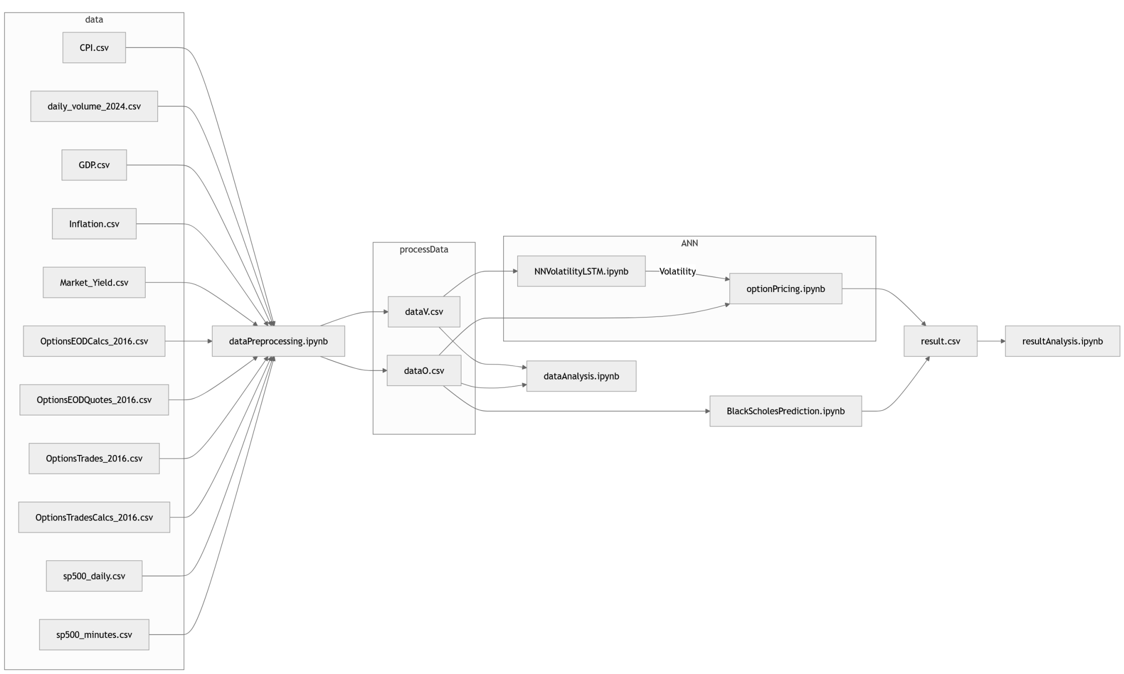
Research Project Report

March 24, 2025

1 Introduction

This document will clearly outline the advancement of the research project. Based on the Scrum and sprint methodology, I will update the document every week, including what is new and what is next.

