Deep Representation Learning for Cluster Level Time Series Forecasting

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Presentation Outline

Introduction

- In today's data-driven world, time series forecasting is one of the intensively investigated temporal data mining technique.
- In practice, time series are defined by taking a set of ordered observations where the ordering is based on one of the common independent variables.
- The ordering of individual observations in turn introduces shapes (patterns) that are key inputs to temporal data mining techniques.

Introduction

- Time series defined by ordering angular distance measurements.

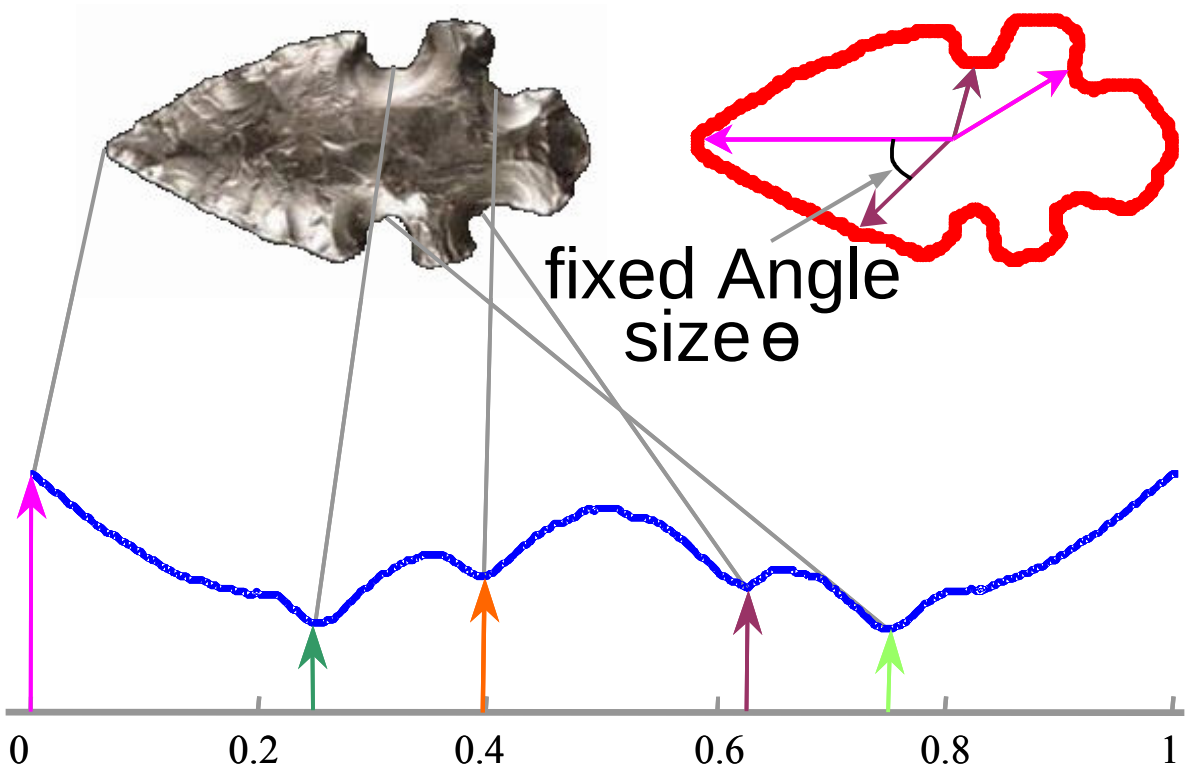


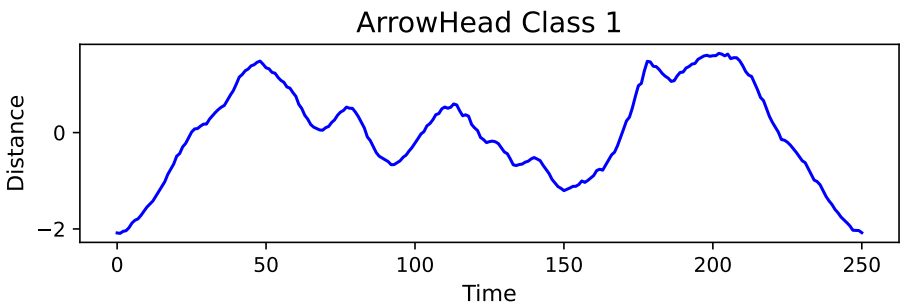
Figure 1: Extraction of time series from an image of an arrowhead [4]

