Supplementary Material for Interpreting atypical conditions in systems with deep conditional Autoencoders: the case of electrical consumption

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In this supplementary material, we present the choices of architecture, parameters and hyperparameters we did for our models used in the experiments.

1 Conditional Autoencoders to learn conditional similarities over expert knowledge

Learning CVAEs effectively VAEs, and CVAEs by extension, have been notoriously difficult to train [4], [1]. There is indeed a trade-off between the quality of reconstruction and the expressiveness of the latent space, which are competing if not dealt properly. Two recent works helped addressed recurrent problems in training them. The first one [3] suggests to reduce gradually the importance of the KL divergence regularization, to first learn a proper latent space geometry in an exploration phase, and then refine the reconstruction and similarities through a diffusion or exploitation phase as inspired by the Information Bottleneck principle [5]. We confirm, especially when learning CVAEs, that a relatively high λ, can be used as a pretraining phase to learn both the dimensionality of the latent space and a proper conditional embedding. The second work demonstrates the learning benefits of skip connections in the generator part[2], and we effectively find out that it enables a proper learning through a greater λ. Finally, we use a single batch normalization layer at the conditional output, before concatenating it with the Autoencoder latent space, which enables learning it properly systematically without overfitting (see Figure in paper). As normalizing every inputs usually helps learning with variables of different types and scales, we believe this actually helps intermix our conditional embedding with the latent space as inputs of the generator. We report a useful λ range with skip connections of [0.4-0.7], and of [0.3-0.5] without them, through cross validation experiments with $CVAE_{W,M,T}$ model.

2 Parameters & Hyperparameters in experiments

Parameters have not been tuned in any experiment. In particular the dimensions of layers and embeddings were chosen by default to follow a smooth decay given respective input dimensions. All along our experiments, the dimensions of our Autoencoder are [48,35,24,12,4] from inputs to the latent space in the encoder, and symmetrically for the decoder, apart from its additional succesive skip connections. The conditional layer dimensions, upfront the conditional embedding vector output, are listed in the experiments Table in the paper. A layer of dimension 5, similar to the dimension of the latent space, is used for the conditional embedding, which merges every individual conditional network in an overall embedding to input into the Autoencoder. Adam was used with default parameters in Keras 2.2.4 as the optimizer. Mini-batches are of size 32.

Hyperparameters which were explored were related to the number of epochs to pre-train and then train on the model, as well as the λ-term value along training. Pre-training phases for VAE and CVAEs lasted 500 epochs for single conditions, up to 1000 epochs for multiple conditions, to reach proper factorization in latent space, with a constant λ of 0.5 chosen after cross validation as explained ins Section 3. Then, a learning phase of 2000 epochs with a decreasing λ of 0.001 per epoch was computed for every experiment to reach comparable or lower reconstruction error than the simple VAE.

References

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