# Multivariable Time Series Forecasting for Trading Abuse with Deep Learning



**Artificial Intelligence with Deep Learning (2023-2024)** 

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URL: <a href="https://github.com/cp2mkc0c023760he/2024-Final-Project">https://github.com/cp2mkc0c023760he/2024-Final-Project</a>

#### **Motivation**

- Two team members are involved in a trading company, and during the initial kickoff, they proposed to evaluate if an abuser could use a **Deep Learning** models to **predict** the next **symbols prices**, focusing on applying **mitigations** to **protect** the company.
- For the other two team members, the proposal was attractive because they find interesting the Financial market.
- Deepen into understanding how is working time series data making use of the state of the art models.



### **Proposal**

#### 1. Neural Architecture

- a. Custom LSTM
- b. Transformer <u>Informer</u>

#### 2. Computational Requirements

- a. Runpod NVIDIA RTX 4090
- b. Colab Pro NVIDIA T4 Tensor



#### 3. Data

- a. Custom dataset based on public obtained data (tick / 10 mins)
- b. Selection of 18 EUR currency pairs from 2015 to the end of 2023

#### **Milestones**



- M0. Research
- M1. **Custom** dataset
- M2. Selection of symbols to predict (EUR pairs)
- M3. Initial versions of LSTM and Transformer models
- M4. Hyper parameter tuning
- M5. Final version and backtesting of the models
- M6. Results comparison between models
- M7. Evaluate **different** symbols

## Results: LSTM 1/2

Num Layers: 1

LR: 9,21e-5

Hidden Dim: 200

Batch Size: 128

Input Dim: 124

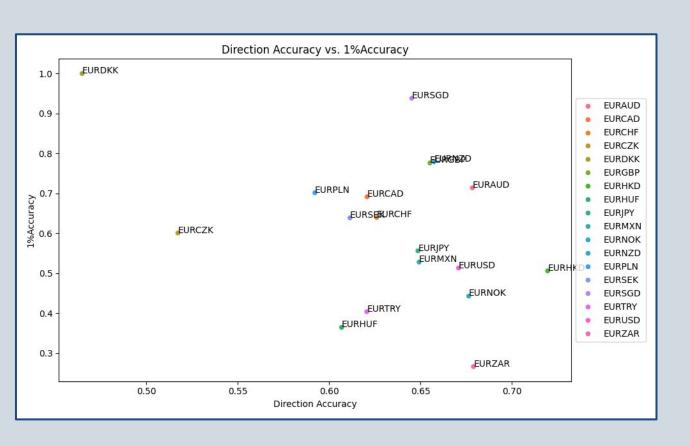
Seq Len: 60

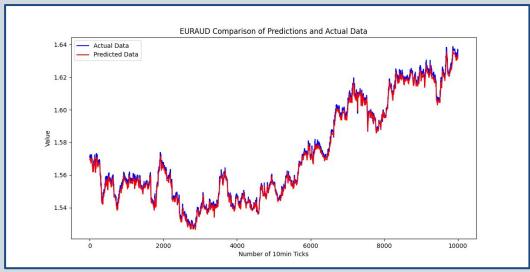
Output Dim: 1

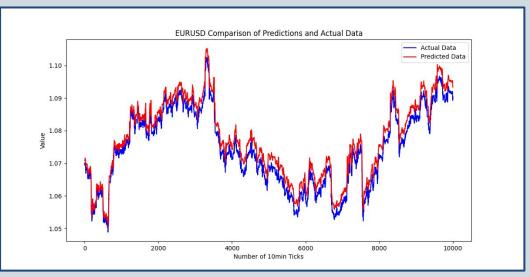
Metrics (LSTM)	Test
MAE	0.077
MSE	0.024312633
RMSE	0.0897
R-squared	0.8232
Accuracy (Direction)	0.6331
Accuracy (1%)	0.5053