Introduction

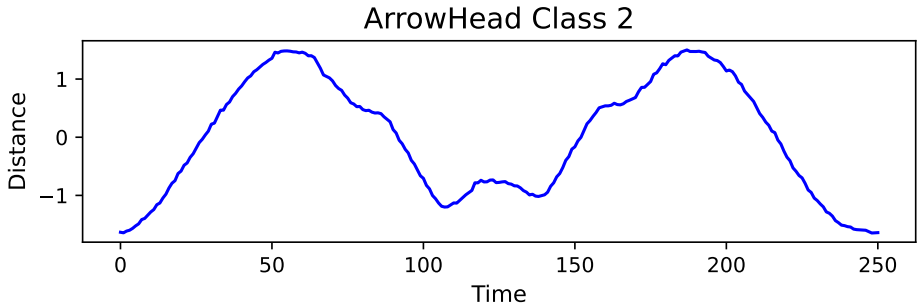
- Shapes, features, or patterns could be used in the context of different objectives

(a) *Avonlea* Arrowhead

(b) *Clovis* Arrowhead



(c) Time series for *Avonlea* Arrowhead



(d) Time series for *Clovis* Arrowhead

Figure 1: Shape based categorization of stone Arrowheads [2]

Introduction

- In this aspect, time series forecasting aims to optimize using (1).

$$\hat{X}_{i,t:t+p} = f(X_{i,t-L:t-1}, Y_{i,t-L:t-1}) \tag{1}$$

- Consequently, given a forecasting model f(.):
  - $\hat{X}_{i,t:t+p}$ implies predictions.
  - X ($X_{i,t-L:t-1}$ implies L previous observations.
  - $Y_{i,t-L:t-1}$ implies exogenous variables

Statement of the problem

- How do clustering and forecasting correlate?
  - Identification of exogenous variables.
  - Summarizing patterns within groups.
  - Reducing the number of required models.

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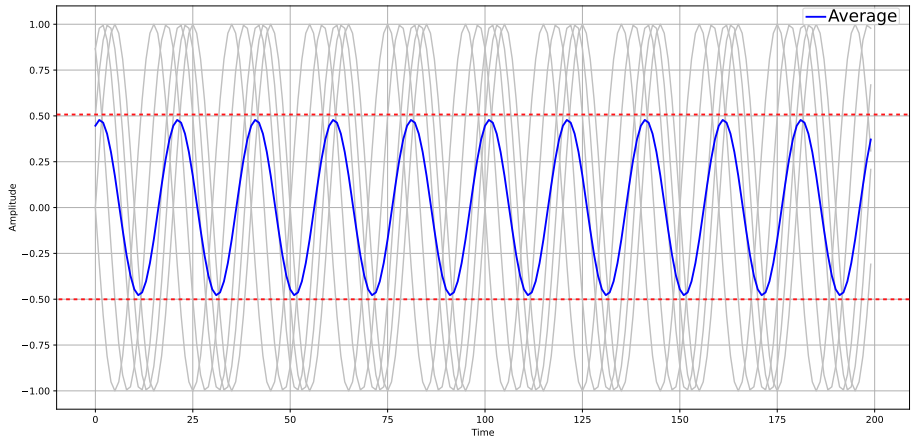
- For instance, lets consider temporal datasets representing [1, 5, 6].
  - Radio nodes are not isolated entities.
  - Hundreds if not thousands of radio stations.

Statement of the problem

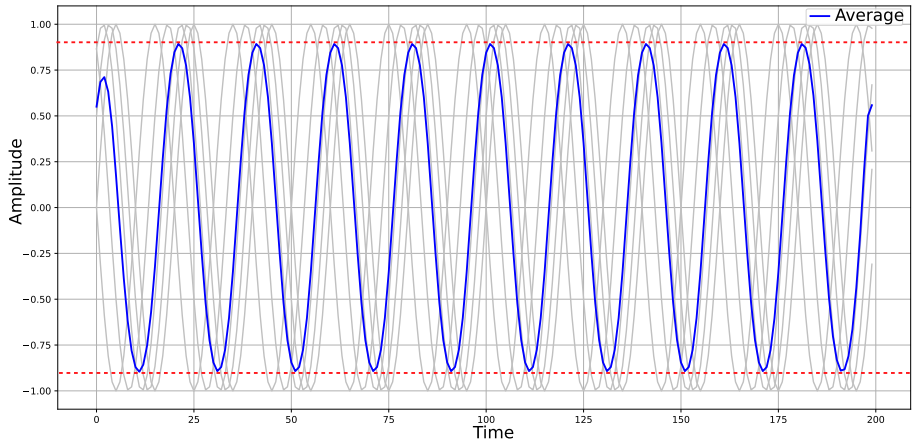
- An improper clustering approach could affect the quality of cluster level forecasts.

