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

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Presented Case Specifications

Hipothesis: 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 representation

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 $n = 1, 2, ..., n$ 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 data

Timestamp: The date and time for each interval.
Open: The first price of the interval.
High: The highest price during the interval.
Low: The lowest price during the interval.
Close: The last price of the interval

Intra-day micro-information:
volatility: HL_t , **price-change:** CO_t
uptrend: HO_t , **downtrend:** OL_t

Candlestick Visual Representation *(Figure 1)*

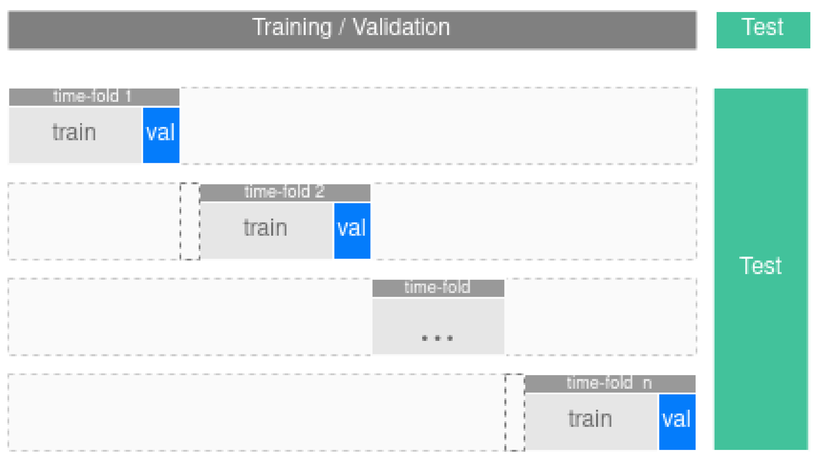
The base calculations are:

$HL_t = High_t - Low_t$
$OL_t = Open_t - Low_t$
$CO_t = Close_t - Open_t$
$HO_t = High_t - Open_t$

T-Fold-SV *(Steps)*

1.- Folds Formation
Depends on labeling, can be calendar based.
2.- Target and Feature Engineering
In-Fold exclusive or Global and then divide.
3.- Information Tensor
To asses information sparsity among Folds.
4.- Model Training
Hyperparameter optimization Train-Val sets.
5.- Generalization Assesment
Out-Of-Sample and/or Out-Of-Distribution.

1: Folds Formation *(Figure 2)*



2: Target Variable (labeling)

A continuous variable prediction (regression problem), into a discrete variable prediction (classification problem), a time-based labeling can be stated as:

$\hat{y}_t = sign\{CO_t\}$

2: Feature Engineering

with $\{OL\}_{t-k}$, $\{HO\}_{t-k}$, $\{HL\}_{t-k}$, $\{CO\}_{t-k}$ for values of $k = 1, 2, ...K$, with K as a proposed *memory* parameter. Then perform some fundamental operations: Simple Moving Average SMA_t, lag: LAG_t, Standard Deviation: SD_t and Cumulative Sumation: $CUMSUM_t$.

3.1: Information Representation and Sparsity Metric

A gamma distribution to fit the PDF of two set of variables, and the Kullback-Leibler Divergence to measure the similarity between the two:

$$f(x) = \frac{\beta^{\alpha}}{\Gamma(\alpha)} x^{\alpha-1} e^{-\beta x} \quad \text{for} \quad x > 0 \quad \alpha, \beta > 0 \tag{1}$$

$\Gamma(\alpha)$: The gamma function $\forall\, \alpha \in \mathbb{Z}^{+}$ and the $D_{KL}(P||Q)$: Kullback-Liebler Divergence, which for unknown continuous random variables, P, Q, or for p, q as empirically adjusted Probability Density Functions (PDF) is denoted by:

$$D_{KL}(P||Q) = \int_{-\infty}^{\infty} p(x) log\left(\frac{p(x)}{q(x)}\right) dx \tag{2}$$

3.2: Information Tensor

3.3: Tensor Characterization

Predictive Modeling: Part 1

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

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

Where $\Sigma_{j=1}^{n} \|w_j\|_1 = L_1$ and $\Sigma_{j=1}^{n} \|w_j\|_2^2 = L_2$ are also known as *Lasso* and *Ridge* respectively, with C as the coefficient to regulate the effect between the two.

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

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.
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