Symbols (LSTM)	Accuracy (Direction)	
	Test	Cross validation
EURAUD	0.6947	0.5033
EURNOK	0.6798	0.5025
EURNZD	0.668	0.5046
EURHKD	0.7162	0.5037
EURTRY	0.6088	0.4991

#### Results: LSTM 2/2







## Results: Transformer 1/2

Num Layers: 6+4
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LR: 6e-4

FF Layers: 32\*2

Batch Size: 128

Input Dim: 184

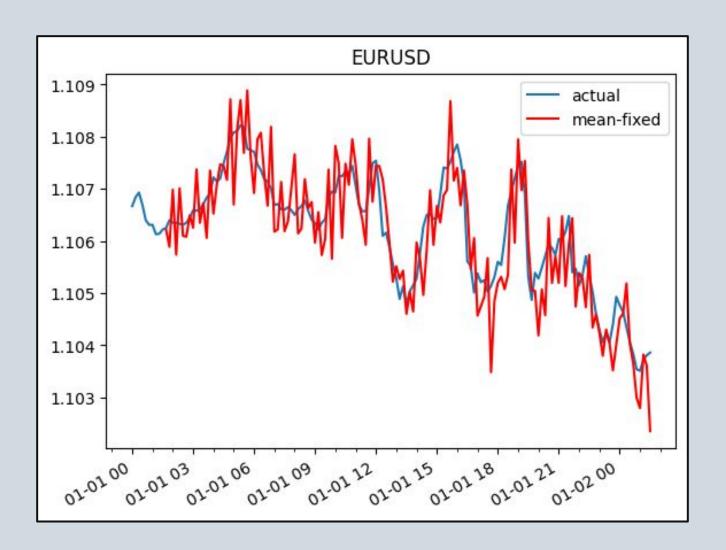
Seq Len: 60

Output Dim: 1

Metrics (Transformer)	Test
MAE	0.19251388
MSE	0.06772889
RMSE	0.19251388
R-squared	-0.0734812
Accuracy (Direction)	0.48996914
MASE	39.2545892
SMAPE	0.45019365

Symbols (Transformer)	Accuracy (Direction)	
	Test	Cross validation
EURUSD	0.52777778	0.502777776
EURSGD	0.49305556	0.504166666
EURSEK	0.46527778	0.518055554
EURCHF	0.42361111	0.540277776
EURDKK	0.35416667	0.50555556

## Results: Transformer 2/2



# **Results: Comparative**

Metrics (All Symbols)	LSTM	Transformer
MAE	0.077	0.192513875
MSE	0.024312633	0.067728887
RMSE	0.0897	0.192513876
R-squared	0.8232	-0.073481209
Direction Accuracy	0.6331	0.489969136

Symbols (LSTM)	Accuracy (Direction)	
	Test	Cross validation
EURAUD	0.6947	0.50336389
EURNOK	0.6798	0.50255579
EURNZD	0.668	0.50466371
EURHKD	0.7162	0.50370695

Symbols (Transformer)	Accuracy (Direction)	
	Test	Cross validation
EURUSD	0.52777778	0.502777776

### Conclusions 1/2

- Gained experience applying LSTM/Transformer models for Time Series Forecasting
- Backtesting, pipeline alignment and custom metrics help to compare model results
- For the symbols chosen **our LSTM** model **performs better** than the **Transformer**:
  - They predict a few symbols pairs (5/18): EUR (AUD|NOK|NZD|HKD|USD)
    - **Test** accuracy (direction): between 50 % and 71 %
    - Cross validation accuracy (direction): greater than 50 %
- Our models:
  - Seem to detect different patterns (different best predicted symbols)
  - Require more testing on other symbols to evaluate its performance

### Conclusions 2/2

- Creating a dataset is a complex and time consuming task
- Feature engineering, since financial data is complex, needs to be researched
- Any operation become CPU/GPU intensive when dealing with huge datasets and must be optimized
- Classical ML algorithms (improved with XGBoost) might perform better

# Questions

