Dynamic RNN State Updates for Irregular Multivariate Time Series Classification

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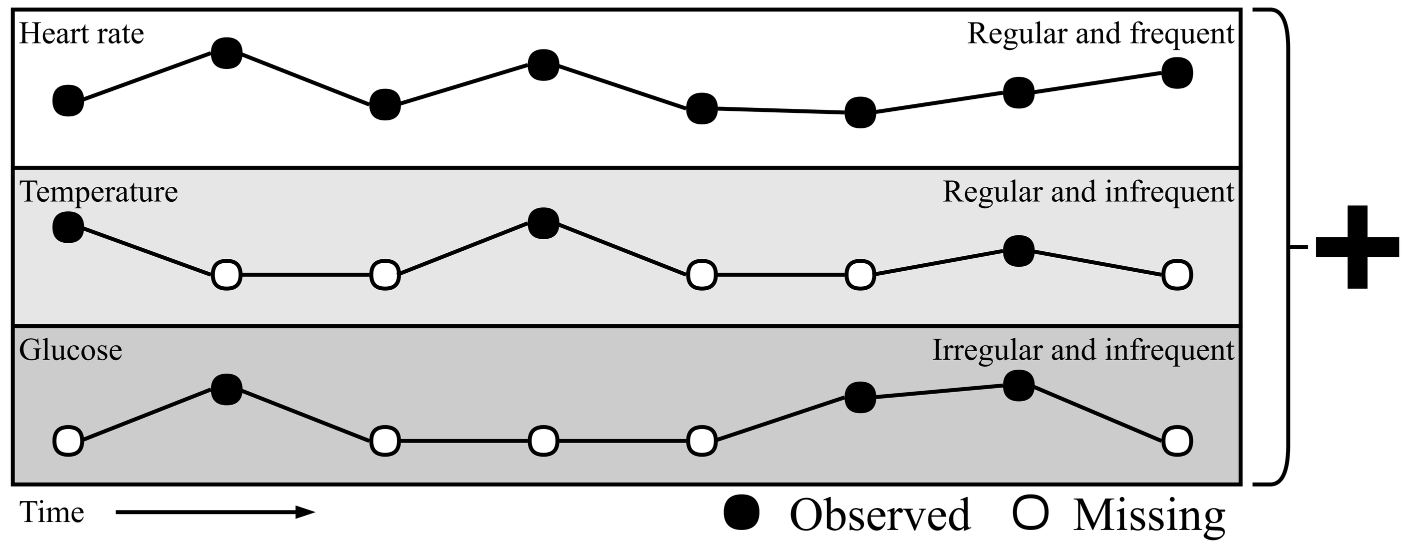
Irregular Multivariate Time Series

Variables have different sampling rates. Empty spaces between observations can be informative. Prior to classification, timestamps must be aligned.

Three common challenges with such data:

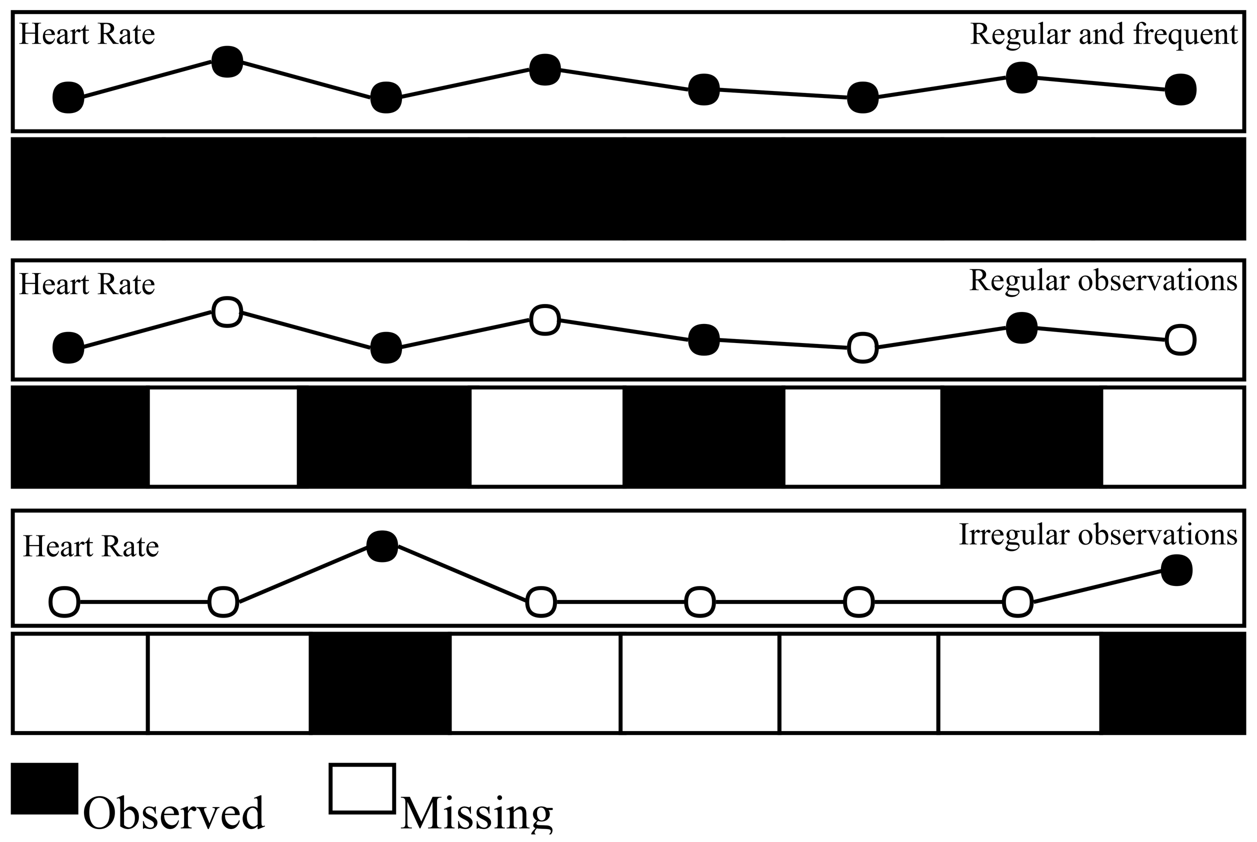
- Irregular observation rates require time-alignment.
- Missing values may or may not be informative.
- High sampling-rate lead to long sequences. As dependencies grow over time, it becomes more challenging to remember only useful information.

Problem Setting



Traditional approaches

- Up-sampling slow variables vs. down-sampling fast variables.
- Combinations of different information sources (time delta, masking vector) are fed to RNNs.
- Some approaches also try to find meaningful values to impute.



Missingness-Informed State-Skipping RNN

Intuition: Update the cell memory only when useful information is observed.