Example 2.1

- Let's consider sinusoids at phase shifts of $[0, \pi/3, \pi/6, \frac{2\pi}{3}, \textit{ and } \pi]$.



(a) An arithmetic mean



(b) SDBA mean [3]

Figure 2: Impact of temporal distortion on the estimation of cluster centorids

Proposed Approach

- In this work, we mainly aimed to show the potentials of deep representation learning in cluster formation and cluster centroid estimation.
- Consequently, we propose to:
  - Cluster datasets collected from a wireless network in the latent space of a Convoluational neural network.

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  - Estimate time domain cluster centroids using a multi-tasking Autoencoder.

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  - Estimate time domain cluster centroids using a multi-tasking Autoencoder.
  - Incorporate spatial information into a forecasting model.

Proposed Approach

- Datasets?
  - Data traffic load offered to 729 base stations located within Addis Ababa, Ethiopia.
  - Four months of measurement, i.e., September 2019 - December 2019.
  - Measurement is in Tera Bytes.
- Forecasting model?
  - K-Seasonal AutoRegressive Integrated Moving Average (K-SARIMA).

$$(\phi_p(L)\Phi_P(L^{s_k}))(1-L)^d(1-L)^{D_{s_k}}(X_t-\mu) = (\theta_q(L))(\Theta_Q(L^{s_k}))\varepsilon_t \quad (2)$$

Proposed Approach

- For the deep clustering, we propose the network arrangement shown in Figure 6.

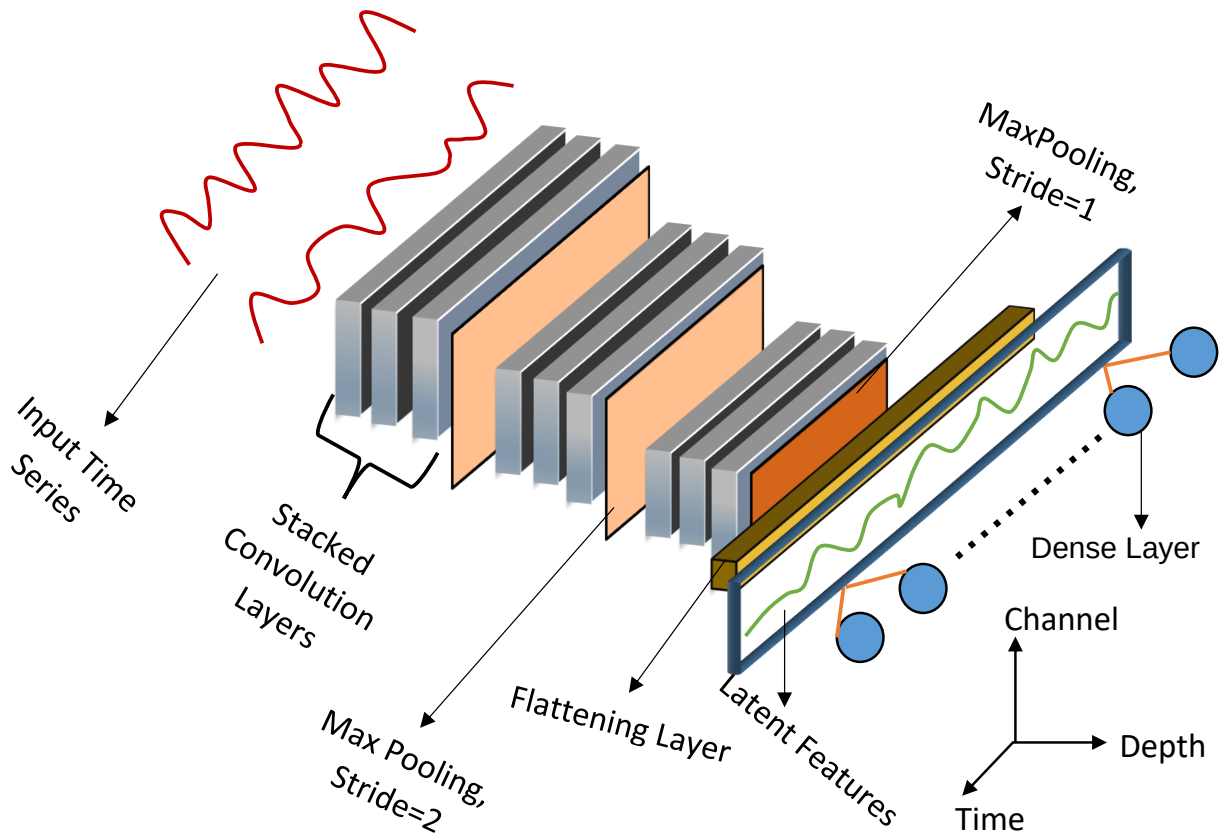


Figure 3: Proposed deep embedding clustering network

Proposed Approach

- The network was trained to optimize for the objective function given in (3) [8].

