Integrated Dimensionality Reduction and Sequence Prediction using LSTM

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Problem

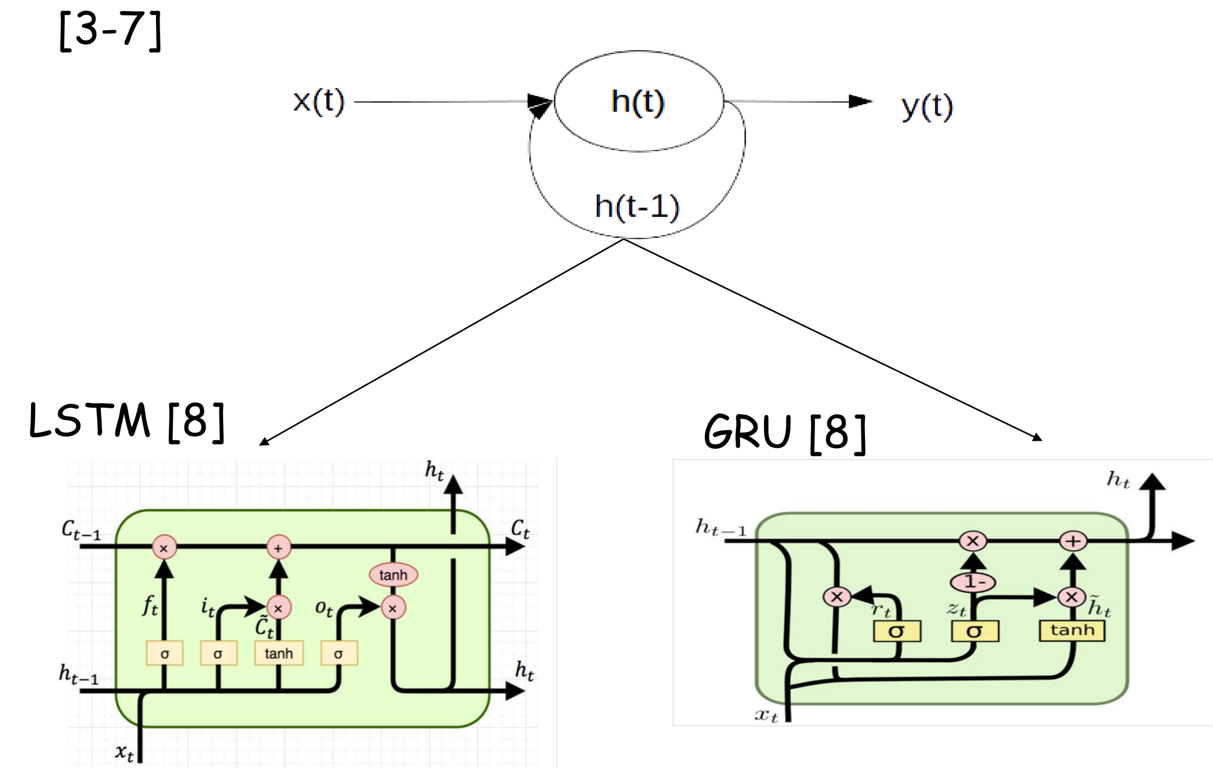
- Most industrial or complex processes present temporal dependencies which stretch over a long time.
- The underlying patterns in these processes can be extremely non-linear.
- Use of linear predictive model (ARMA/ARIMA[1]) is not suitable.
- Hidden Markov Model[2] has prediction limitation when dealing with temporal dependencies that stretch over long durations.