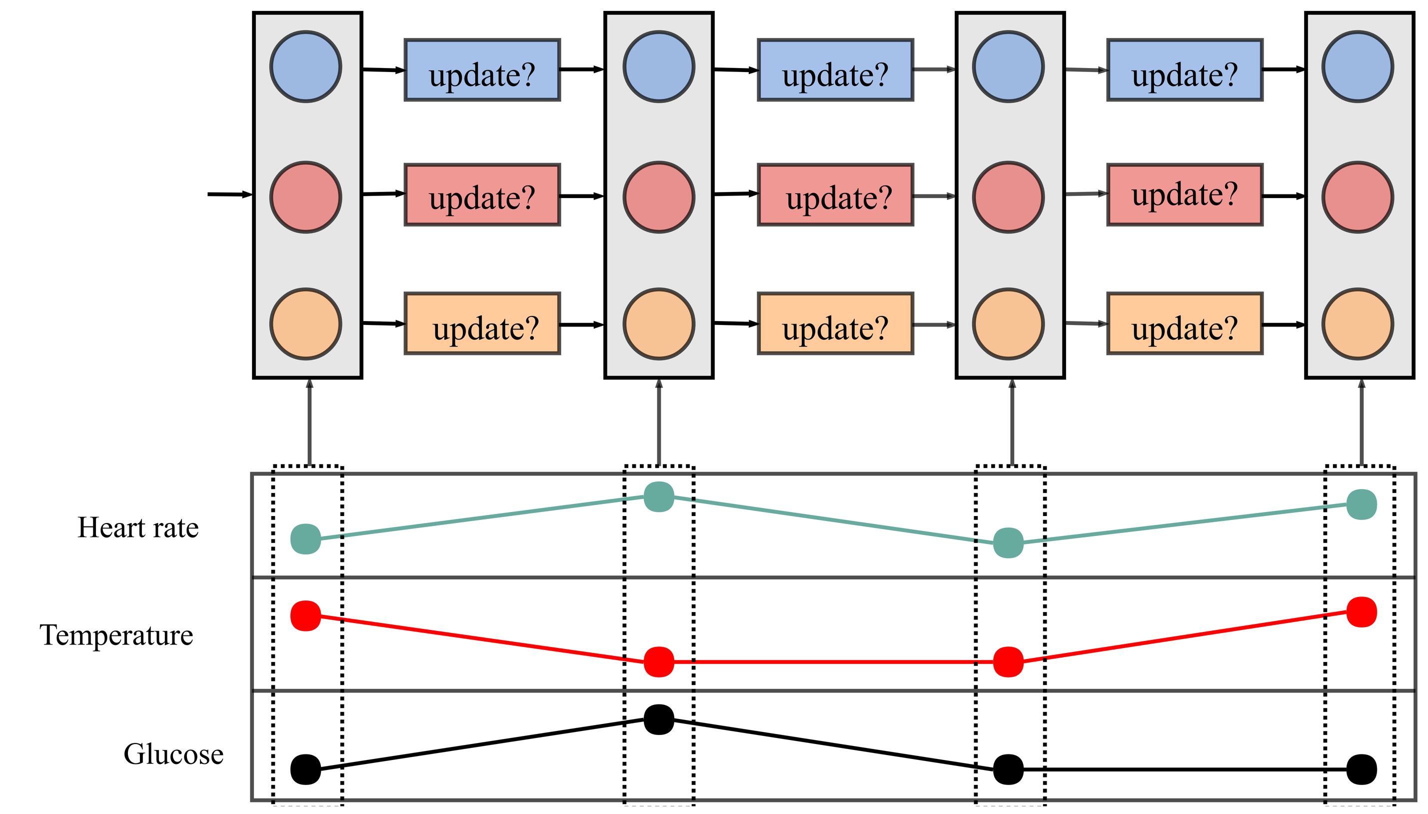


Figure 1: Mechanics of partial state-updates.

Representation generation in MISS-RNN:

$$\begin{aligned}
\gamma_t &= -\exp\{-max(0, W_\gamma \cdot \delta_t + b_\gamma)\} \\
\hat{x}_t &= m_t x_t + (1-m_t)(\gamma_{x_t} x_{t'} + (1-\gamma_{x_t})\tilde{x}) \\
\hat{S}_{t-1} &= \gamma_{S_t} * S_{t-1} \\
\tilde{S}_t &= \mathrm{GRU}([\hat{x}_t, m_t], \hat{S}_{t-1}) \\
u_t &= \mathrm{binarize}(\sigma(W_s \cdot \tilde{S}_t + b_s)), \text{ s.t. } u_t \in \mathbb{R}^h \\
S_t &= u_t \odot \tilde{S}_t + (1-u_t) \odot S_{t-1}
\end{aligned}$$

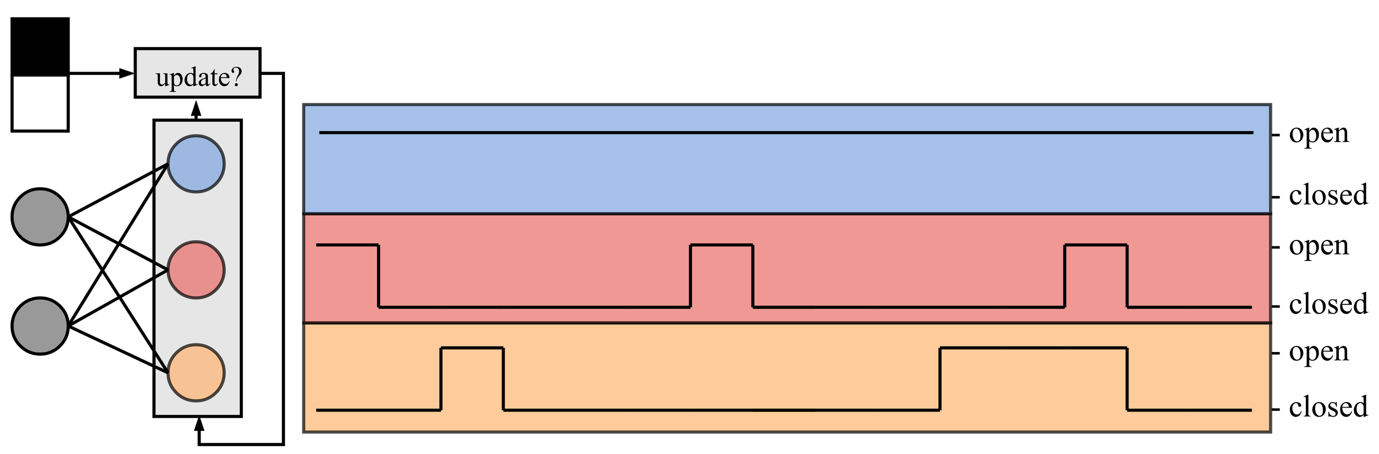


Figure 2: Resulting dynamics in hidden state updates patterns.