$$L = KL(P||Q) = \sum_i \sum_j p_{i,j} \log \frac{p_{i,j}}{q_{i,j}} \tag{3}$$

where,

$$p_{i,j} = \frac{\frac{q_{i,j}^2}{\sum_{j=1}^{K} q_{i,j}}}{\sum_{j=1}^{K} \frac{q_{i,j}^2}{\sum_{j=1}^{K} q_{i,j}}}, \qquad q_{i,j} = \frac{\left(\frac{1+||Z_i-\mu_j)||_{l2}}{\alpha}\right)^{\frac{-\alpha+1}{2}}}{\sum_{j=1}^{K}\left(\frac{1+||Z_i-\mu_j)||_{l2}}{\alpha}\right)^{\frac{-\alpha+1}{2}}}$$

- In order to define latent space cluster centroids ($\mu_j's$) a classic K-Means is used.

Proposed Approach

- The DEC arrangement can not generate time domain estimates. [7].

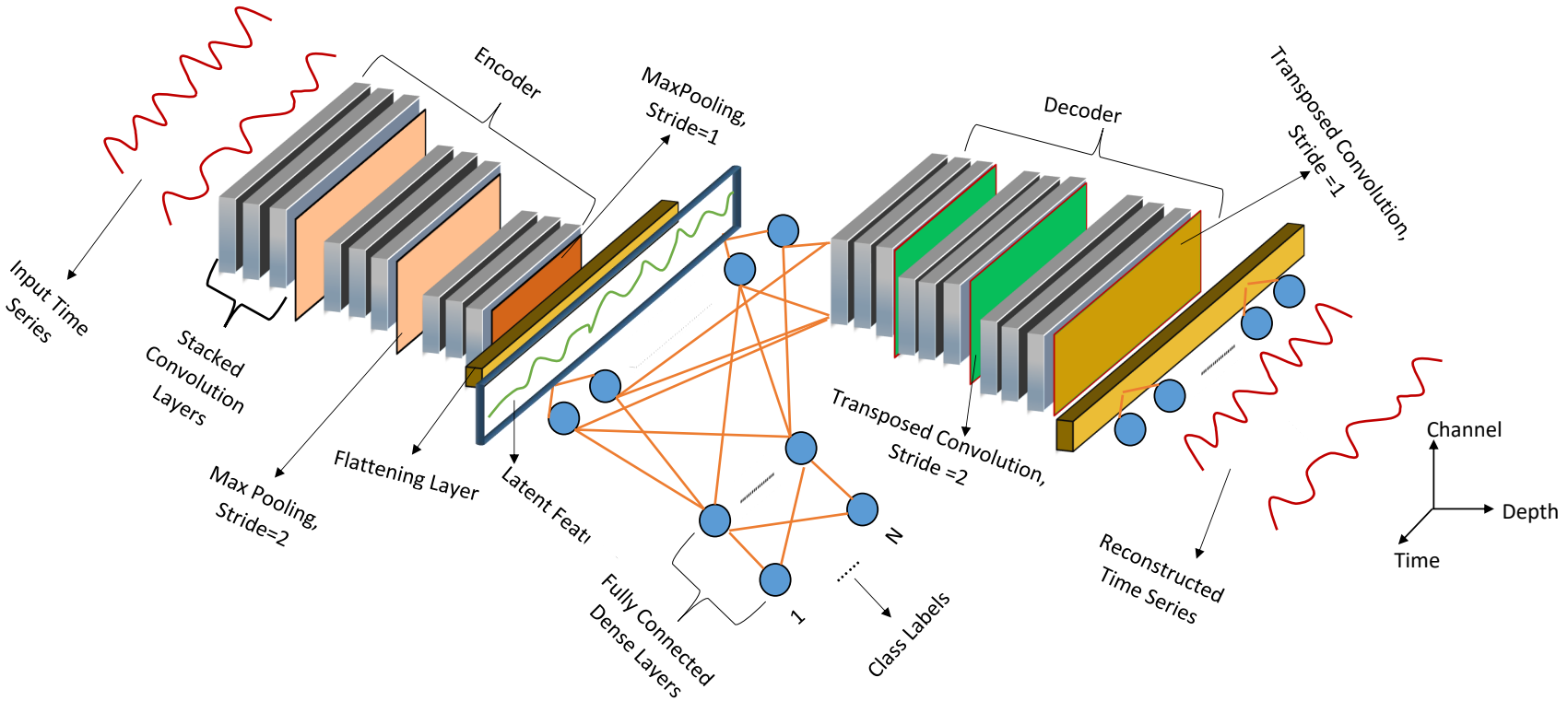


Figure 4: Proposed multi-tasking autoencoder

Proposed Approach

- The multi-tasking network was trained to optimize for the objective function given in (4) [8].
  - Latent means are estimated by taking an arithmetic mean.
  - We use the decoder to reproject latent means.

