Classification of Irregularly Sampled Clinical Time-Series Data with Convolutional Neural Networks

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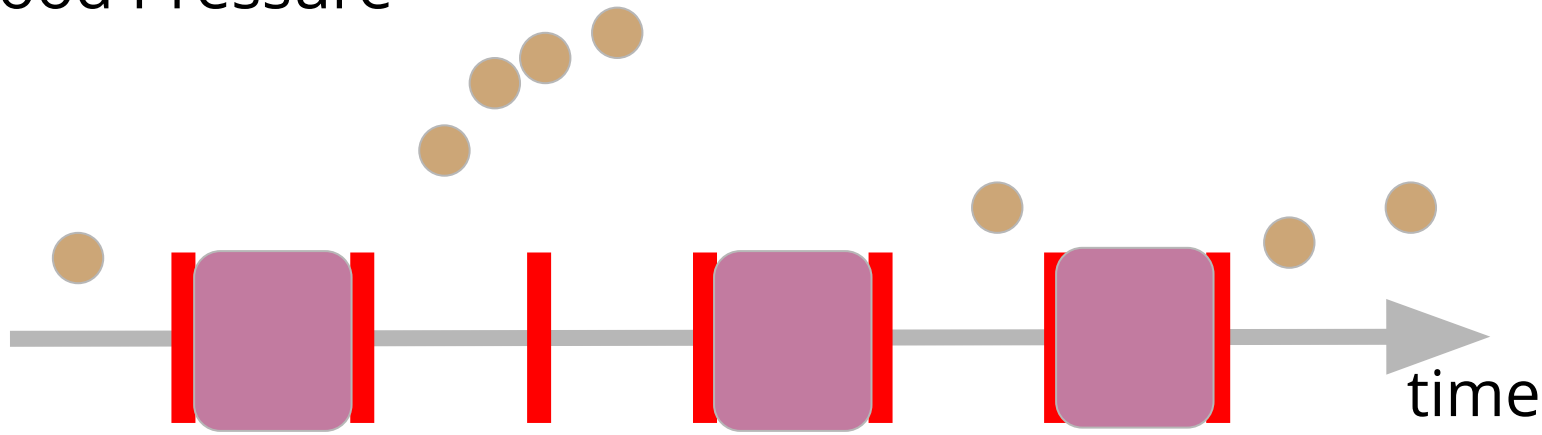
Irregularly sampled health data

Blood Pressure



Challenge: data are no missing at random, how to handle irregularities in sampling

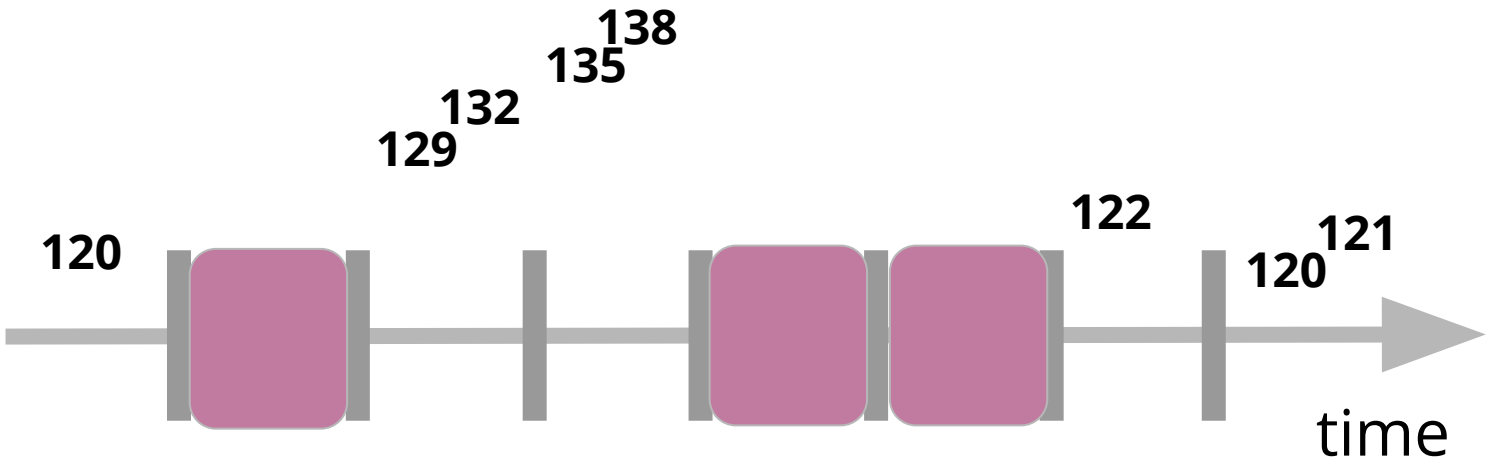
The Proposed Model

- **Hypothesis:** explicitly accounting for missinginess will outperform a model that ignores missingness
- **Idea**: use additional input to CNN that encodes missingness

- **Approach**: compare a baseline CNN to one that explicitly accounts for missingness

