MSc in Artificial Intelligence

Deep learning

Cryptocurrency price prediction

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Introduction

In the recent years, cryptocurrencies have been very popular because of their values change over time in a great extend.

In this project we tried to predict:

- Cryptocurrency's price over time (Regression problem)
- Cryptocurrency's trend (Classification problem)

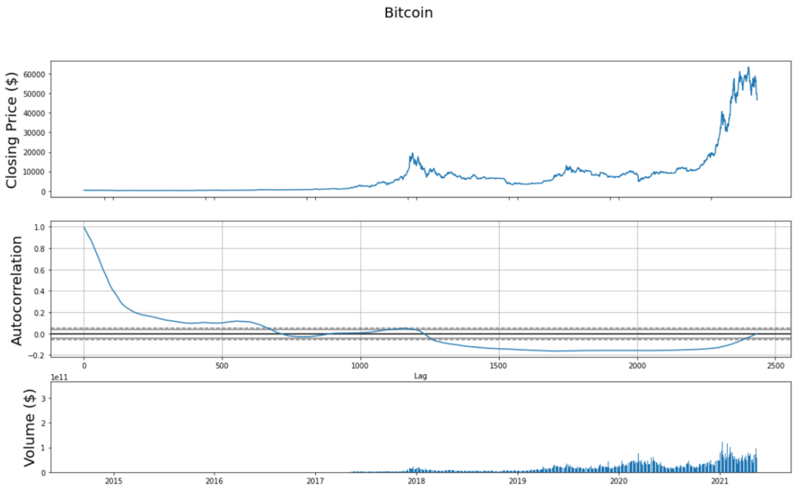
Using:

- Cryptocurrencies historical data
- Social media feed

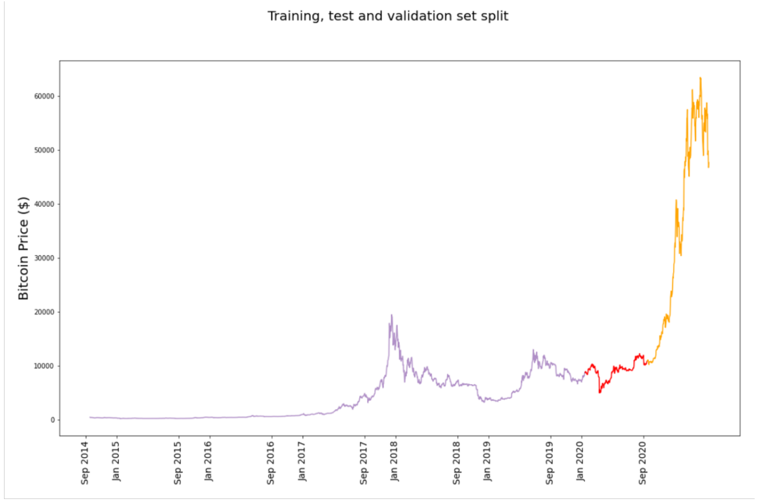
Worked with Tensorflow library using layers:

- LSTM
- GRU

Data preprocessing



- 80% train set
- 20% validation, testing
  - 50% each one
- Differ among the experiments

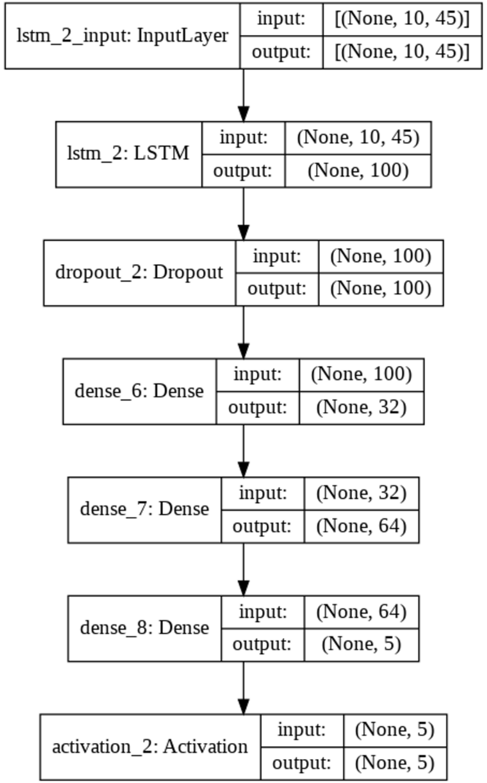


- Autocorrelation changes through time
- Price increases over time
- **Solution?**
  - Used windows normalization of 10 days