$$L_{Multi}(X, \hat{X}, Cat, p_{cat}) = \frac{1}{N}\sum_{i=1}^{N}||X_i - \hat{X}_i||_{l2} - \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{C} Cat_{i,j} \ln^{p_{i,j}} \quad (4)$$

Proposed Approach

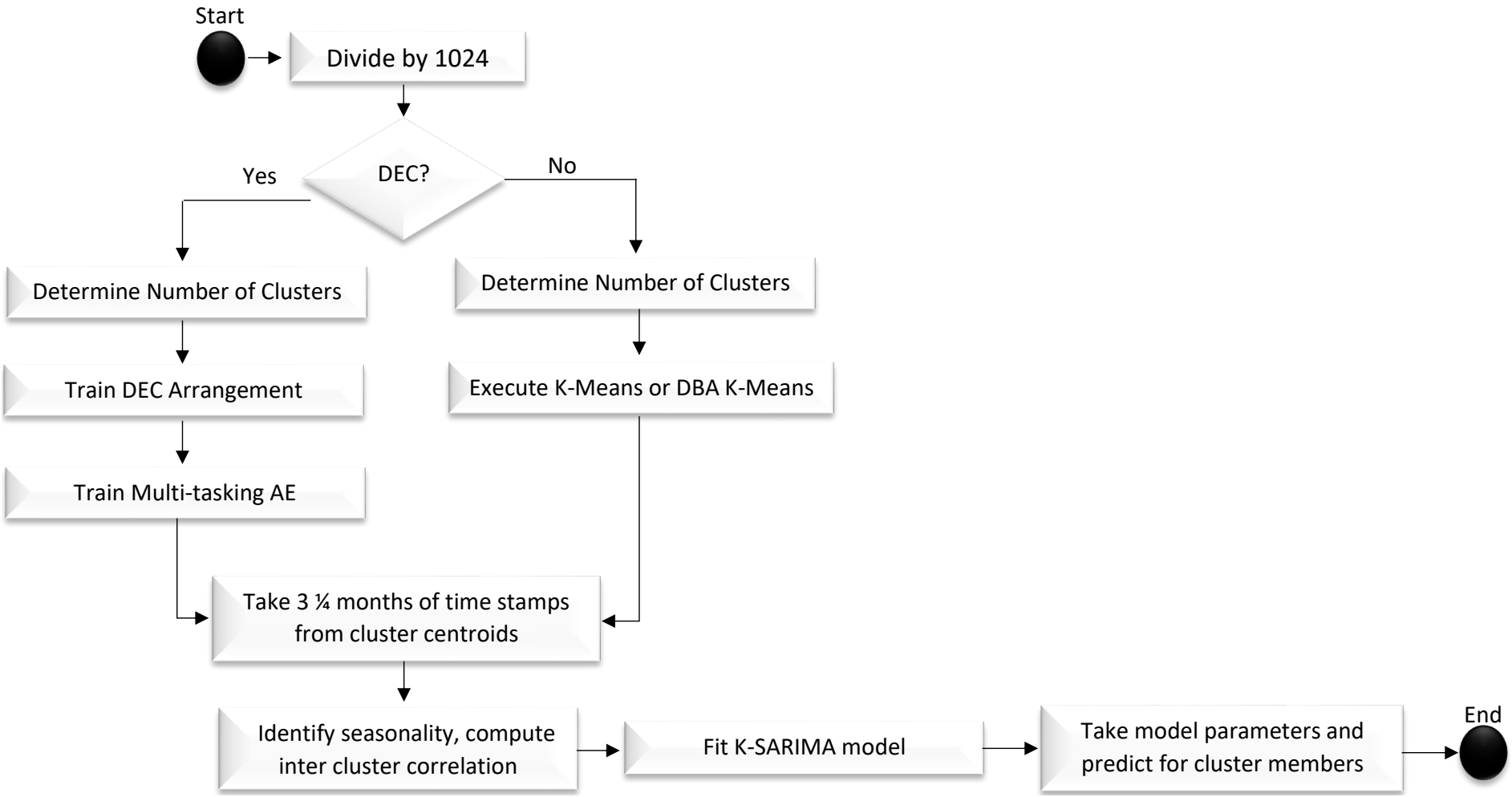


Figure 5: Experimental setup

Results and Discussion

- We started our analysis of the dataset by observing their intra cluster inertia, i.e., in order to determine the number of clusters.