Irregularities in the Data

Blood Pressure



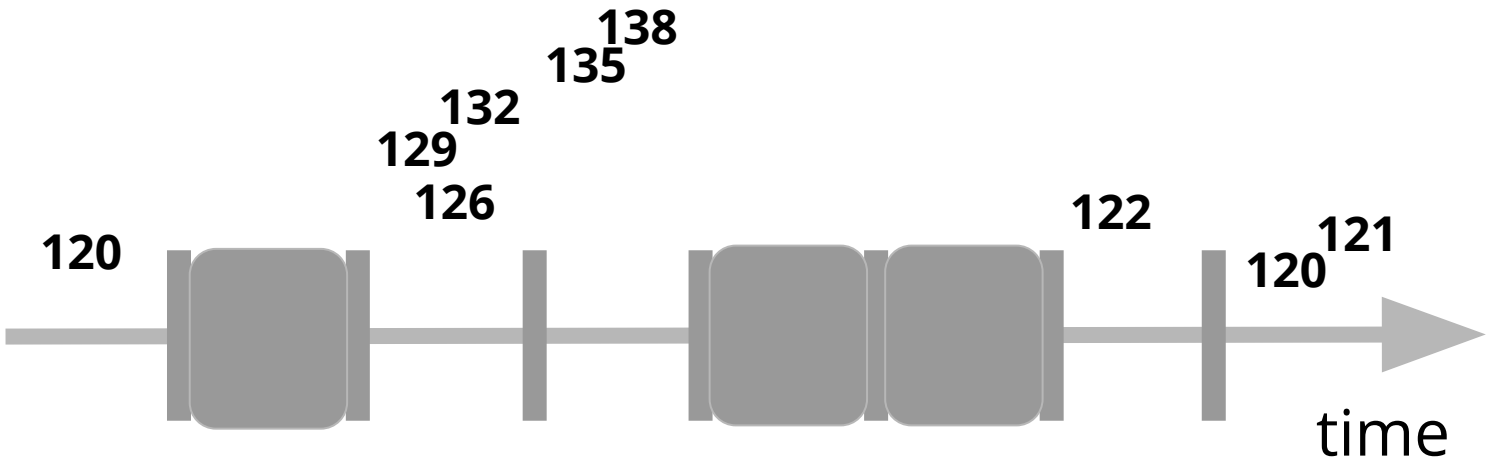
Time interval	1	2	3	4	5	6	7	8
BP	120	nan	130.5	136.5	nan	nan	122	121
Missing indicator	0	1	0	0	1	1	0	0