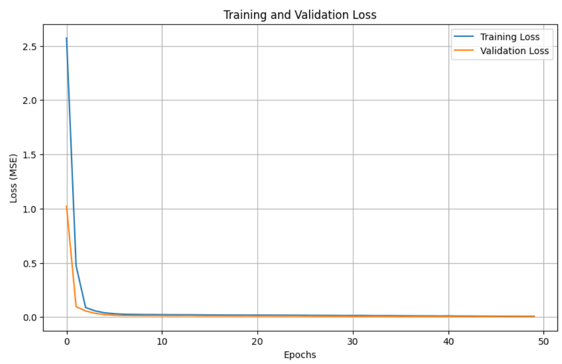


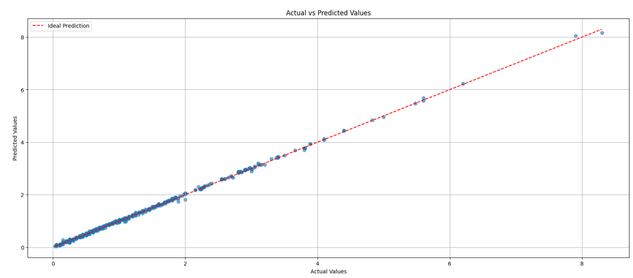
Iteration 1

February 3, 2025

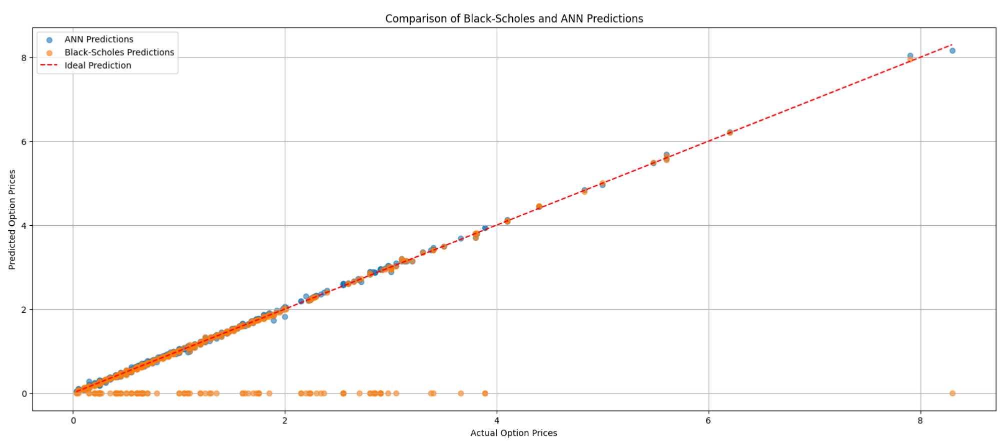
What Is New?

- Created and trained a ANN MLP model for option pricing, using Black-Scholes parameters to target option prices.





- Compared the model's performance against Black-Scholes models:



- Started to build a custom LSTM model with NumPy. For now, I think Python allows better flexibility and development time than C++, while still maintaining decent performance using only NumPy. I want the model to be compatible with TensorFlow formatting for easier use.

What Is Next?

- Finish the custom MLP model.

- Outliers suppression

Iteration 2

February 10, 2025

What Is New?

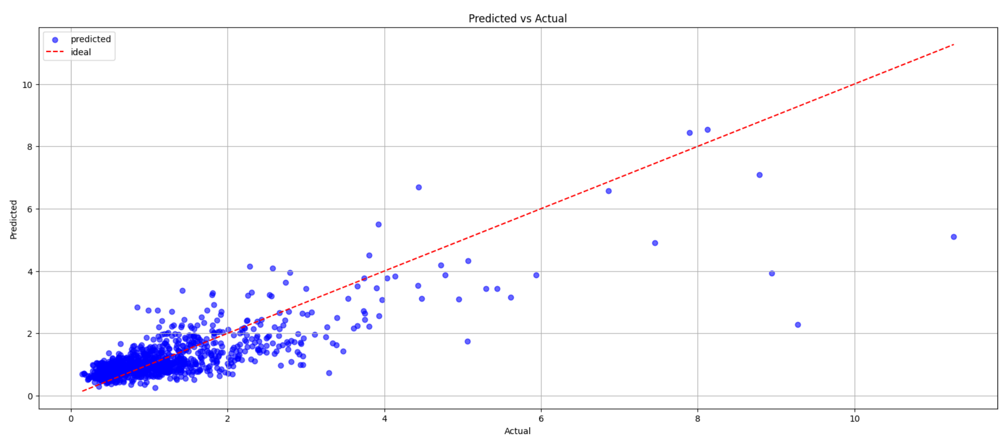
- First principle implementation of artificail neural network **multilayer perceptron**. Can be found here : /code_/models/annModels.py

- ```
  mlp = am.MLP(n_input=22, n_hidden1=64, n_hidden2=32, n_output=1)
  epochs = 5000
  learning_rate = 0.001

  #Training
  history = mlp.train(X_train_normalized, y_train, epochs, learning_rate)

  # Predict
  train_preds = mlp.forward(X_train_normalized)
  y_pred = mlp.forward(X_test_normalized)

  #---
  Final Training Loss: 0.41194406219492513
  Final Test Loss: 0.41460153925356924
  ```



What Is Next?