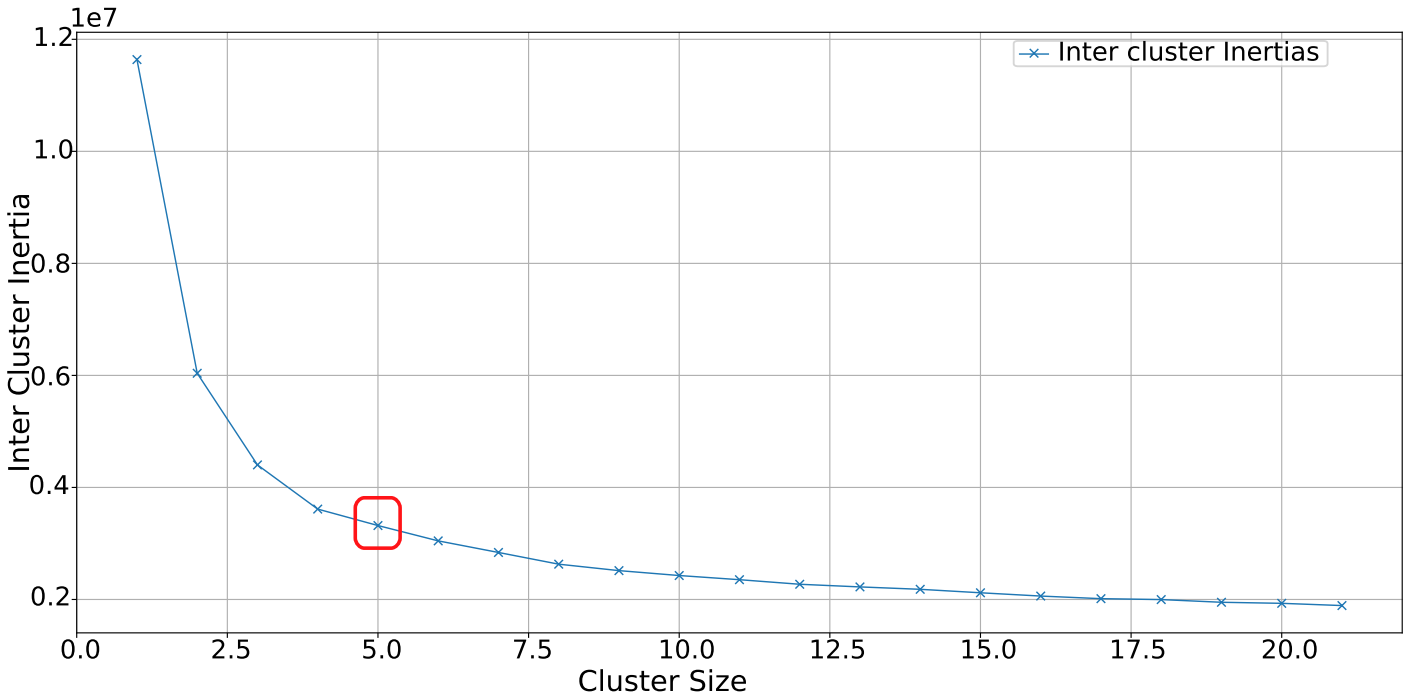
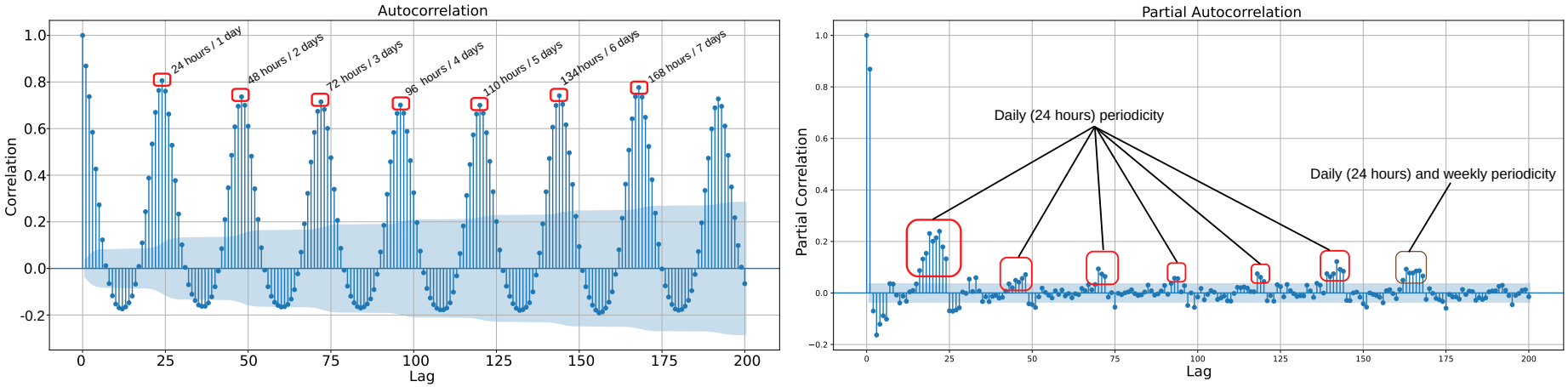