Relative Intensity of Measurements

Blood Pressure

Total count: 1+3+2+1+2=9

Average count: 9/8=1.125

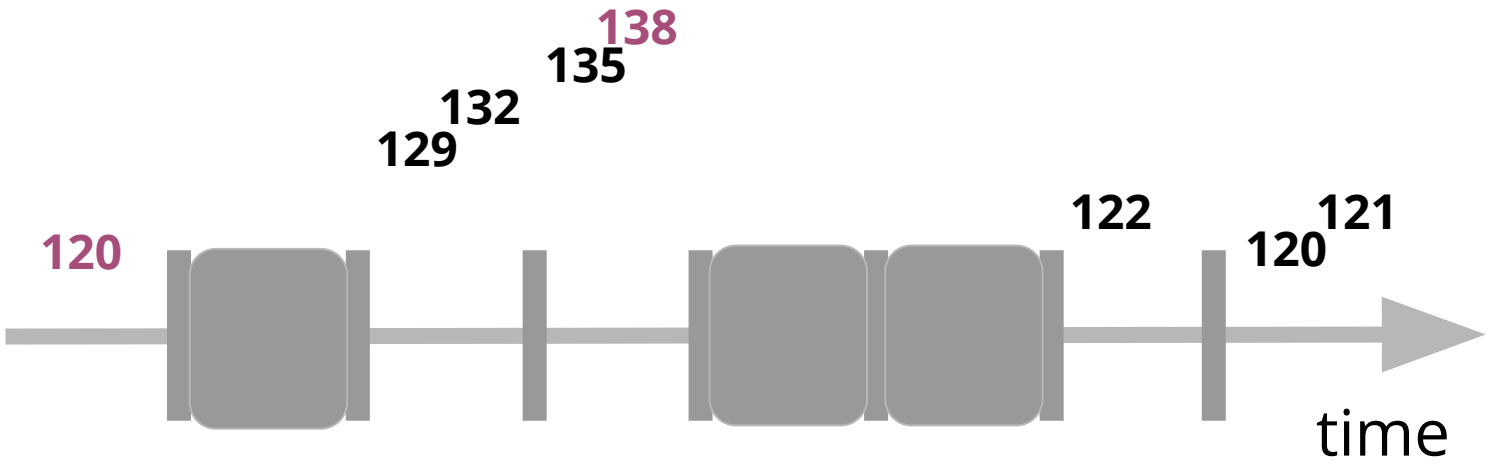


Time interval	1	2	3	4	5	6	7	8
Count	1	0	3	2	0	0	1	2
Ci/C_avg								

***just divide count in time interval by the average number of measurements**

Carry-forward Imputation

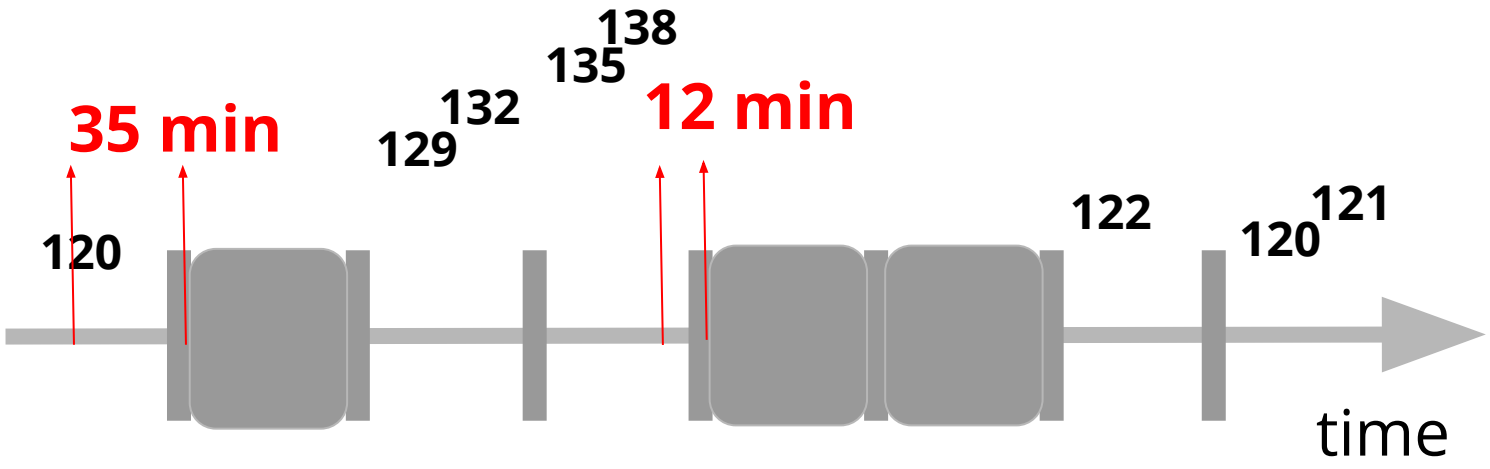
Blood Pressure



Time interval	1	2	3	4	5	6	7	8
Mean BP	120		130.5	136.5			122	120.5

Unreliability Metric

Blood Pressure

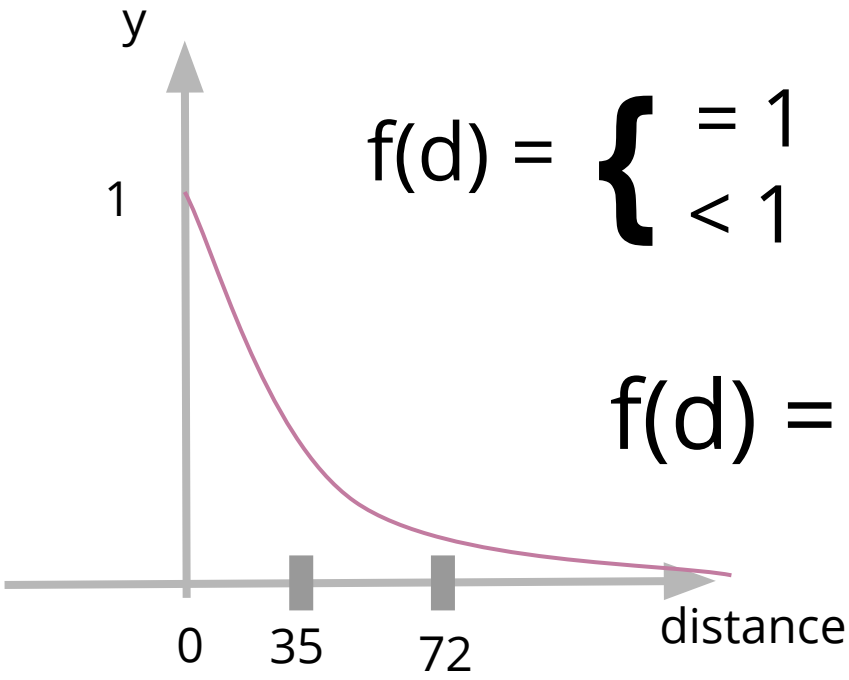


Time interval	1	2	3	4	5	6	7	8
Distance	35		8	12			36	43

*distance from the last measurement

Unreliability Metric

Time interval	1	2	3	4	5	6	7	8
Distance	35	95	8	12	72	132	36	43
Missing indicator	0	1	0	0	1	1	0	0



$$f(d) = \begin{cases} = 1 & \text{if not missing} \\ < 1 & \text{if missing} \end{cases}$$

