## Discussion of: "Teaching Economics to the Machine" Hui Chen, Yuhan Cheng, Yanchu Liu, Ke Tang

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AMES

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# Background

- Widespread applications of AI/ML in economics and finance
- The obstacles of applying ML in economics
  - Lack of massive sets of high-quality data in economics
  - Low signal-to-noise in economic and financial data
  - The black-box nature of ML
- The advantages of ML
  - The ability to self-correct from data
  - Eliminate the influence of human subjective factors
  - Rich flexibility

## Basic idea

• Tradeoff between theory and data

	Pros	Cons
Theory	Economic insights	Poor fit with data
Machine learning	Rich flexibility	Over-fitting

- Motivation: How to take advantage of the best of both methods?
  - "Teaching Economics to the Machine"!

## Basic idea

- How to teach economics to the machine?
  - Transfer learning!
- Core idea:
  - Source domain: Teach economics to NN
    - Construct a NN model using the simulated data generated by the structural model
    - Torture the NN with large learning rates without any concerns for noise
  - Target domain: Update the NN via transfer learning
    - Update the NN model based on real data
    - Only fine-tuning the original NN
      - Use the weight of source domain as the starting point
      - Use a lower learning rates to control overfitting

## A Transfer Learning Framework

- An economic model  $g(\mathcal{M}_i) \ g : \mathbb{R}^m \to \mathbb{R}^k$
- A neural network  $F(\mathcal{M}_i, \mathcal{Z}_i) \ F : \mathbb{R}^h \to \mathbb{R}^k$  with  $X_i = (\mathcal{M}_i, \mathcal{Z}_i)$  and h>m
- Motivation: Teach NN the knowledge about  $g(\cdot)$  before training with real data
- Source domain:
  - Generate simulated training sample data based on  $g(\mathcal{M}_i)$
  - Estimate  $F(\mathcal{M}_i, \mathcal{Z}_i)$  with simulated data
- Target domain:
  - To update  $F(\mathcal{M}_i, \mathcal{Z}_i)$  with real data
  - Restrict  $F(\mathcal{M}_i, \mathcal{Z}_i)$  to be not too far from  $g(\mathcal{M}_i)$

## **Empirical: Option Pricing Performance**

- Input of the pricing NN model
  - $X_i = (S_i, K_i, T_i, vol_i, d_i, r, \mathcal{Z}_i)$ , Z is other characteristics

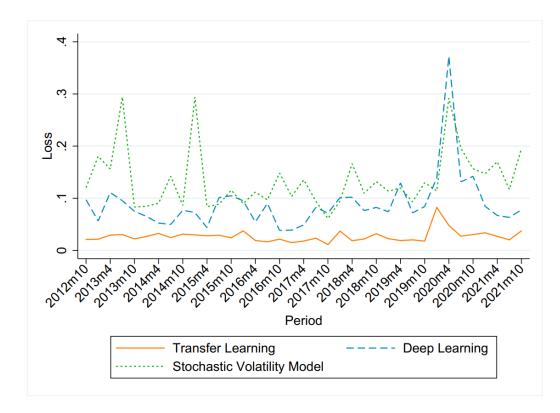


Figure 1: Implied Volatility Mean Absolute Error of Option Pricing Models.

## Empirical: Option Hedging Performance

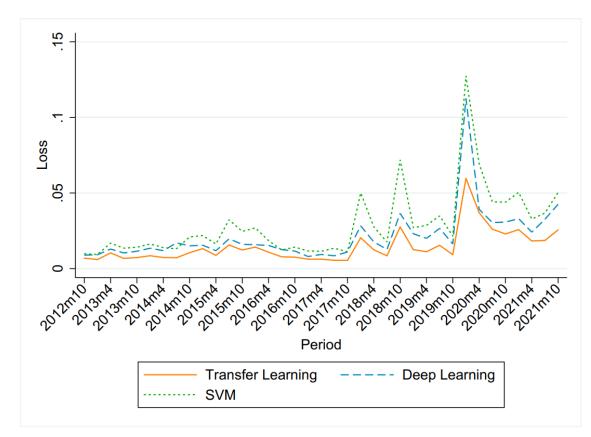


Figure 3: Hedging Error of transfer learning, Stochastic Volatility Model and deep learning. The table reports the hedging error curves of the three types of models from 201210 to 202112. The frequency of error evaluation is the same as the frequency of model retraining, that is, model retraining and model evaluation are done every three months. The loss function of the model is chosen as weighted MAE. The weight is chosen as  $1/(\delta + \epsilon_c)$ .

## Why is Transfer Learning Better?

- Structural shocks and rare event issues
  - It is difficult for pure data-driven models to uncover such change
  - Researchers can set an extremely wide DGP range to cover extreme economic conditions
- Smoothness of TL
- Attribution analysis

## Comment-1: The use of the economic model $g(\mathcal{M}_i)$

- Comment-1.1:
  - Poorer economic model performance -> Poorer Transfer Learning performance?
- Empirical tests:
  - Two subsamples based on BS-model performance: BS-strong vs BS-weak
  - The outperformance of TL compared with DL should be stronger in the BS-strong subsample
- Comment-1.2:
  - Restrict  $F(\mathcal{M}_i, \mathcal{Z}_i)$  to be not too far from  $g(\mathcal{M}_i)$
- Any metric to measure the distance between  $F(\mathcal{M}_i, \mathcal{Z}_i)$  and  $g(\mathcal{M}_i)$ ?
- Optimal distance? How does it vary with market economic condition?

## Comment-2: The construction of Z

- The economic model  $g(\mathcal{M}_i)$
- The neural network  $F(\mathcal{M}_i, \mathcal{Z}_i)$  with  $X_i = (\mathcal{M}_i, \mathcal{Z}_i)$
- In the source domain, the Z is randomly generated and treated as noise

#### • Alternative-1:

- In the source domain training, use real data  $X_i = (\mathcal{M}_i, \mathcal{Z}_i)$ , and calculate the  $g(\mathcal{M}_i)$
- Cons: small sample, cannot cover extreme economic conditions

#### • Alternative-2:

- Artificial trading market to generate other characteristics Z
- Cons: additional and complicated work

## Conclusion

- An interesting paper with clear and intuitive motivation
- Economic theory + machine learning makes it more attractive
- Look forward to reading the updated version