- Paramater optimization for custom model implementation ?
- Would a Transformer work better ? - Wiki Transformer
  - Very likely, However, to get a working transformer model, the data volume is much more advanced than we currently use.
  ```

Iteration 3

February 17, 2025

What Is New?

- Finnish data gathering with scipt :/code_/tools/getData.ipynb, all the assets data are gather in /data/stocks (around 200 symbols)
- Transformer implementation in progress
- Benchmark against LSTM model
- Paramater optimization for custom model implementation ?

What Is Next?

- Document on maths behind models (models.pdf)

Iteration 4

February 24, 2025

What Is New?

- LSTM implementaiton in progress
- FFNN MLP and LSTM mathematics models

What Is Next?

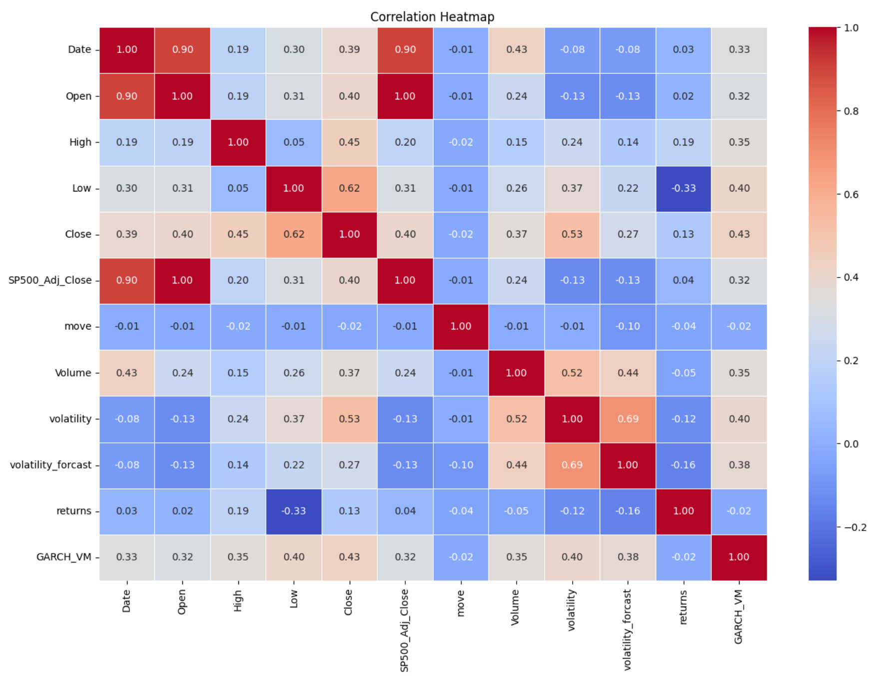
- Identifies specific aspect of volatility time series (mean reversion, volatility clustering, heavy tail)
- identifies drawback in LSTM architecture for specific financial time series
- Optimize model for financial time series
- identify best loss function for volatility time series

Iteration 5

March 3, 2025

What Is New?

- Data Work
  - Compare to litterature
  - Normalize data to improve models performances
  - Select relevant feature to work with the model (clean confusion matrix)
- Litterature about new/modify LSTM model for financial time series prediction
- Document on volatility model updated



What Is Next?

- Improve mathematical relationship of LSTM models with litterature and financial time series properties.

Iteration 6

March 10, 2025

What Is New?

- The volatility time series have some properties as for exemple **volatility clustering**. It implied that huge amplitude volatility periode are follow by small volatility changes and back to huge periode. The default LSTM network isn't aware of that so we can try to implement this in the forget gate to keep this informaiton inside the network. For instance we can propose a solution like this

  $$F_t = \sigma\left(W_f \cdot [H_{t-1}, X_t] + b_f - \mathbf{k}\boldsymbol{\sigma}_{\mathbf{t}}\right)$$

  Where the new term $k\sigma_t$ represente the a contante k that is a leanring parameter to scale the impact on the network and σ_t that is the volatility estimation value.

What Is Next?

- Implementaiton
- Benchmark against default LSTM and Black-Scholes
- Litterature

Iteration 7

March 24, 2025

Litterature review

1. AT-LSTM: An Attention-based LSTM Model for Financial Time Series Prediction
   Adding and attention layer to LSTM model. Appliyng weight to input feature thanks to an attention layer. Then, in a second stage, the attention model select all relevant features for LSTM input model.

MAPE on DJIA	
LSTM	*0.00625*
AT-LSTM	*0.00486*