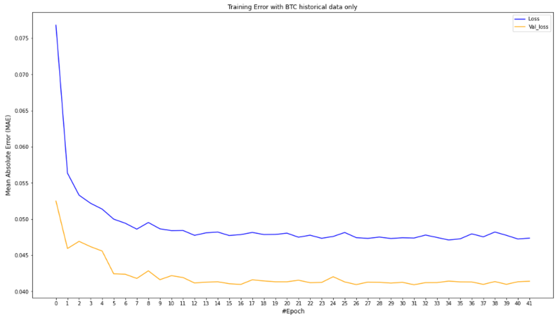
Regression with historical data - Hypertuning

After tuning (Hyperband alg.) the model, we ended up in the following:

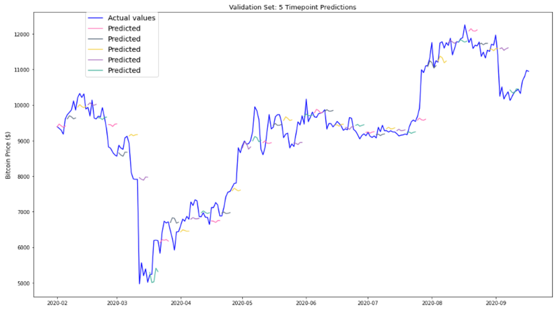
- Combinations of different coins increases performance.
- Batch size 64.
- LSTM output units 100.
- Adam optimizer
- MAE loss
- Feature set:
    - Close
    - Open
    - High

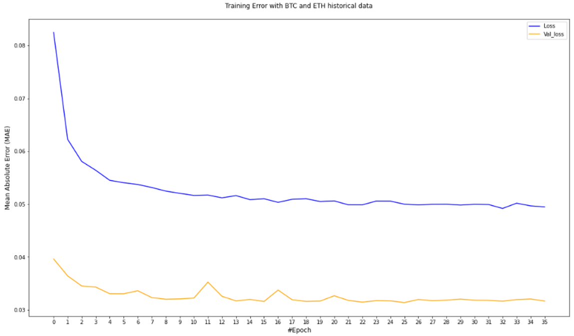


Regression with historical data - Results

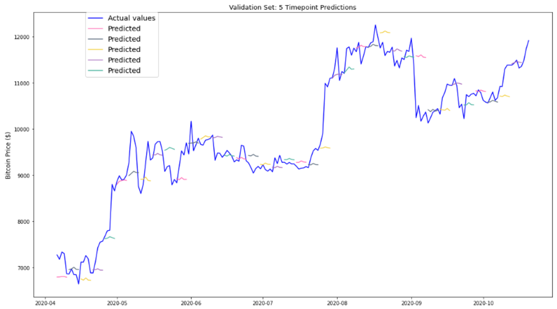


Only BTC dataset





BTC and ETH dataset

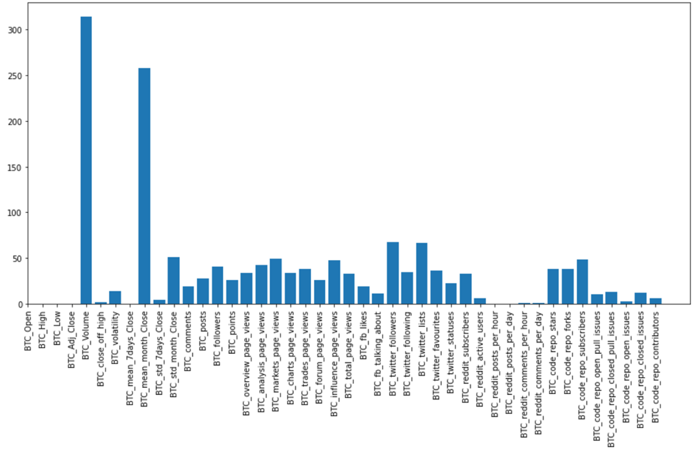


Test set average MAE:

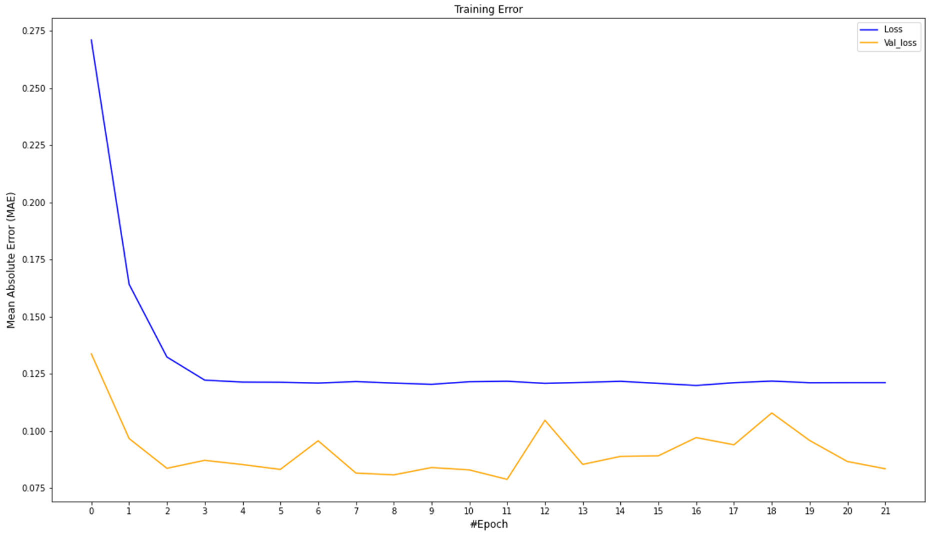
- BTC Data, 0.056
- BTC and ETH Data, 0.066

Regression with historical data and Social media feed

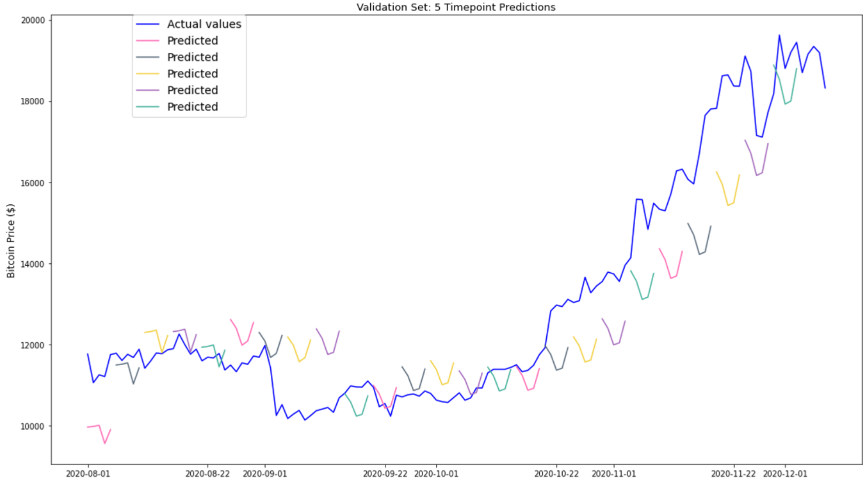
- **Social media feed data starts from 2017.**
- **From the 33 available chose 5 after data preprocessing:**
  - Twitter followers
  - code repo subscribers
  - Twitter favourites
  - Twitter following
  - Reddit subscribers