$$f(d) = e^{-distance * missing}$$

Convolutional Layer

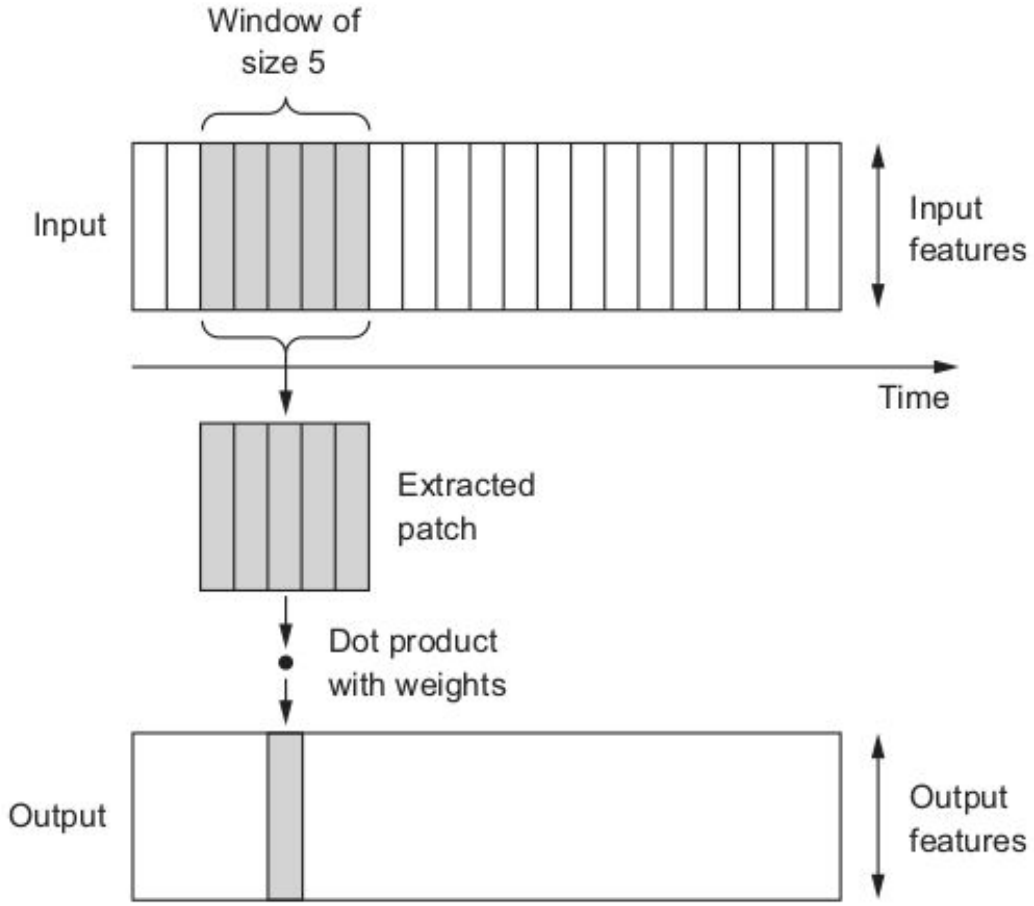
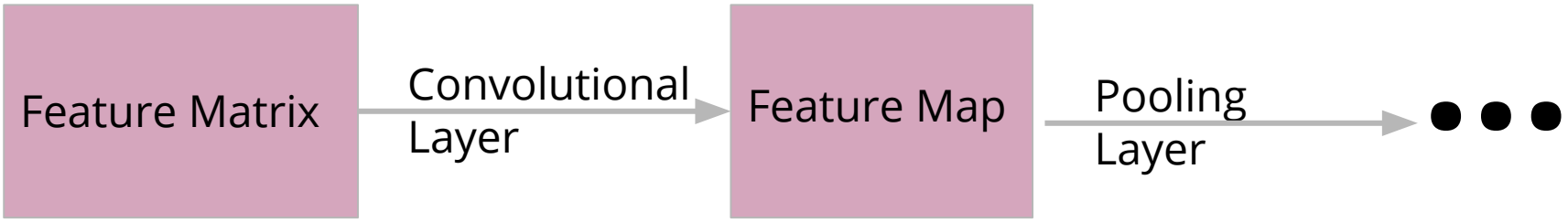
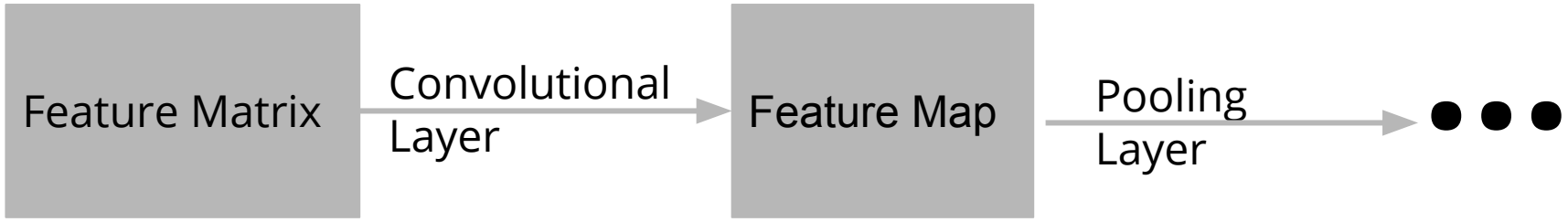


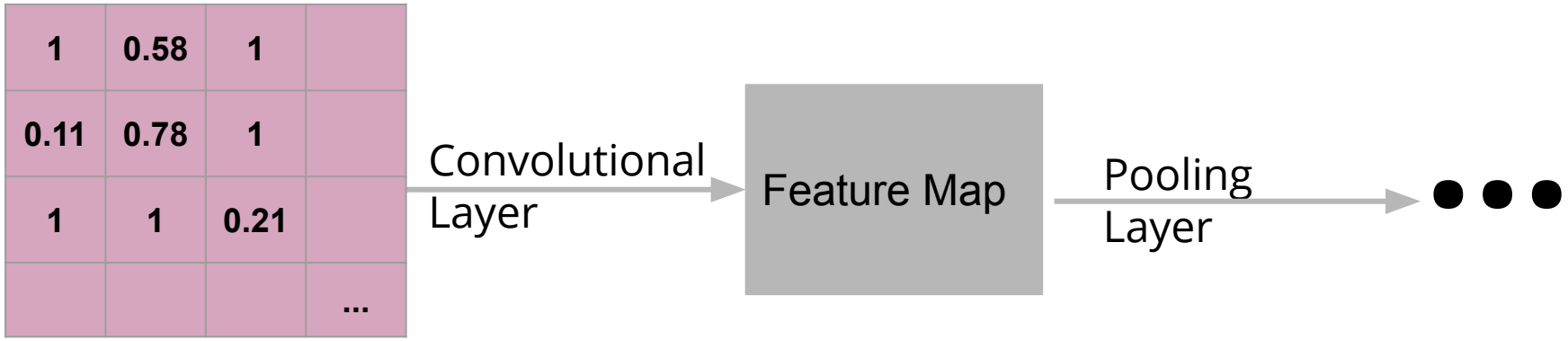
Figure 6.26 How 1D convolution works: each output timestep is obtained from a temporal patch in the input sequence.

