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A META-ANALYSIS OF VARIOUS METHODS DEPLOYED FOR TIME SERIES MODELLING

Siddhant Kumar Jha[*1]

[*1]Research Intern, James Cook University, Seres Labs India, India.

ABSTRACT

Time Series Prediction Analysis is a common practice for testing Machine Learning Algorithms, for return rates and accuracy analysis in the concerned domain. This, however, has not left the field with a variety of shortcomings ranging from significant inaccuracy from traditional statistical modelling techniques to inconsistency in the prediction of parameters from preliminary *Machine Learning* algorithms in place. Various Deep Learning Algorithms and Statistical techniques have been deployed overtime to solve the problem at hand and in this paper, we attempt to give a brief structured overview of the various models in questions compared over Accuracy and other parameters.

Keywords: Machine Learning, Deep Learning, Time Series Analysis, Semi-Supervised Learning, RNN.

I. INTRODUCTION

Time Series Predictive modelling has become an important part of the industry and research fields in recent times. The application of the concept ranges from Backtracking of historical Data, for *Historiographic Economic analysis* as well as data-driven *Financial Projection analysis* to develop an understanding of the implications and wide-ranging consequences of recessions, and other fiscal policies [3].

Time Series Analysis is also an important tool, for deployment in non-temporal Data Bases as an extraneous variable for normalization of data discrepancies, worked out as a method of elimination of non-temporal derivatives [1].

This although sufficiently describes the importance of the Time Series Analysis itself, the broader question of the study is to analyse which algorithms when deployed in test cases correspond to time-series Analysis problems [4].

The study will also attempt to categorize the various methods in common practices, indexed over their viability and accuracy.

II. METHODOLOGY

2.1 DTW-D Semi-Supervised

Semi-Supervised Learning is a generalized Machine Learning method, which trains a model on simultaneously low amounts of labelled data and larger quantities of unlabelled data [1].

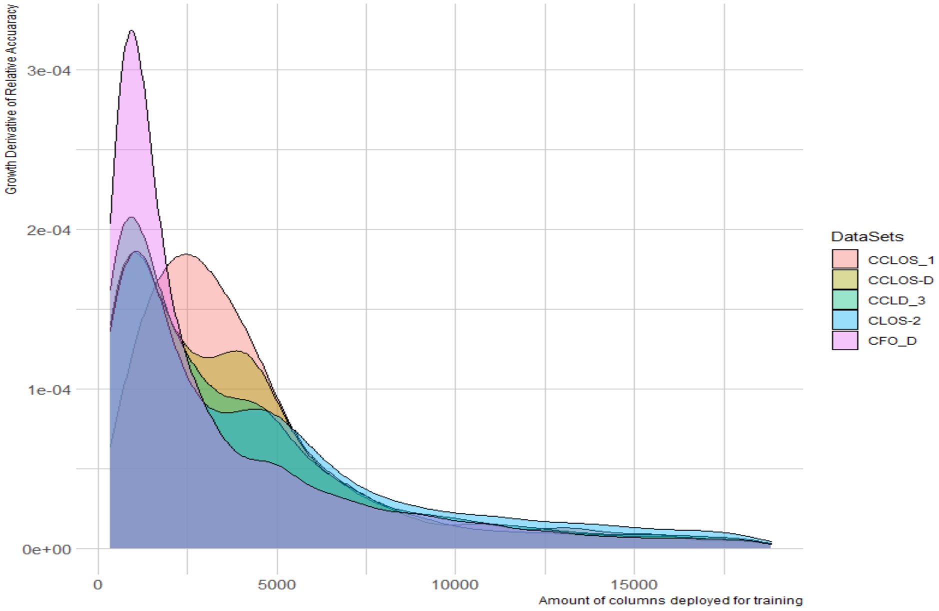
Given two sequences, $X = (x_1, x_2, ..., x_n)$ and $Y = (y_1, y_2, ..., y_m)$, and the warping scope w, score $V(X[i_s: i_e], Y[j_s: j_e])$ of $X[i_s : i_e]$ and $Y[j_s : j_e]$ defined as follows:

$$V(X[i: i(b)], Y[j: j(b)]) = v\big(i(e), i(j)\big)$$

$$v(i,j) = \begin{cases} \varepsilon b - \big||x(i) - x(j)|\big| + v(i, j-1) \\ \varepsilon b(h) - \big||x(i) - x(j)|\big| + v(i-1, j) \\ \varepsilon b(d) - \big||x(i) - x(j)|\big| + v(i-1, j-1) \\ 0 \end{cases}$$

$$(i = 1, .., n; j = 1, ..., m \ [2]$$

The method deployed is a generic analysis as indicated in the equation noted above.



Above: Density distribution of the Growth derivative plotted against the amount of data available for training the model, CFO_D dataset seems to have the steepest growth in accuracy over the lowest amount of data, although after a point growth in data just gives diminishing returns due to overfitting.

