

# T-Fold Sequential Validation Technique for Out-Of-Distribution Generalization with Financial Time Series Data

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## Presented Case Specifications

**Hypothesis:** There exists a set of conditions under which a cross-validation process can be defined and conducted in order to achieve Out-Of-Sample and Out-Of-Distribution Generalization when performing a Predictive Modeling Process using Financial Time Series Data.

**Dataset:** Continuous futures prices of the UsdMxn (U.S. Dollar Vs Mexican Peso), extracted from CME group MP Future Contract. Prices are Open, High, Low, Close in intervals of 8 Hours, **OHLC** data. GMT timezone-based and a total of 66,500 from 2010-01-03 18:00:00 to 2021-06-14 16:00:00.

**Experiment:** A classification problem is formulated as to predict the target variable,  $CO_{t+1}$ , which is defined as the sign( $Close_{t+1} - Open_{t+1}$ ). For the explanatory variables, the base definition is to use only those of endogenous nature, that is, to create them using only **OHLC** values.

## A discrete multi-period characterization

Let  $V_t$  be the value of a financial asset at any given time  $t$ , and  $S_t$  as a discrete representation of  $V_t$  if there is an observable transaction  $Ts_t$ . Similarly, if there is a set of discrete  $Ts_t$  observed during an interval of time  $T$  of  $n = 1, 2, \dots, n$  units of time,  $\{S_T\}_{T=1}^n$ , can be represented by  $OHLC_T : \{Open_t, High_t, Low_t, Close_t\}$ . The frequency of sampling  $T$ , can be arbitrarily defined.

## OHLC representation

For every  $OHLC_T : \{Open_t, High_t, Low_t, Close_t\}$ :

**Timestamp:** The date and time for each interval.

**Open:** The first price of the interval.

**High:** The highest price registered during the interval.

**Low:** The lowest price registered during the interval.

**Close:** The last price of the interval.

## Candlestick Visual Representation



Figure 1: OHLC Prices Representation

## Type 1

A simple text to describe the type of Folds

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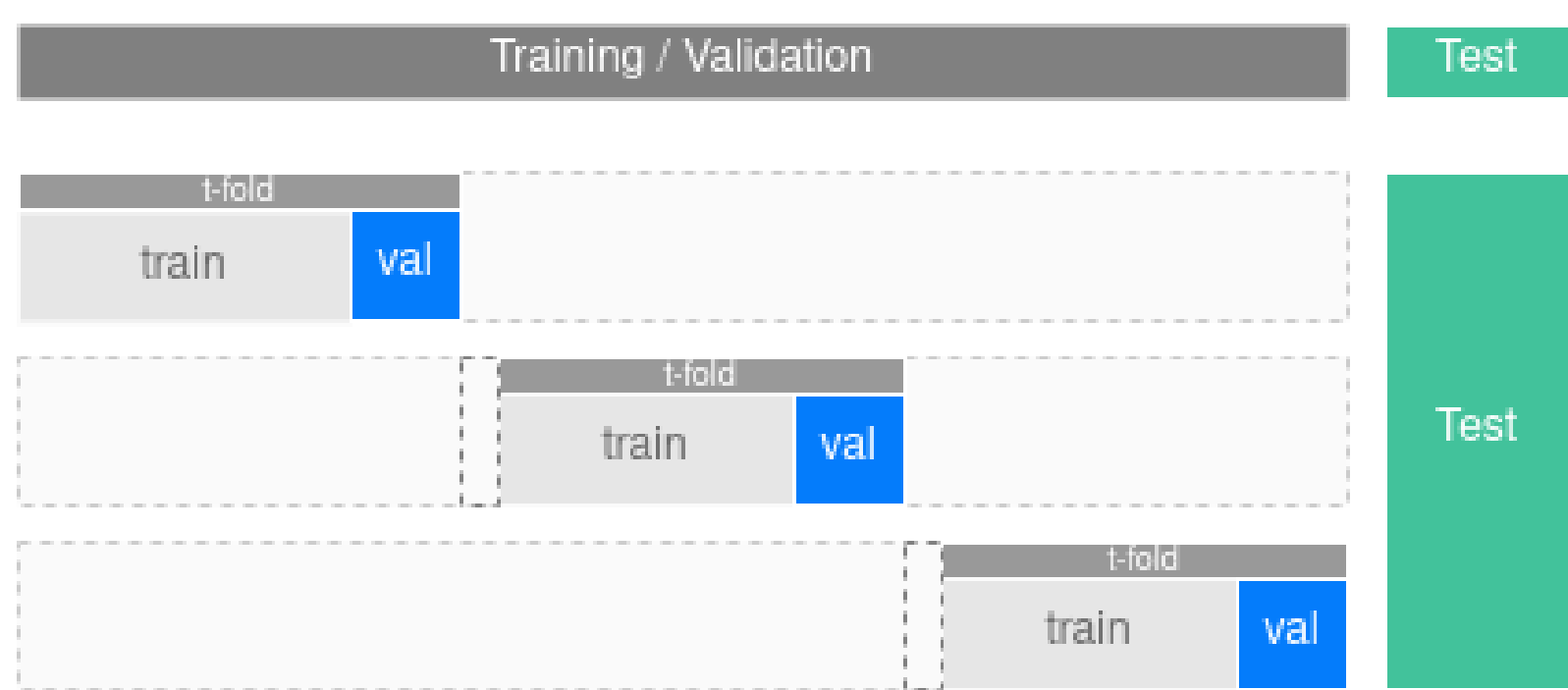