Regression with historical data and Social media feed - Results



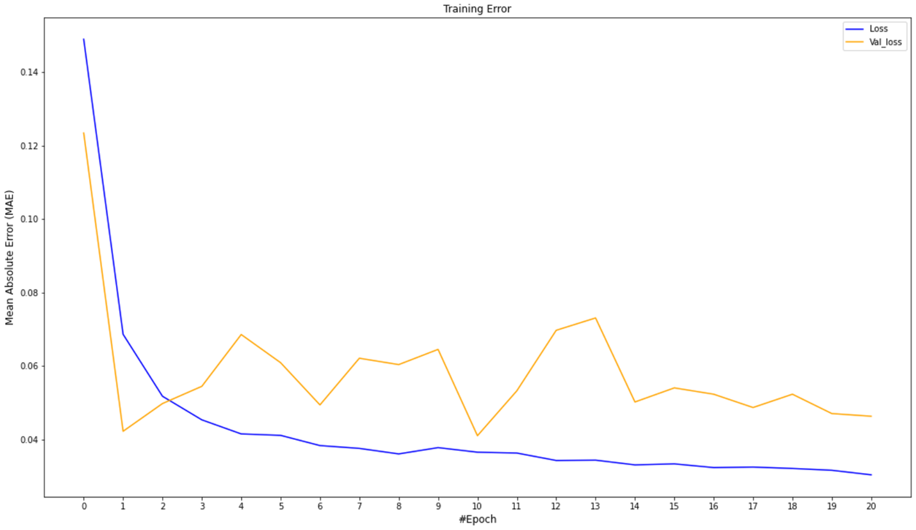
BTC, ETH and with social media dataset, with specified features

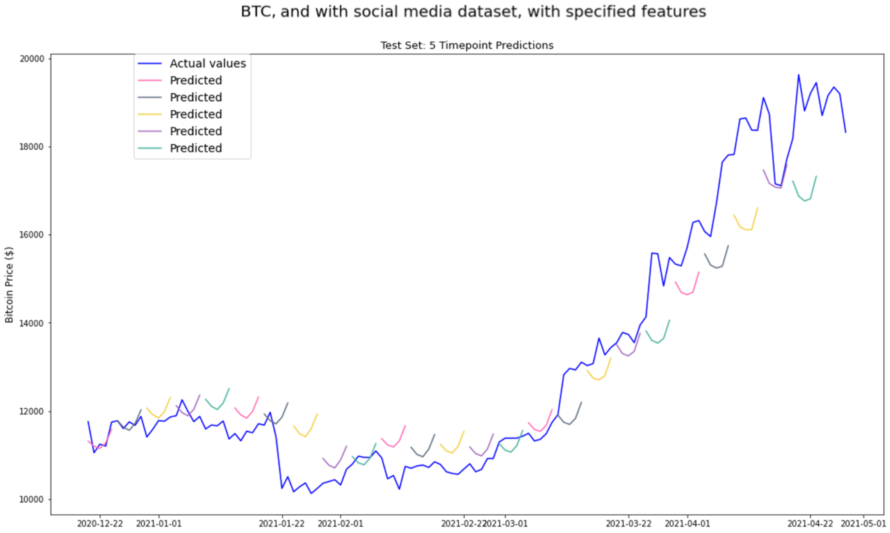


Test set average MAE:

- 0.22

Regression with historical data and Social media feed - Results
(MinMax normalization in whole dataset, social media included)