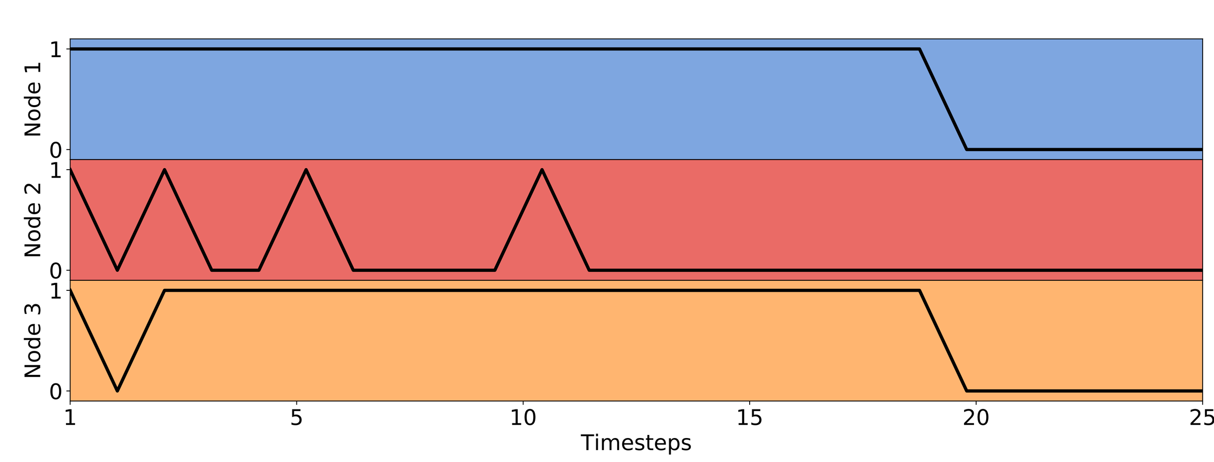


Figure 3: Disentangled updates in sub-representations.

Evaluation Data

Synthetic dataset:

- Balanced dataset of 1000 time series, each is 100 timesteps long.
- Each time series is a sequence of 0's. Positive examples have a 1 at a random location. Gaussian noise is added.
- Remove 2 values from uniform locations from positive examples, remove 4 from negative.
- Impute surrogate values for missing values.

Results

Method	Accuracy
Mean Imputation	59 ± 0.0
Zero Imputation	59 ± 0.0
Forward Imputation	59 ± 0.0
SkipRNN [1]	59.0 ± 0.0
GRU-D [2]	80.24 ± 22.26
Mask + Mean Imp. [3]	72.4 ± 26.66
PhasedLSTM [4]	59 ± 0.0
Mask and diff input	72.40 ± 26.66
SkipRNN + Mask	71.6 ± 22.83
Mask as updates	59 ± 0.0
Input mask and full-skip	81.5 ± 20.95
Mask informs skipping	$59 \pm + 0.0$
Input-mask + mask-inform	83.6 ± 22.0
Full-skipping w/decay impute	91.6 ± 5.04
MISS [proposed]	$\mathbf{94.72 \pm 2.69}$

References

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[2] Z. Che, S. Purushotham, K. Cho, D. Sontag, and Y. Liu, "Recurrent neural networks for multivariate time series with missing values," *Scientific reports*, vol. 8, no. 1, p. 6085, 2018.

[3] Z. C. Lipton, D. C. Kale, and R. Wetzel, "Modeling missing data in clinical time series with rnns," in *Machine Learning for Healthcare*, 2016.

[4] D. Neil, M. Pfeiffer, and S.-C. Liu, "Phased lstm: Accelerating recurrent network training for long or event-based sequences," in *Advances in Neural Information Processing Systems*, pp. 3882–3890, 2016.

Acknowledgements

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