Architecture of a Convolutional Neural Network

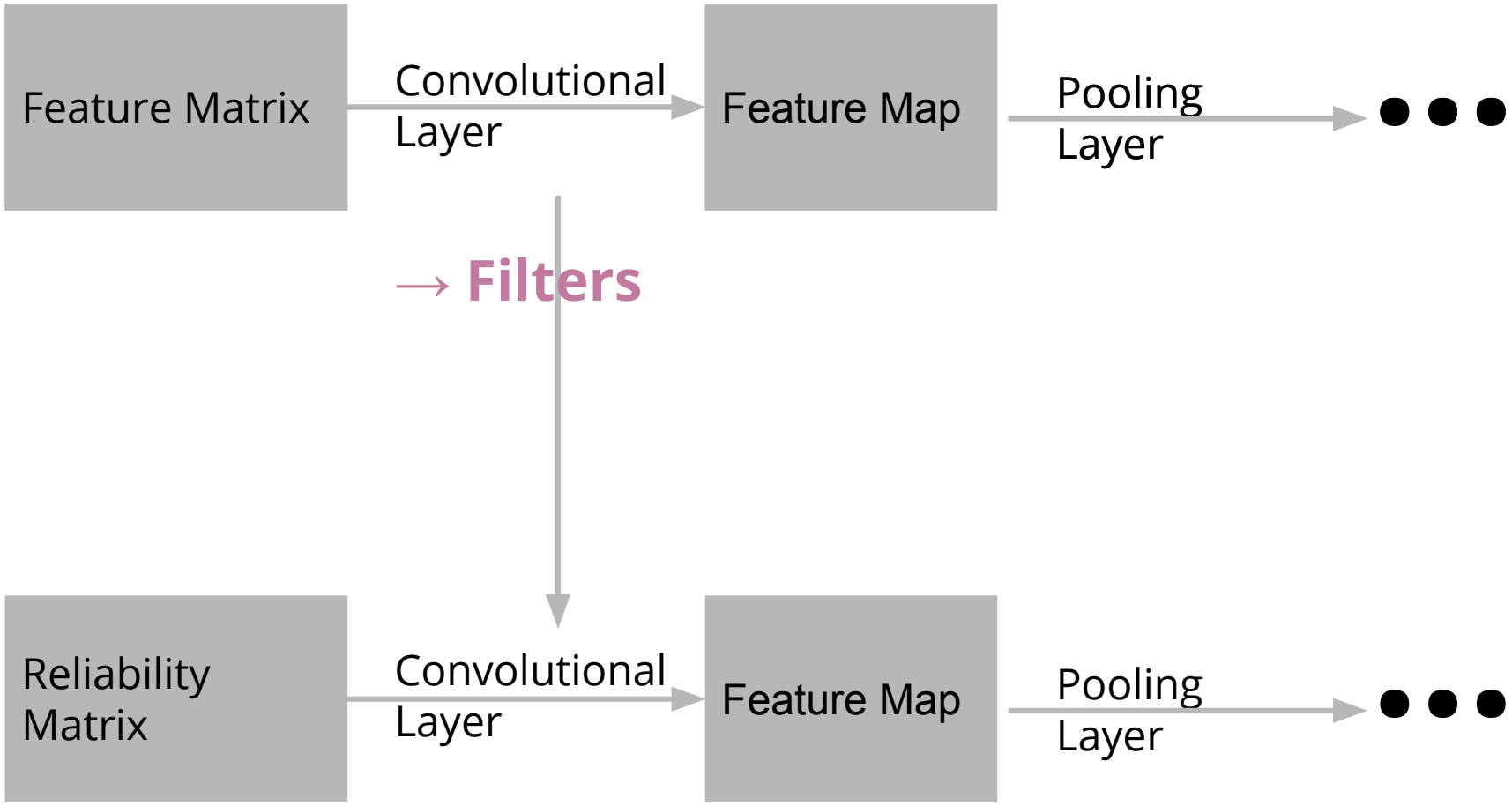


Convolutional Layer





Our Proposed Model



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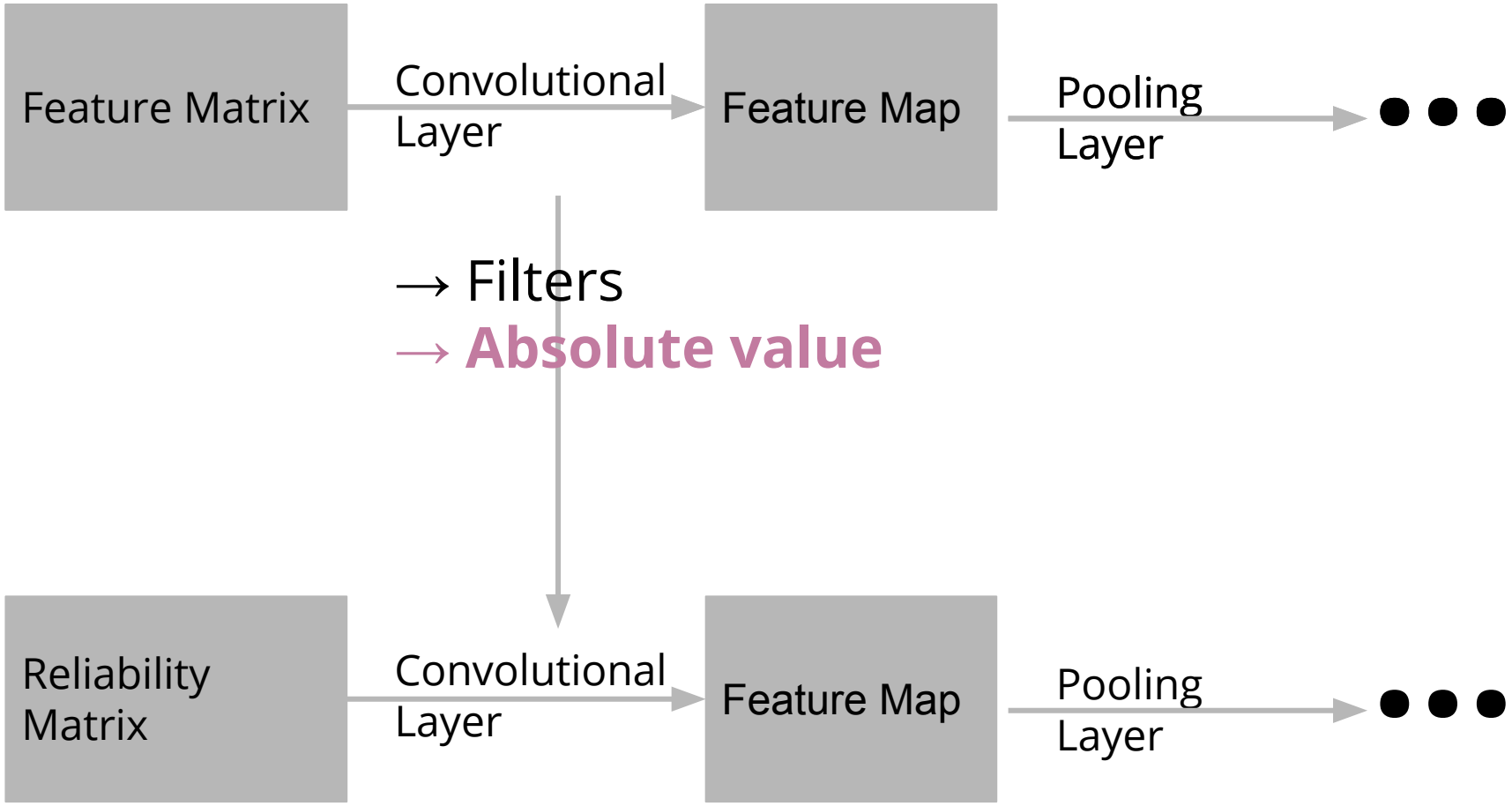