Figure 6: Intra cluster inertia

Results and Discussion

- In order to determine the order of the S-ARIMA model, i.e., (p,q,d) and (P,Q,D), we analyzed autocorrelation and partial autocorrelation of the cluster centroids.



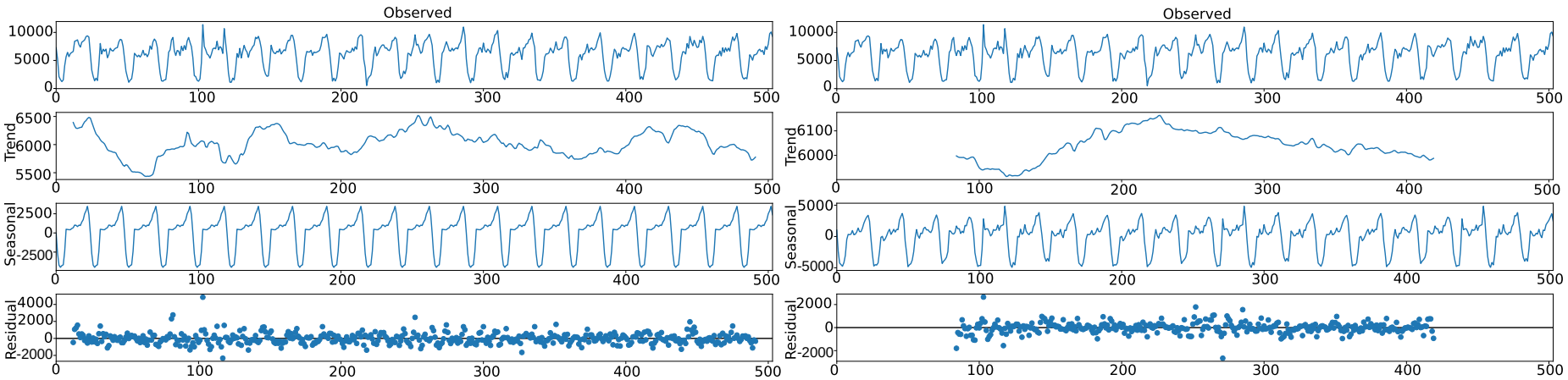
(a) Autocorrelation

(b) Partial autocorrelation

Figure 7: Seasonality analysis via autocorrelation and partial autocorrelation

Results and Discussion

- The daily and weakly seasonality is also evident in the decomposition of the cluster centorids and sample series taken from the entire dataset.



(a) Daily seasonality **(b)** Weekly seasonality

Figure 8: Decomposition of cluster centorids

- D-SARIMA $(2,\ 1,\ 2),\ (2,\ 0,\ 0)_{24},\ (2,\ 0,\ 0)_{168}$

Results and Discussion

Figure 9: Clusters identified by the DEC arrangement

Results and Discussion

Figure 9: Clusters identified by the DBA K-Means

Results and Discussion

- We used the parameters of the fitted D-SARIMA model to forecast for individual cluster members, i.e., for forecasts labeled with *CS*.

Table 1: Comparison of cluster level and data level forecasting

Techniques	Errors	Cluster 0	Cluster 1	Cluster 2	Cluster 3	Cluster4	Average
DEC_CS	RMSE	1.104	1.050	0.409	1.524	0.863	0.990
	MAE	0.816	0.778	0.305	1.145	0.671	0.743
DEC_Clust_BS		1.417	1.205	0.426	1.867	0.992	1.181
		1.092	0.932	0.308	1.158	0.758	0.909
DBA K-Means_CS	RMSE	0.714	2.129	1.079	0.416	1.468	1.161
	MAE	0.524	1.715	0.789	0.318	1.156	0.901
DBA_K-Means_Clust_BS		0.868	2.012	1.205	0.330	1.652	1.214
		0.664	0.565	0.919	0.239	1.288	0.935
K-Means_CS	RMSE	1.131	0.938	0.389	1.774	1.906	1.228
	MAE	0.859	0.739	0.293	1.452	1.522	0.973
K-Means_Clust_BS		1.263	0.961	0.388	1.664	1.993	1.254
		0.968	0.735	0.282	1.289	1.562	0.967

Results and Discussion

- DEC D-SARIMA, DBA K-Means, K-means (RMSE,MAE): (0.758, 0.596), (0.802, 0.617), (0.847, 0.669).