2. Improved Financial Predicting Method Based on Time Series Long Short-Term Memory Algorithm
   Automated capital prediction strategy, first by analysing the fluctuation and tail risk. Then by use ARIMA and Prophet models. Finally time series modeleing of the wavelet LSTM for a two part analysis of the linear separated wavelet and non-linear embedded wavelet to predict volatility.

Model	Redeem		Purchase		Yield	
	R^2	RMSE	R^2	RMSE	R^2	RMSE
ARIMA	0.6290	0.5222	0.6091	0.5801	0.4183	1.3628
Prophet	0.7677	0.3497	0.7494	0.3959	0.4105	1.4210
Proposed model	0.8539	0.2406	0.8692	0.2318	0.8281	0.3002

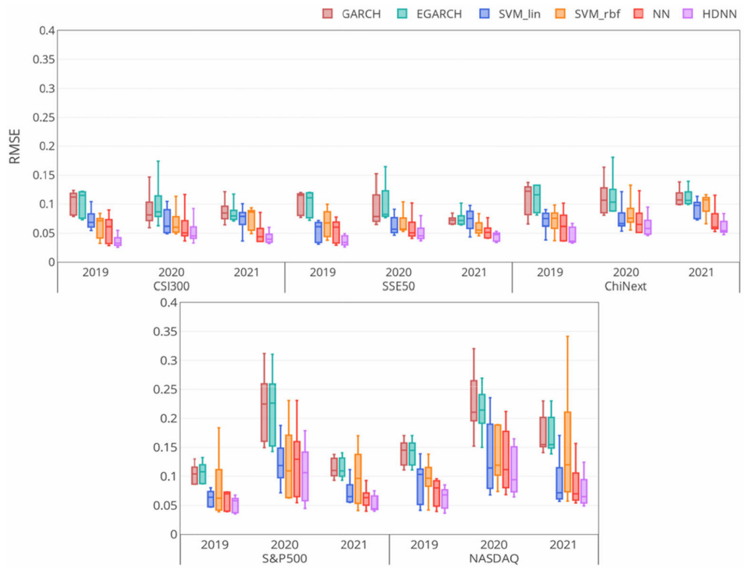
3. Prediction of Financial Time Series Based on LSTM Using Wavelet Transform and Singular Spectrum Analysis
   Imporove LSTM prediction capabilities by using data denoising methods including wavelet transformation (WT) and singular spectrum analysis (SSA) on the closing DJIA, divided in short, meduim and long term time periode. The LSTM data denoising performe better than raw data for data prediciton on all tree time periodes.

   Table 5: 6-hour DJIA closing price forecast results.

	RMSE	MAE	MAPE	SDAPE
LSTM	6.1655946	4.5780000	0.0001503	0.0001356
RNN-dropout	5.3630017	4.3020694	0.0001413	0.0001053
LSTM-dropout	4.5014469	3.2249583	0.0001059	0.0001032
SSA-LSTM	1.1753464	0.9942363	0.0000326	0.0000206
WT-LSTM	1.9164739	1.4123594	0.0000464	0.0000426

4. Black-Scholes-Artificial Neural Network : A novel option princing model
   Comparaison of multiple option pricing model and intruduction of a new model call BSANN, a basic ANN MLP model in [11-15-1] performing better than tranditionnal methodes.

5. Volatility forcasting using deep neural network with time-series feature embedding
   Propose a hybrid deep neural network model (HDNN). Encoding one-dimensionnal time-series data into two-dimensionnal GAF images to use a CNN with 2D concolutions layers, then performe feature embeding and dense layers regression to predict the volatility



6. Volatility forcasting using deep recurrent neural networks as GARCH models
   Propose new method to predict volatility time series by using a combination of GARCH and and deep neural network. Also introduce a mehanisme to identifiy ideal sliding windows side for volatilty. With evaluation of GRU, LSTM, BiLSTM

Table 6 Performance results for the Volatility prediction of the ASX200 Time Series using Recurrent Neural Networks

	Train dataset			Test dataset		
	ALL-GARCH(1,1) with			ALL- GARCH(1,1) with		
	BILSTM	LSTM	GRU	BILSTM	LSTM	GRU
RMSE	**0.1205**	0.2979	0.3391	**0.2106**	0.2226	0.2594
MAE	**0.0934**	0.1952	0.2163	**0.1382**	0.1737	0.2078
MAPE(%)	**7.7217**	9.49156	10.3561	**8.5580**	10.9473	13.1652
R^2	**0.9725**	0.8321	0.7825	**0.4968**	0.4380	0.2368
Spearman	**0.9570**	0.8788	0.8711	**0.7785**	0.6719	0.6788