Objectives

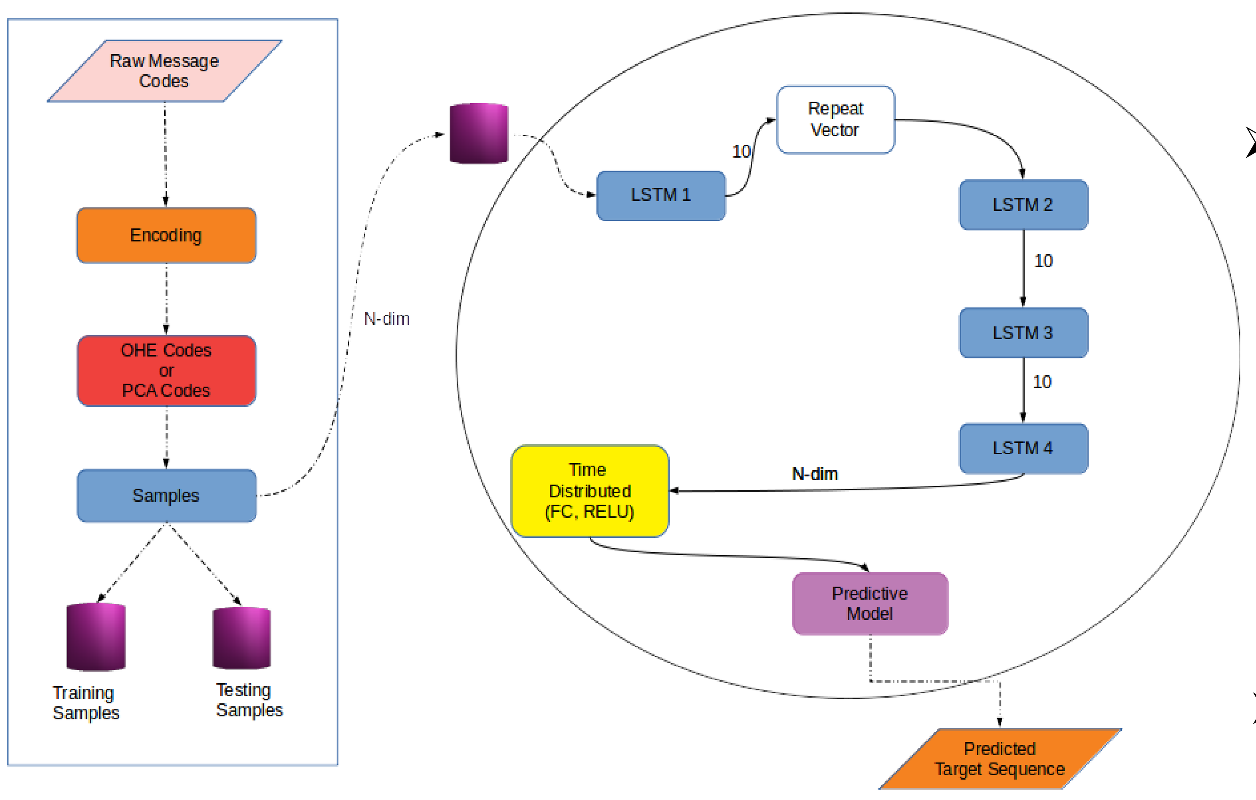
- Use of external and a proposed integrated dimensionality reduction LSTM predictive systems for predicting message logs from industrial machines.
- Conversion of nominal codes (raw codes) to other vectorial paradigms to obtain better correlated patterns.

Methods

- External Methods: Recurrent Neural Networks (RNN) [3-7]



- Proposed Method: Integrated Dimensionality-reduction LSTM



- ➢ Encoding Section: One LSTM
- ➢ Decoding Section: Three LSTMs
- ➢ Repeat Vector: Interlinks the encoding and decoding components
- ➢ Time Distributed: the final feature dimension from the last LSTM is wrapped with a time-distributed algorithm that presents the reproduced data in a sequential series.

Data Representations

One-Hot-Encoding Codes

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	...	63
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	...	...
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	...	...
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	...	...
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	...	...
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	...	...
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	...	...
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	...	...
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
9992	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	...	...
9993	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	...	...
9994	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	...	...
9995	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	...	...
9996	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	...	...
9997	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	...	...
9998	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	...	...
9999	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	...	...

3-DIM Principal Component Analysis (PCA) Codes

	PC 1	PC 2	PC 3
0	0.8211	-0.1157	-0.0232
1	0.8211	-0.1157	-0.0232
. . .	. . .	. . .	. . .
9997	0.1326	0.4218	0.4549
9998	0.1326	0.4218	0.4549
9999	0.1326	0.4218	0.4549

Data sizes: ~15.4M total samples

SMALL DATA SIZE
One Subset containing 10K samples

LARGE DATA SIZE
10 Subsets, where each subset contains ~1.54M samples

Results

- ➢ ID-LSTM Prediction on OHE codes during training and testing phases (left plot) and index predictions (right plot) over a duration of 10K time-counts.

