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Online Knowledge Distillation for Financial Timeseries Forecasting

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- Introduction
- Proposed Method
- Experimental Evaluation
- Conclusions







 Deep Learning (DL) led to state-of-the-art performance for several tasks, including financial time-series analysis.

- Several DL-based approaches have been proposed to this end.
 - Classification-based setups typically prevail.
 - Other approaches do exist, e.g., Deep Reinforcement Learning.





- **Deep Neural Network (DNN) classifiers** can be used to this end in several different settings.
- Such networks operate on various information regarding a time-series.
 - e.g., past daily returns of an asset, volatility, etc.
- Typical setup: **predict the return over a specific horizon**, e.g., daily returns.





- However, employing DNNs on financial time-series analysis tasks is a notoriously difficult and unstable problem.
- The noisy nature of the data leads to considerably different behaviours between models, even when trained with exactly the same hyperparameters.
 - Affects a wide range of settings and setups, e.g., both classification and reinforcement learning-based.





Comparing five different training runs using different initializations of the same deep residual CNN.



- The classification set-up always introduces an additional hyperparameter.
 - Threshold for price movements to be assigned to each of the available classes (e.g., up, down, stationary).
- The aforementioned instability issues could be (partially) attributed to the existence of near-conflicting ground truth annotations.
- When similar input samples carry different annotations, the network is forced to overfit the noise component of the data.

 Aim: Mitigate the intense overfitting problem caused by conflicting annotations in financial trading agents.

- Contribution:
 - Employed ensemble-based online knowledge distillation to transform the hard ground truth labels into soft and more meaningful representations.
 - Stabilize the training process and the performance of the networks.

FOREX Dataset Structure

- Features: [R_{t-w+1}, ..., R_t]
- Labels: [Buy, Sell, Exit] Classes' split based on R_{t+1}. All classes are perfectly balanced in train set

- Knowledge distillation can be used to transform the handcrafted labels to more meaningful representations.
- More information regarding the similarity of samples with the available classes is introduced.

Basic Knowledge distillation set-up:

- Train 1 teacher network for some epochs with the handcrafted labels.
- Use the teacher network to produce soft representations that will be used for the student's training.

Drawbacks

- The teacher can be unreliable as it was trained with conflicting hard representations.
- Computational intensity as this is a two-step process that cannot be parallelized.

Ensemble Based Knowledge Distillation

Steps:

- 1. A number (e.g., 5) teacher networks are trained for N epochs (e.g., 10) with hard labels.
- 2. The training stops and labels are extracted for all data from the teachers ensemble.
- 3. One student network is trained with soft labels coming from the ensemble.

Developed a Deep Learning financial trading agent via
Ensemble Based Online Knowledge Distillation.

 Teacher networks are used to gradually transform the initial hard ground truth labels into more meaningful and less conflicting representation.

Ensemble Based Online Knowledge Distillation

Advantages:

- Easy to use one step end-to-end process.
- Reduces computational complexity as teachers and student can be trained in parallel.

Experimental Evaluation

FOREX Dataset

37 different currency pairs were used such as *EUR/GBP, EUR/USD, CHF/JPY, GBP/CAD, USD/NOK* with a total of 114,234 samples.

Model Architecture

On all following experiments the exact same network architecture and hyper-parameters were used, with the only difference being in the applied knowledge distillation method.

Experimental Set-Up: Walk Forward Testing

Experiments/ Train-Test	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Experiment 1			Train set			Test set				
Experiment 2				Train set			Test set			
Experiment 3					Train set			Test set		
Experiment 4						Train set			Test set	
Experiment 5							Train set			Test set
						Ļ	↓	Ļ	Ļ	↓
					ſ	Out of sample predictions				

The presented Results are an average of the test metrics of all 5 sub-experiments.

Results Comparison

Conclusions

Conclusions

- Developed an end-to-end **Ensemble Based Online Knowledge Distillation** scheme that effectively mitigates the instability problem.
- A Teachers' ensemble can successfully be used to extract the new ground truth annotations.
- The proposed method can successfully be used to mitigate the intense instability and overfitting issues in financial trading.

Future research directions:

 Self-distillation approaches can potentially reduce the impact of noisy handcrafted labels on teacher models and further improve the performance of the method.

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Find more about DeepFinance project at <u>deepfinance.csd.auth.gr</u>

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Thank you for your attention!

Questions?

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