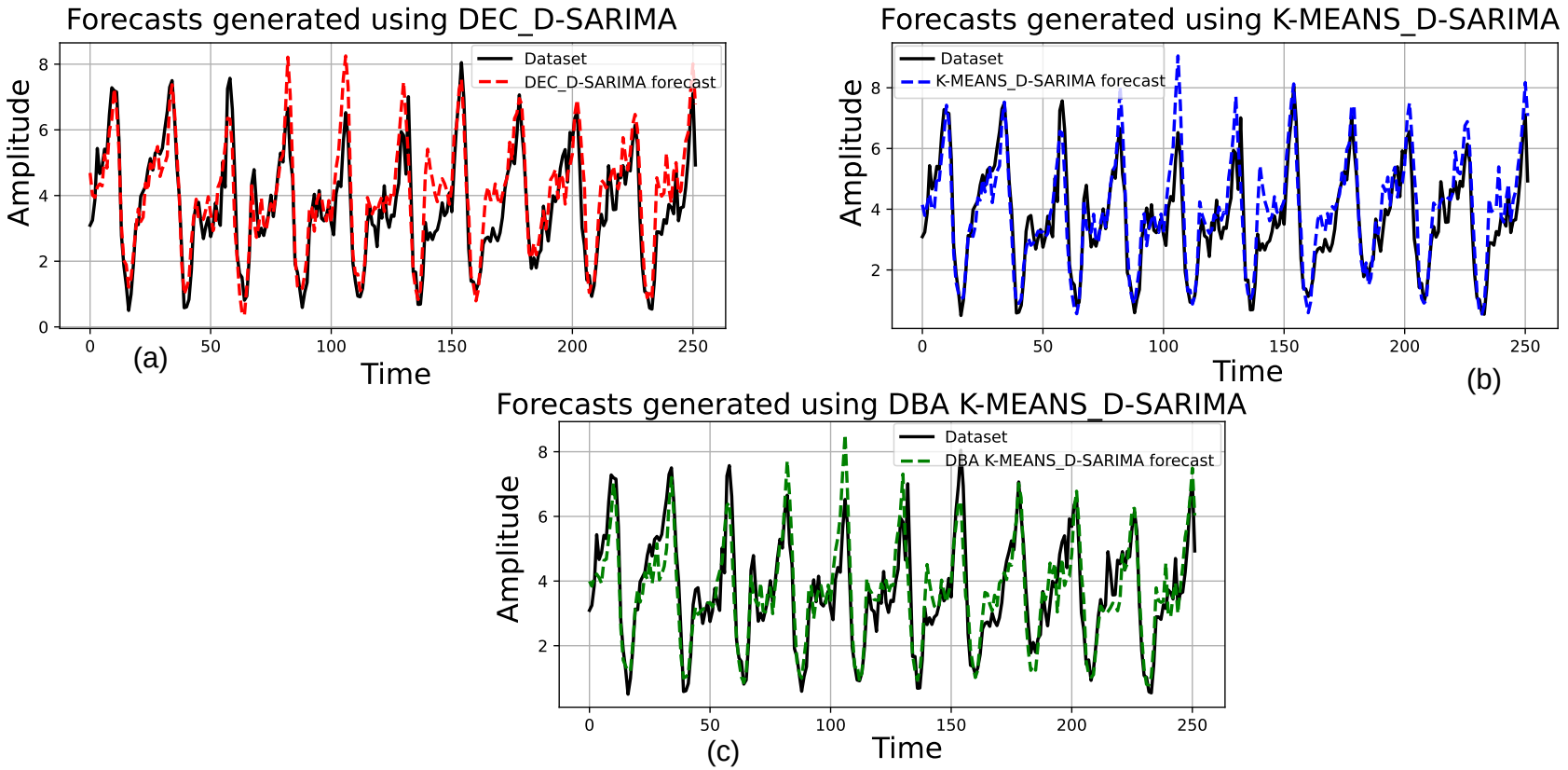


Figure 10: Sample cluster level forecasts

Conclusion

- In this paper, we argued that the effects of temporal distortion should be addressed in cluster level forecasting.
- In this regard, we showed the potential of of representation learning in improving the performances of readily available forecasting models.
- In reality, the potential is not limited to aiding linear models. In contrary, the reported results could further be improved with the integration of more resilient forecasting models.

Thank You!

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