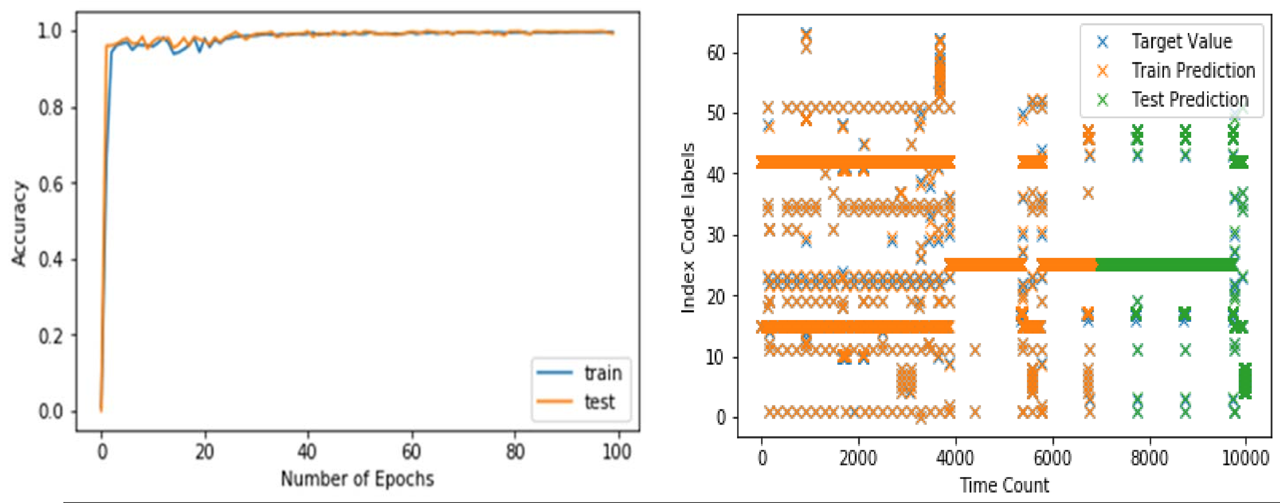


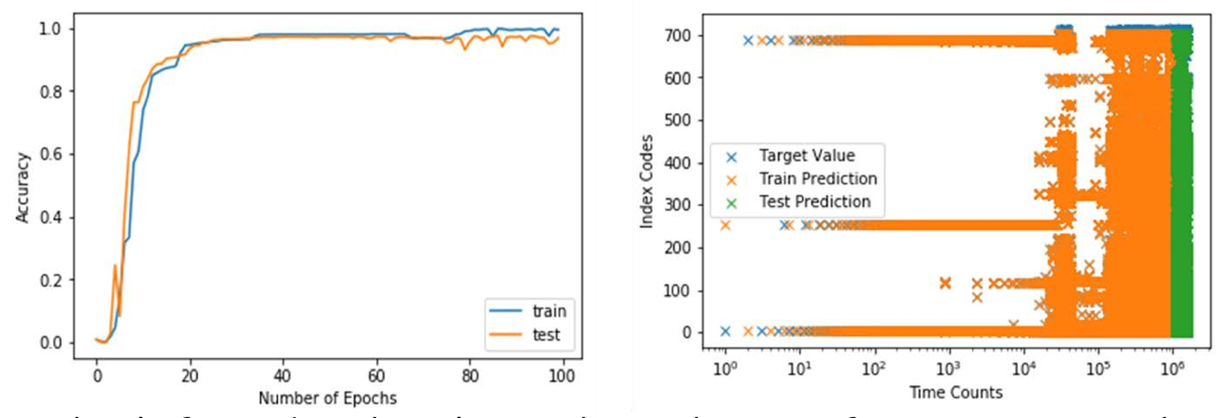
Table 1: Prediction accuracies for the different approaches for 10K Samples

Methods	Train	Test
ID-LSTM-I-OHE-Codes	**0.9957**	**0.9920**
ID-LSTM-I-20-DIM-PCA-Codes	0.9763	0.9843
ID-LSTM-I-40-DIM-PCA-Codes	0.9760	0.9733
ID-LSTM-I-10-DIM-PCA-Codes	0.9316	0.9727
ID-LSTM-I-5-DIM-PCA-Codes	0.9139	0.9593
ID-LSTM-I-4-DIM-PCA-Codes	0.9424	0.9410
ID-LSTM-I-3-DIM-PCA-Codes	0.9463	0.9593
ID-LSTM-I-2-DIM-PCA-Codes	0.9424	0.9590
ID-LSTM-I-1-DIM-PCA-Codes	0.8729	0.9340
SL-LSTM-I-1-DIM-PCA-Codes	0.8757	0.9340
SL-GRU-MSE-SI-1-DIM-PCA-Codes	0.8715	0.9316
SL-GRU-MAE-SI-1-DIM-PCA-Codes	0.8715	0.9316
SL-LSTM-MAE-SI-1-DIM-PCA-Codes	0.8715	0.9316
SL-LSTM-MSE-SI-1-DIM-PCA-Codes	0.8715	0.9316
SL-LSTM-I-Raw-Codes	1.429x10-4	0.0000
SL-GRU-MSE-SI-Raw-Codes	2.858x10−4	0.0000
SL-GRU-MAE-SI-Raw-Codes	2.858x10−4	0.0000
SL-LSTM-MSE-SI-Raw-Codes	2.858x10−4	0.0000
SL-LSTM-MAE-SI-Raw-Codes	1.429x10-4	0.0000