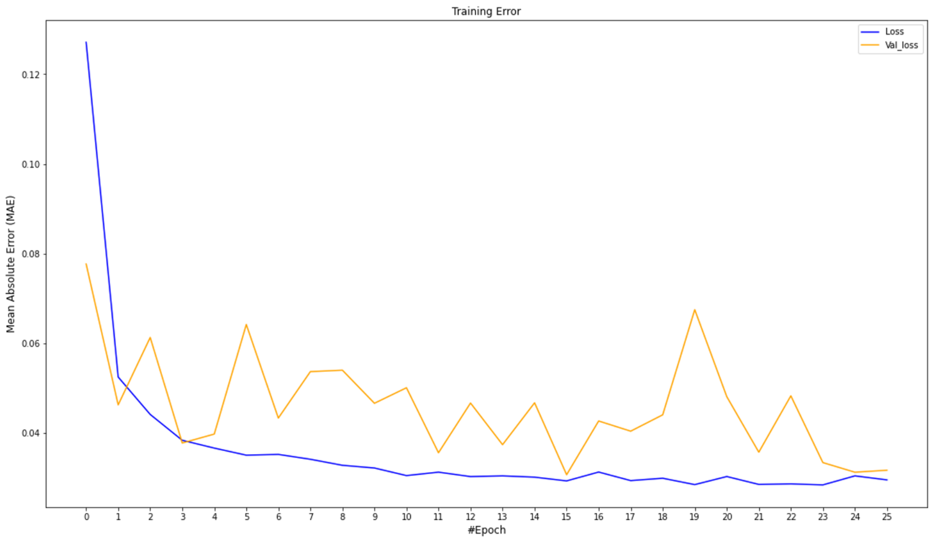


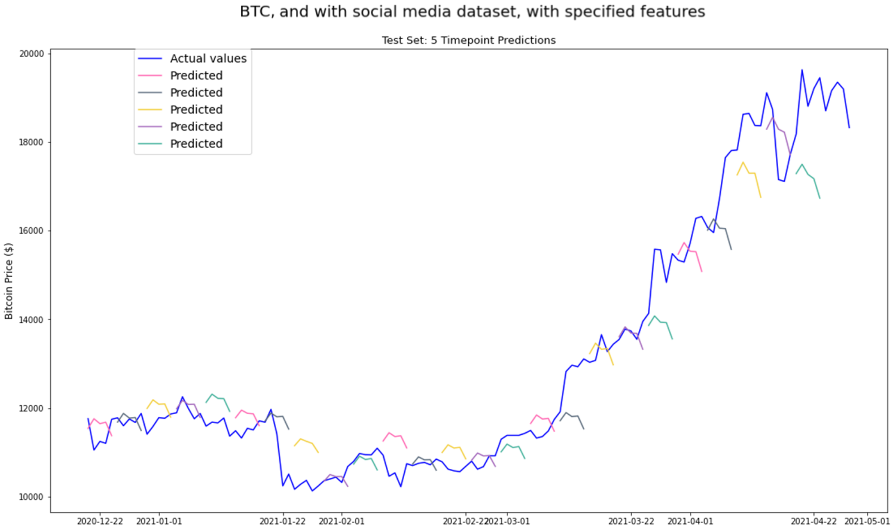
Test set average MAE:

- 0.90

Validation loss above training loss here!

Regression with historical data and Social media feed - Results
(MinMax normalization in whole dataset, social media not included)





Test set average MAE:

- 0.28

Seems social media actually decrease performance!

Classification with historical data

- Even if we couldn't achieve to predict the actual prices, the predictions follow the trend.
- Instead of trying to predict the actual prices we will try to predict whether we will have a close price **increase** or **decrease**.

P_t: close value, **μ_{P_t}**: Last 30 days average

$$p_t \geq \mu_{p_t} - 1\%\,\mu_{p_t}, \qquad \mu_{p_t} = \frac{1}{30}\sum_{i=-30}^{-1} p_{t-i}$$

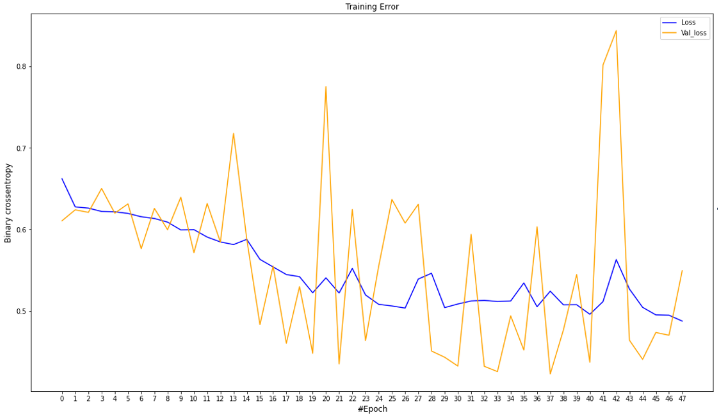
positive (1), else negative (0)

