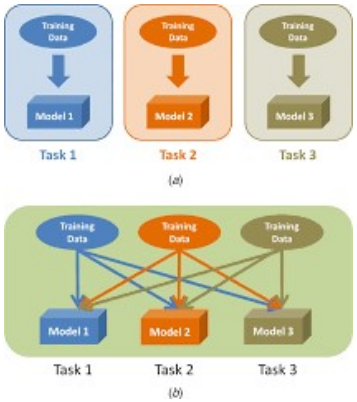
Introduction

- ANNs are commonly used for making predictions in the stock market
- Non-Linear variations of stock prices
- Should we use the same network for all stocks or a different network for each stock?
- A series of experiments were performed on 9 years of data of 35 companies registered in TSE
- ANN was trained to optimize a financial criterion



Literature Review – Multi Task Learning

- ANNs with tabula rasa learning
- Generalization error to be minimized by selecting a small hypothesis
- Tasks may be learned in parallel to improve generalization
- Multi-Task Learning – Networks are trained in parallel and some or all hidden layers are shared between the networks
- The values of some or all the parameters are constrained
- It is also possible that some layers are not shared and the parameters remain free

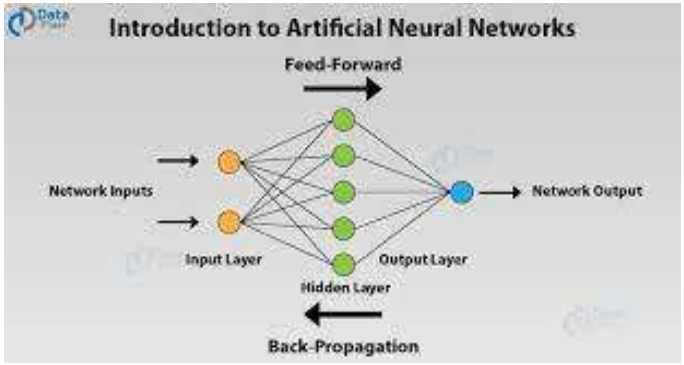


Literature Review – Application to Stock Selection(1)

- Multi-Task Learning for stock selection and portfolio management
- Conducted an experiment with 35 risky assets (stocks of large companies of TSE) and 1 risk free asset
- Each month, one can buy or sell some of these assets
- Multiple training experiments were performed on different training windows, with different initial weights
- Training algorithm based on optimization of parameters with respect to a financial criterion
- The outputs of the network feed a trading module
- Trading provides a new set of weights for the assets as the output

Literature Review – Application to Stock Selection(2)

- We use feed forward network and backward propagation to obtain the final set of weights for the assets
- This helps to optimize the financial criterion
- This process yields a larger profits when compared to training a network so as to minimize the mean-squared error



Results

- Experiments with four different types of parameter sharing and two different architectures(5-3-1 and 5-3-2-1) were performed
- Four types of parameter sharing –
- 1. Same parameters for all stocks
- 2. Sharing parameters of the first hidden layer only
- 3. Sharing only output parameters
- 4. Independent models for each stock

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Table 1: Comparative results for the 5-3-1 architecture: four types of sharing are compared with the buy-and-hold benchmark (see text).

	buy & hold	share all	share hidden	share output	no sharing
Average yearly return	8.3%	13%	23.4%	24.8%	22.8%
Standard deviation (monthly)	3.5%	4.3%	5.3%	5.3%	5.2%
Beta	1	1.07	1.30	1.26	1.26
Alpha (yearly)	0	9%	20.6%	21.8%	19.9%
t-statistic for alpha = 0	NA	11	14.9	15	14
Reward to variability	0.9%	9.6%	22.9%	24.7%	22.3%
Excess return above benchmark	0	4.7%	15.1%	16.4%	14.5%
Maximum drawdown	15.7%	13.3%	13.4%	13.3%	13.3%

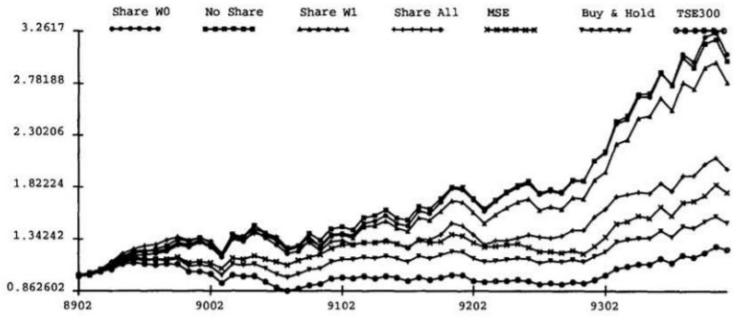

Figure 1: Evolution of total worth in the 5-year test period 02/89-01/94, for the 5-3-1 architecture, and different types of sharing. From top to bottom: sharing the hidden layer, no sharing across stocks, sharing the output layer, sharing everything, sharing everything with MSE training, Buy and Hold benchmark, TSE300 benchmark.

- From the observation table and the graph we observe that for 5-3-1 architecture, the results of the ANN yield better yearly returns as compared to the buy and hold benchmark.
- Beta gives a measure of systematic risk.
- Alpha represents a measure of excess return adjusted for beta.
- Many other terms such as ‘ Sharpe ratio ’, maximum drawdown, excess return, etc. are defined to consider factors like risk involved, overall returns , etc.

Conclusions

- Sharing some parameters yields better yearly returns(for both architectures) than when not sharing any parameters and the risk involved is comparable to benchmarks like buy and hold or TSE300.
- Improvement in the results is observed when some parameters are shared(constrained) while the other parameters are not shared(free).
- The performance obtained in this way is much better i.e. above 14% yearly returns, than compared to standard benchmarks like TSE300 and buy-and-hold (around 8% yearly returns).

Finally we conclude that multi-task learning models are a great choice for stock selection and portfolio management since very large returns are obtained by parameter and hidden layer sharing at risks comparable to the other market benchmarks.

THANK YOU