NOTE

- A separate dimensionality reduction by PCA is not needed: the ID-LSTM uses 10 hidden dimensions in the bottleneck layer.
- One-hot-encoding is a must: do not try to predict arbitrary raw integer codes

- ➢ ID-LSTM Prediction on OHE codes during training and testing phases (left plot) and index predictions (right plot) over a duration of ~1.54M time-counts for subset 9.



- ➢ The left and right plots show the confusion matrix, that is; the plot of the output predictions against their target values for both training and testing phases respectively for subset 9.

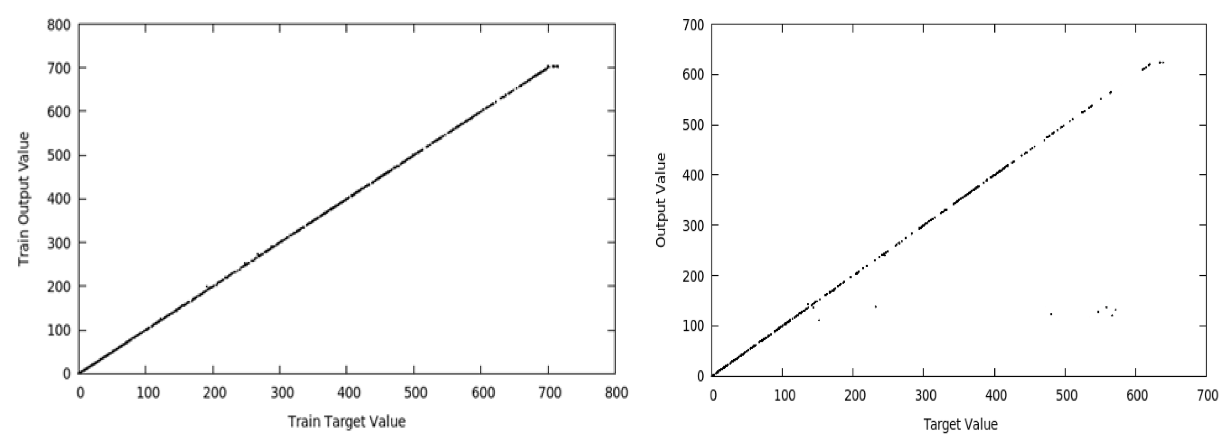


Table 2: Prediction accuracy of the ID-LSTM trained on OHE codes

No of Subsets	Time counts	No . of Index	No. of Machine	Train	Test
Subset 1	0 – 1.54M	948	20	0.9826	0.9751
Subset 2	1.54– 3.09M	606	30	0.9979	0.9695
Subset 3	3.09-4.63M	535	36	0.9886	0.9624
Subset 4	4.63-6.18M	619	48	0.9961	0.9021
Subset 5	6.18-7.73M	620	62	0.9837	0.9806
Subset 6	7.73-9.27M	675	109	0.9962	0.9347
Subset 7	9.27-10.8M	648	64	0.9205	0.9293
Subset 8	10.8-12.3M	679	95	0.9973	0.9576
Subset 9	12.3-13.9M	717	196	0.9943	0.9681
Subset 10	13.9-15.4M	624	263	0.9871	0.9268
Average				**0.9844**	**0.9506**

Conclusion

- We have transformed nominal codes to other vectorial representations with the objective of identifying correlated patterns using one hot encoding (OHE) and principal component analysis (PCA).
- Nominal integer codes are not sensible to use in the RNN.
- A separate dimensionality reduction by PCA is not needed: the ID-LSTM uses 10 hidden dimensions in the bottleneck layer.
- The ID-LSTM on OHE codes yield the best result on a small sample dataset.
- The use of ID-LSTM also obtains good results on reduced dimensional PCA vector codes (20-DIM-PCA)
- The ID-LSTM obtained < 5% error on the predicted OHE codes in a realistically large dataset.
- One-hot-encoding is a must: do not try to predict arbitrary raw integer codes.

Future Directions

- We suggest that it may be possible to combine the proposed model with an early anomaly detection algorithm,
- To allow continuous prediction of physical problems in the machines generating the message logs.
- Optimization of LSTM-based feature dimensionality reduction in a realistically large dataset.

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