Model architecture:

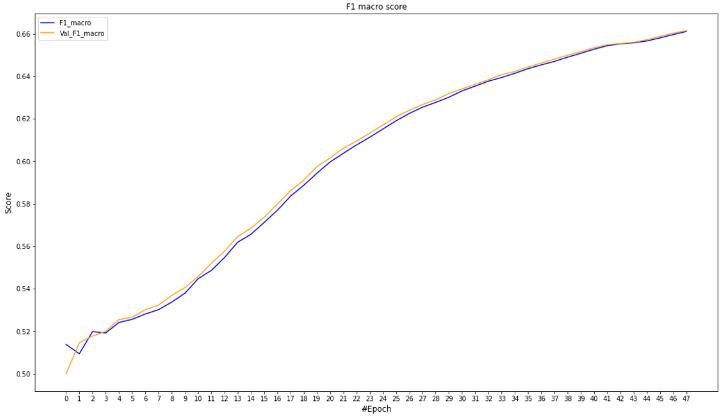
- 20 input GRU neurons
- 256 first dense neurons
- 40% percentage of first dropout
- 128 second dense neurons
- 25% percentage of second dropout

Loss function: Binary cross entropy

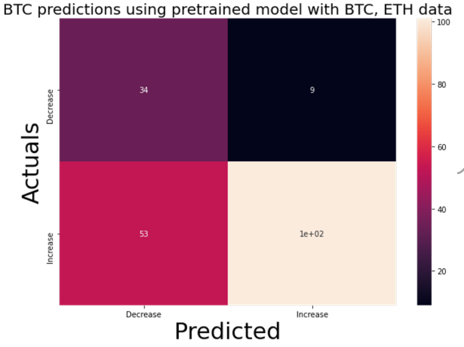
Classification with historical data - Results (1/2)



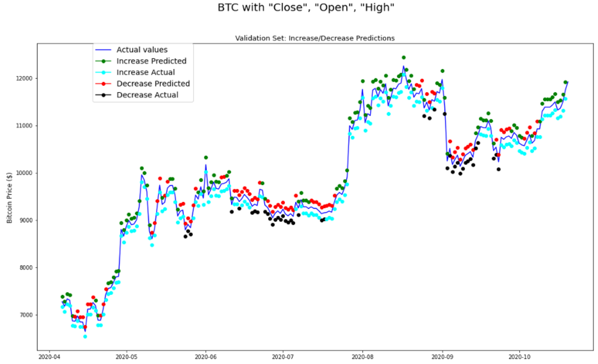
Validation loss decreases with strong oscillation!



Both train and validation F1 increases smoothly!



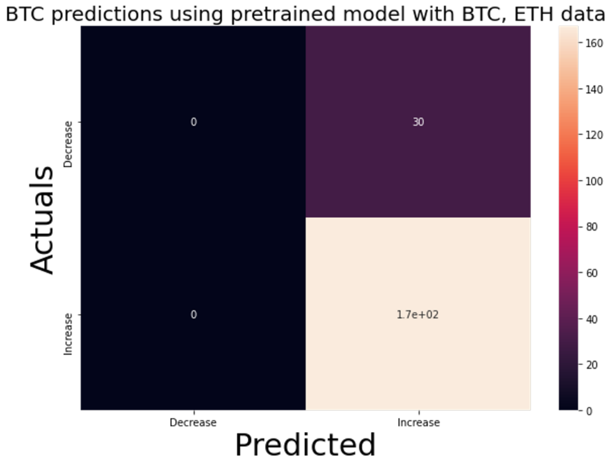
- False **more than half** predicted as *Decrease*
- Almost half of actual *Increase* misclassified
- But, **accuracy = 68%**



Classification with historical data - Results (2/2)