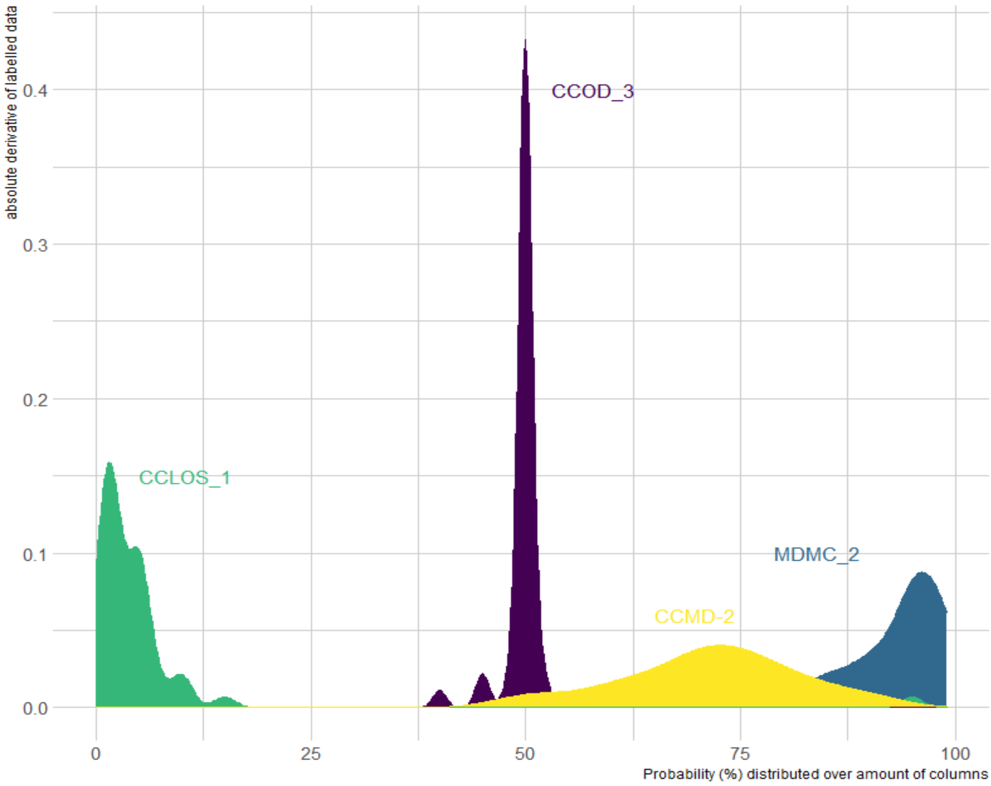
2.2 Shallow RNNs

Shallow RNNs are a set of non-temporal algorithms, used for time series analysis and unified framework deployment differing from Regular RNNs.

$$\hbar(t) = R(\hbar(t-1, x(t)), t \in [T], \qquad y = f(h\{t\})$$

$$v(j) = R(1)(Bj), \qquad j \in [T/k]$$

The model as shown above uses lateral parallelization of the primary parameters says, T, deployed overvalues k1, k2,k3,…kn to develop a streaming distribution [4].



Above: A probability distribution of the accuracy derivative, over different datasets modelled as a subcategory of the data in availability for training the model.

2.3 Diverse Beam Search

Diverse Beam Search works out as a Search Forest regressor algorithm by dividing the column closed data system, into a plurality of different categories.

Let's say there is a general deployable category Y(t'), and works to bifurcate into n, non-empty sets T(c), then dividing into function group G(r)[5].

Unlike RNN we optimize a modified version of the data to add dissimilarity over for the data.

III. RESULTS

Table 1: Below, Results from model training and evaluation, for DTW-D

	CCLOS_2		CCOD_M		Baseline	
	16	32	16	32	16	32
Accuracy (%)	85.77	86.95	88.32	87.77	92.33	90.44
Cost	122	234	997	455	501	320

Table 2: Results from modelling and evaluation for, Shallow RNNs

	CCLOS_2		CCOD_M		Baseline	
	16	32	16	32	16	32
Accuracy (%)	88.96	90.23	79.77	95.99	86.90	96.88
Cost	114	1009	654	709	721	560

Table 3: Results from modelling and evaluation for, DBS

	CCLOS_2		CCOD_M		Baseline	
	16	32	16	32	16	32
Accuracy (%)	87.49	95.22	82.32	84.55	90.33	94.22
Cost	99	340	203	801	509	313

IV. CONCLUSION

From the results of the study, we can conclusively say that ShallowRNNs has the best accuracy, although the cost-effectiveness is rather low. If compared with the highest cost-effectiveness would be Diverse Beam Search deployed over CCLOS_2 and CCOD_M datasets [3], although the baseline evaluation yields a more balanced picture between the two algorithms. The systems under modulation are heterogeneous and obtuse so DBS would be *task-agnostic* and process independently.

V. REFERENCES

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