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September 5, 2023

Western Governors University

D214: Graduate Capstone

Executive Summary

**Problem Statement**

To what extent can NeuralProphet accurately predict variable “cost” for precious metals “Gold”, “Silver”, “Platinum”, and “Palladium” over a forecast period of 365 days?

**Related Hypothesis**

NeuralProphet can predict the market closing price of precious metals over a forecast period of 365 days with at least 75% accuracy.

**Data-Analysis Process**

1. Prepare Jupyter Notebook with Python
2. Clean dataset, assess for duplicates and nulls
3. Convert the datetime ‘date’ column and float ‘close’ column to ‘ds’ and ‘y’ respectively
4. Create the variable ‘m’ to represent the Neural Prophet model for easier coding.
5. Split datasets into train and test datasets (typically 90% train, 10% test). This dataset split allows for evaluation of the models.
6. Fit datasets with the NeuralProphet model for visualization and prediction.
7. Evaluate accuracy with MAE and MAPE

**Findings**

* NeuralProphet time series analysis technique applied to datasets of approximately 5,000 entries had significant overfitting with a dataset train/test split of 80% train and 20% test. The original predictions prior to adjusting overfitting challenge were so erroneous that only one of the four projected forecasts had at least 75% accuracy. All models met the hypothesis of at least 75% accuracy once the train/test split was adjusted to 90% train and 10% test.
* Gold, silver, and palladium demonstrate positive trends for a growing closing market price with platinum stagnant in trend linearity.
* Silver is the least profitable for active trading due low cost and historical decline since early 2010s.
* Palladium is the riskiest active trading item due to approximately $1,500 in fluctuation intervals.
* The gold forecast and historical data demonstrates the most positive trend of all four metals in addition to having the most profitable closing prices as upward as $3,000 for maximum closing price.

**GOLD:**

Visualization of past and current closing market prices:

A screenshot of a computer

Description automatically generated

Visualization of forecasted closing market prices:

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A screenshot of a computer

Description automatically generatedForecast Evaluation Metric

**SILVER:**

Visualization of past and current closing market prices:

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Visualization of forecasted closing market prices:

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**PLATINUM:**

Visualization of past and current closing market prices:

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Visualization of forecasted closing market prices:

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Forecast Evaluation Metric

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**PALLADIUM:**

Visualization of past and current closing market prices:

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**Limitations of Techniques and Tools**

Though NeuralProphet utilizes new machine learning methods with a hybrid of neural networks and traditional time-series methods, NeuralProphet specifically utilizes a feed-forward neural network (Laptev et al., 2021). Feed forward neural networks are unable to utilize machine learning loops to re-learn and re-analyze previous data. Because of the lack of machine learning loops, datasets used with NeuralProphet must be large enough for the forward-feeding machine learning technique to accurately predict trends and seasonality. Another significant factor for dataset selection for NeuralProphet is appropriate dataset splitting. Overfitting occurs due to default hyperparameters such as no regularization (Cassiman, 2021). Overfitting can be prevented with either a change in the dataset split ratio or with highly tuned hyperparameters rather than fitting and performing predictions with the default NeuralProphet model.

Python presents a limitation in terms of how general-use of a programming language it is. The programming language R was designed specifically for data analysis with intentions of data visualization and statistical use. R, in comparison to Python, accelerates analysis processes such as time series with less implications of human-error (Manokhin, 2023).

**Proposed Actions**

To better increase model use and actionability, two future directions are suggested. The first direction is to perform model updates with each interval period of new data collected. As an example, re-run the model every month for more accurate predictions as new data is collected. A second approach is to decrease the forecast period from 365 days to smaller forecast periods such as quarterly, 30 days, and daily for an increased accuracy. Accuracy becomes worse as forecast period lengths are extended so users and analysts can benefit from forecasting with shorter periods. Overall, Neural Prophet met the hypothesis with approximately 5000 entries for each precious metal to determine a minimum of 75% accuracy for all models.

**Expected Study Benefits**

The default hyperparameters of NeuralProphet produced accuracy results averaging 88.87% with the four models. Due to the high accuracy, specifically seen with the gold; silver; and platinum models, NeuralProphet proves itself as a primary time series analysis tool that is user-friendly for any experience level data analyst. I expect that manually tuning the hyperparameters to adjust to individual datasets can yield better accuracy.

Additionally, with the average forecast model accuracy at 88.87% for a period of 365 days, the model accuracy can yield better results with shorter periods. This model is highly appropriate for quarterly profit measurements with the forecast period prediction at 90 days for the first quarter, 91 for the second and third quarter, and 92 days for the fourth quarter. Weekly model performance can be highly beneficial for active traders as well with an even higher accuracy than the 365 day period and quarterly period.

**Sources**

1. Laptev, N., Triebe, O., & Hewamalage, H. (2021, November). *Neuralprophet: The neural evolution of meta’s prophet*. Meta AI. https://ai.meta.com/blog/neuralprophet-the-neural-evolution-of-facebooks-prophet/#:~:text=NeuralProphet%20improves%20on%20Prophet%20by,with%20standard%20deep%20learning%20methods.
   1. (Laptev et al., 2021)
2. Cassiman, J. (2021, June 22). *Is Neuralprophet Better than prophet for sales forecasting?*. Medium. https://blog.ml6.eu/is-neuralprophet-better-than-prophet-for-sales-forecasting-de45527163dc
   1. (Cassiman, 2021)
3. Valeriy Manokhin, P. (2023, January 26). Python vs R for time-series forecasting. Medium. https://valeman.medium.com/python-vs-r-for-time-series-forecasting-395390432598
   1. (Manokhin, 2023)