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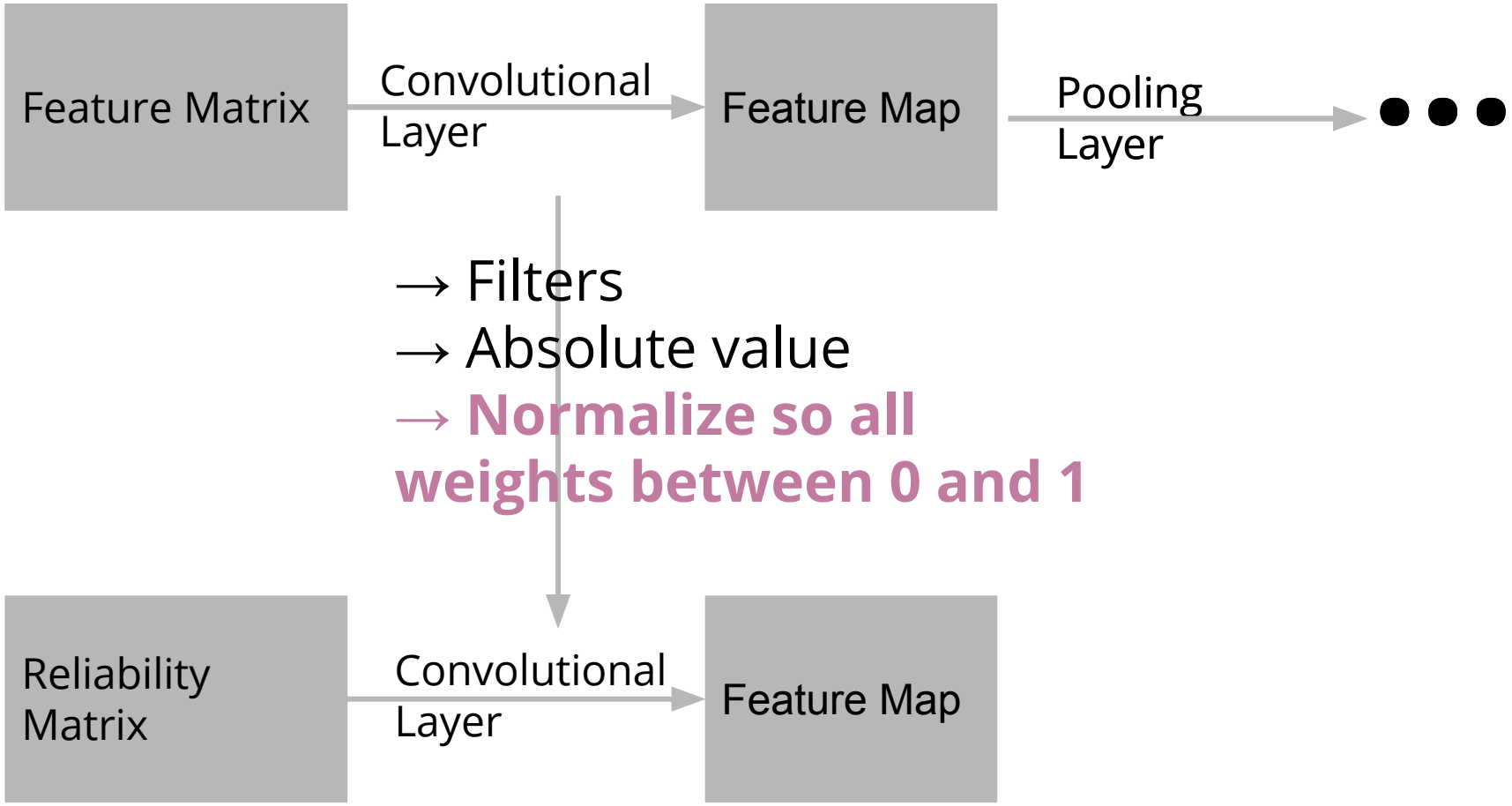