Figure 2: OHLC Prices Representation

## Type 2

A simple text to describe the type of Folds

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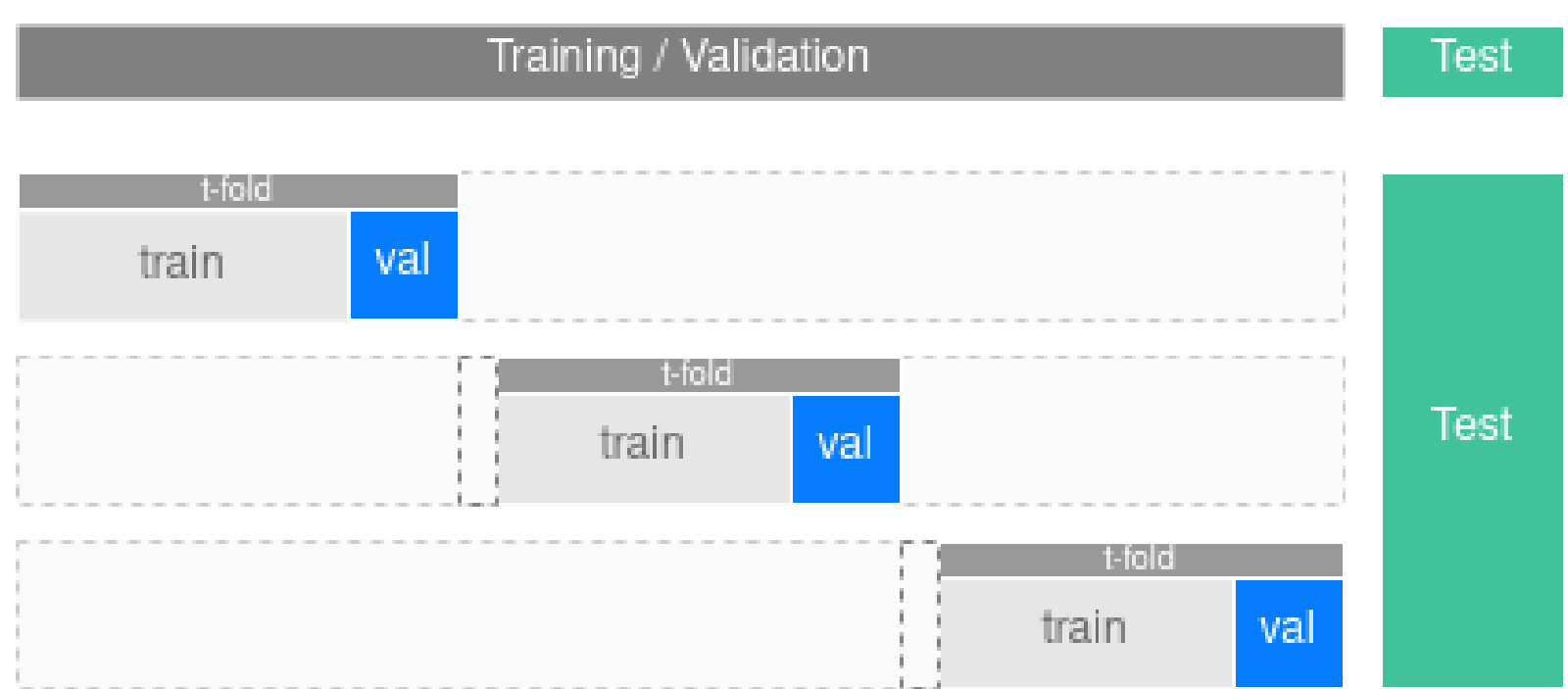


Figure 3: OHLC Prices Representation

## Predictive Modeling: Part 1

One common component of the predictive modeling process is binary-logloss cost function with *elasticnet* regularization:

$$J(w) = J(w) + C \frac{\lambda}{m} \sum_{j=1}^n \|w_j\|_1 + (1 - C) \frac{\lambda}{2m} \sum_{j=1}^n \|w_j\|_2^2 \quad (1)$$

$L_1$ : Also known as *Lasso*

$L_2$ : Also known as *Ridge*

$C$ : A coefficient to regulate the effect between  $L_1$  and  $L_2$

## Predictive Modeling: Part 2

Two models were defined, Logistic-Regression and Multi-layer Feedforward Perceptron.

Metric	ann-mlp	logistic
acc-train	0.9155	0.8311
acc-val	0.8245	0.7368
acc-weighted	0.4486	0.4061
acc-inv-weighted	0.4213	0.3778
auc-train	0.9924	0.9300
auc-val	0.8401	0.8017

Metric	ann-mlp	logistic
auc-weighted	0.4810	0.4521
auc-inv-weighted	0.4353	0.4137
logloss-train	0.2290	5.8333
logloss-val	6.0595	9.0892
logloss-weighted	0.6975	3.2422
logloss-inv-weighted	2.4467	4.2190

## Repository

For more information about the code implementation, data, and file templates go to the GitHub repository for this work.

- [github.com/IFFranciscoME/EcoSta2021](https://github.com/IFFranciscoME/EcoSta2021)

## References

- ▣ [Lopez de Prado, Marcos M \(2018\), \*Advances in Financial Machine Learning\*, Wiley.](#)
- ▣ [Pezeshki et al \(2020\). \*Gradient Starvation: A Learning Proclivity in Neural Networks\*, Mohammad Pezeshki, Sekou-Oumar Kaba, Yoshua Bengio, Aaron Courville, Doina Precup, Guillaume Lajoie, arXiv:2011.09468.](#)
- ▣ [Goddfellow et al \(2017\), \*Deep Learning\*, Ian Goodfellow, Yoshua Bengio, Aaron Courville, MIT Press](#)

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