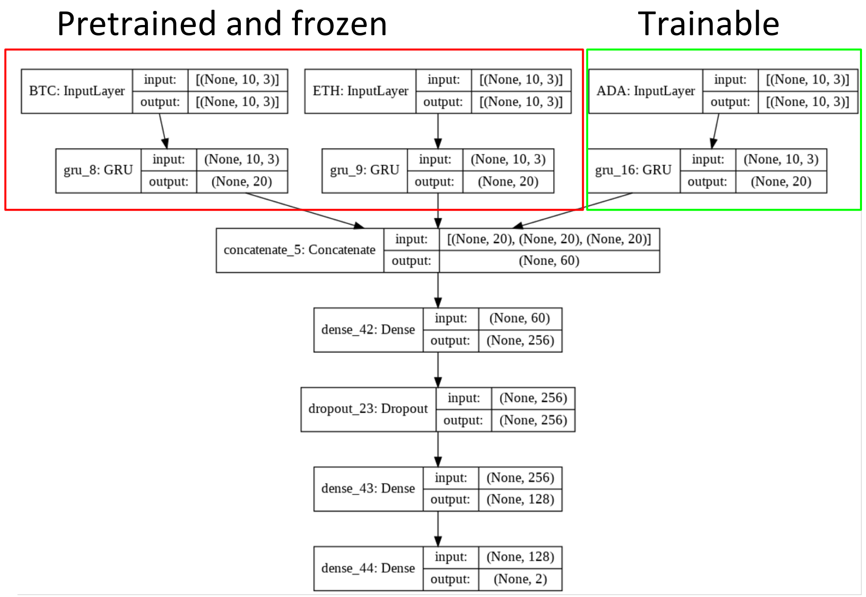
- Even if the validation set's results are somehow good, test set is biased to the ***increase*** class

- ***test f1 score:*** *0.46 (<< validation set's f1 score)*

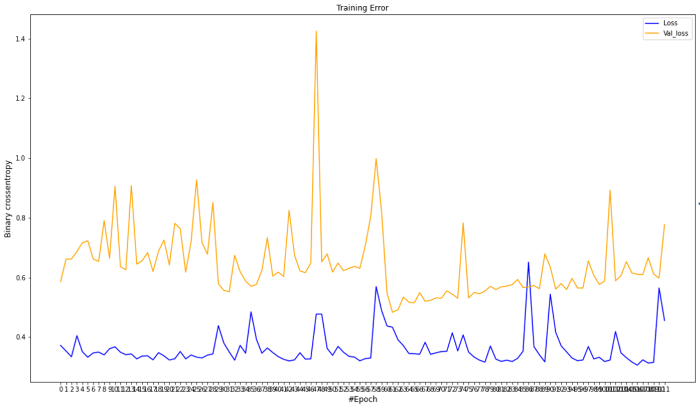


Concatenated models and transfer learning

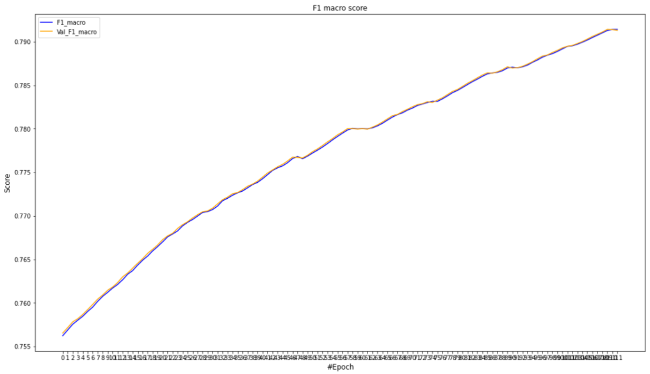
- Train multiple sequential models with different coins
- Combine them into one model using ***concatenated layer***
- Tried in regression problem but the results were not as good.
- Passed trained weights in the concatenated model
- Trained concatenated model by having pretrained ⅔ layers.
- Target coin ADA.