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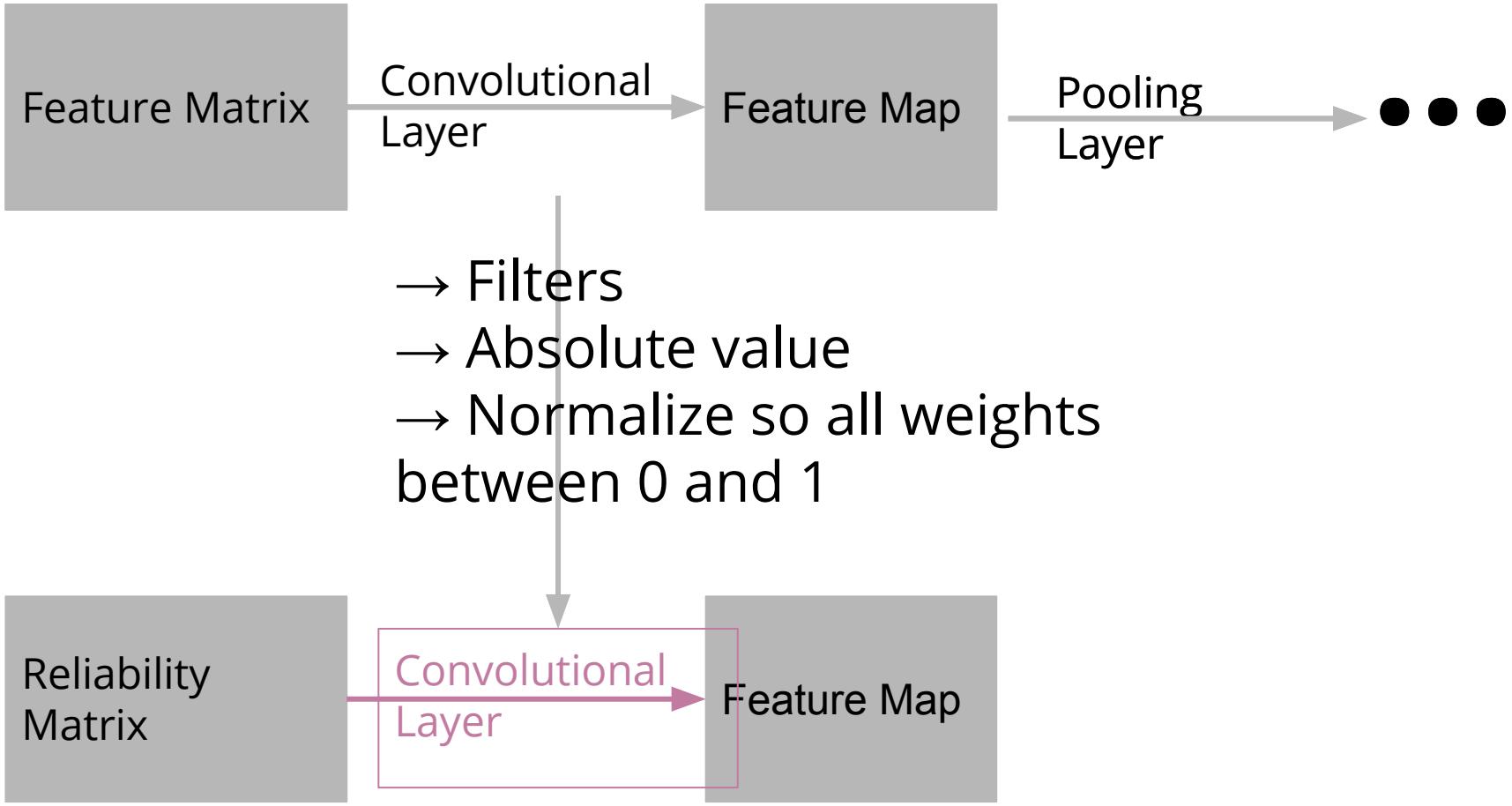

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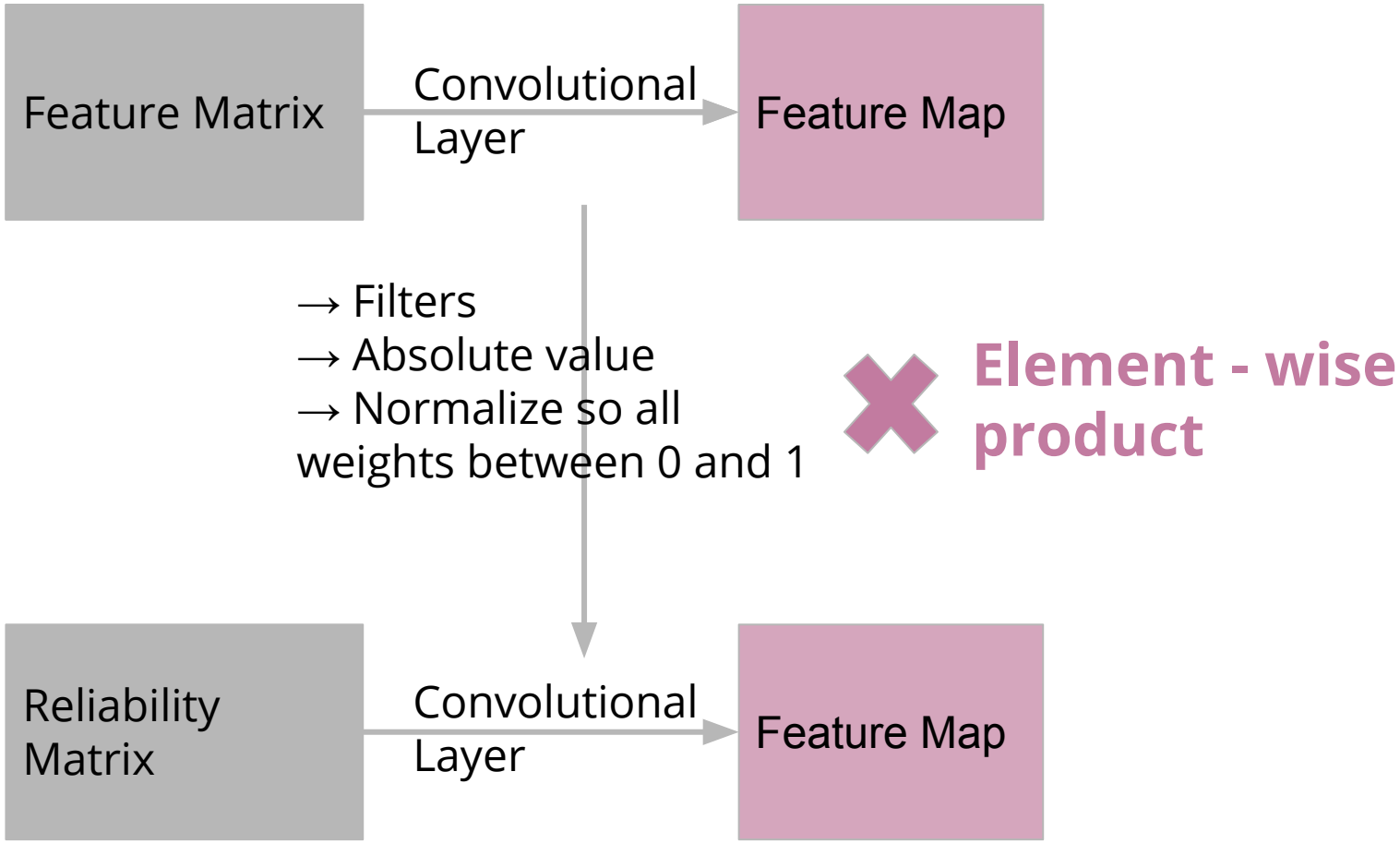