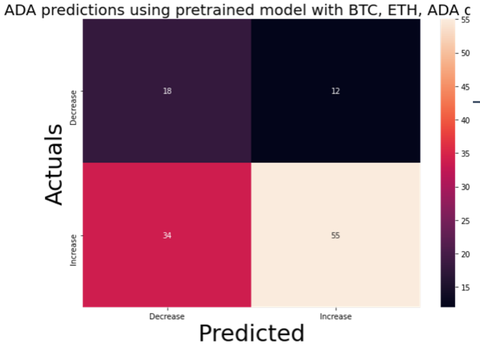
Concatenated models and transfer learning - Results



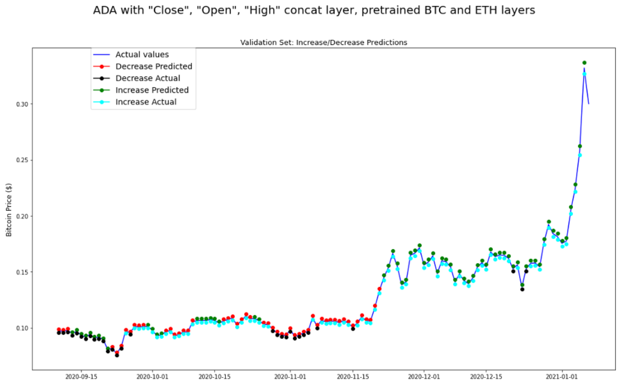
Losses do not decrease



But F1’s still increase and reach higher than before!



Similar results as without transfer learning both for validation and test



Conclusion

- Unfortunately, the results are not as good. But, maybe **there is an explanation!**

- Test *stationarity* with Augmented Decay Fuller statistical test:

ADF for original BTC Time Series:

ADF Statistic: 0.923242

p-value: 0.993386

Future work

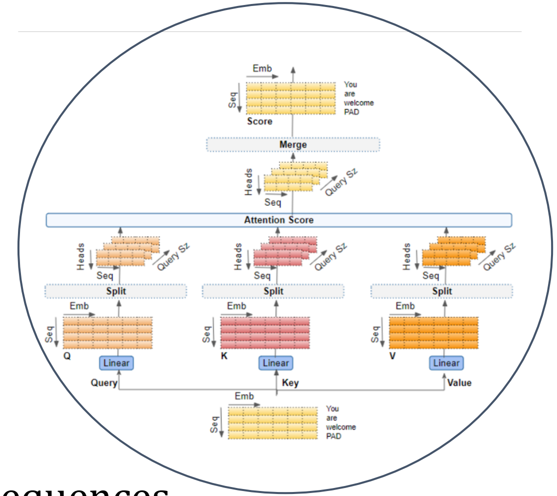


Image taken from [4]

- Perform experiments using ***Transformers*** architecture.

- ***Multi-head attention*** concept is indicated for such complex sequences.

References

1. I. E. Livieris, N. Kiriakidou, S. Stovroyiannisn and P. Pintelas, "An Advanced CNN-LSTM Model for Cryptocurrency Forecasting," *Electronics*, vol. 10, no. 3, pp. 287, Jan. 2021, doi: 10.3390/electronics10030287.
2. E. Christoforou, Z. I. Emiris and A. Florakis, "Neural Networks for Cryptocurrency Evaluation and Price Fluctuation Forecasting," in *Mathematical Research for Blockchain Economy*, P. Pardalos, I. Kotsireas, Y. Guo, W. Knottenbelt, Eds. Springer, Cham, 2020, pp. 133-149, doi: 10.1007/978-3-030-37110-4_10.
3. I. E. Livieris, S. Stavroyiannis, E. Pintelas and P. Pintelas, "A novel validation framework to enhance deep learning models in time-series forecasting," *Neural Computing and Applications*, vol. 32, pp. 17149–17167, 08 Jul. 2020, doi: 10.1007/s00521-020-05169-y.
4. K. Doshi, “Transformers Explained Visually (Part 3): Multi-head Attention, deep dive,” Towards data science [Online]. Available: https://towardsdatascience.com/transformers-explained-visually-part-3-multi-head-attention-deep-dive-1c1ff1024853 [Accessed Jul. 4, 2021].