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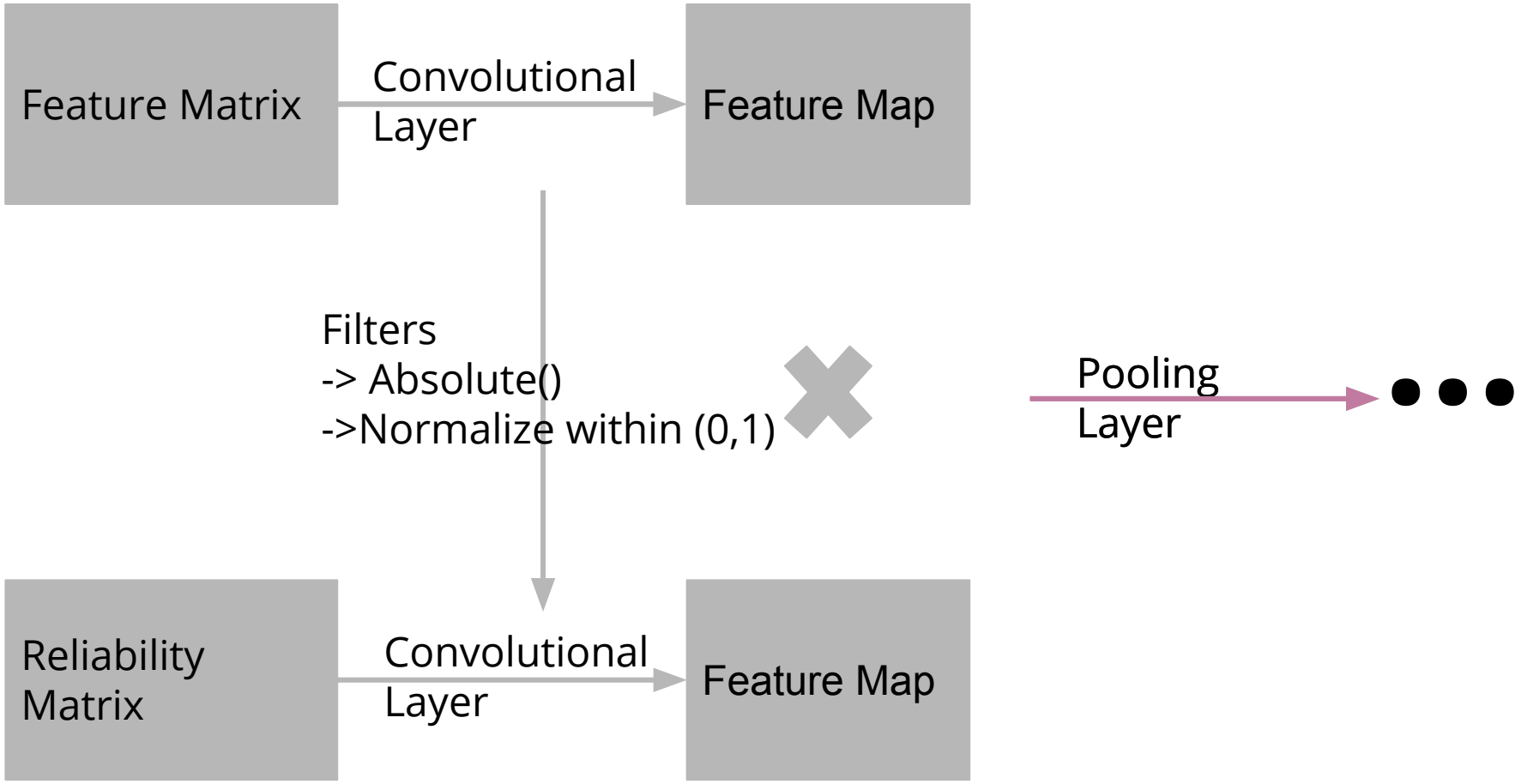

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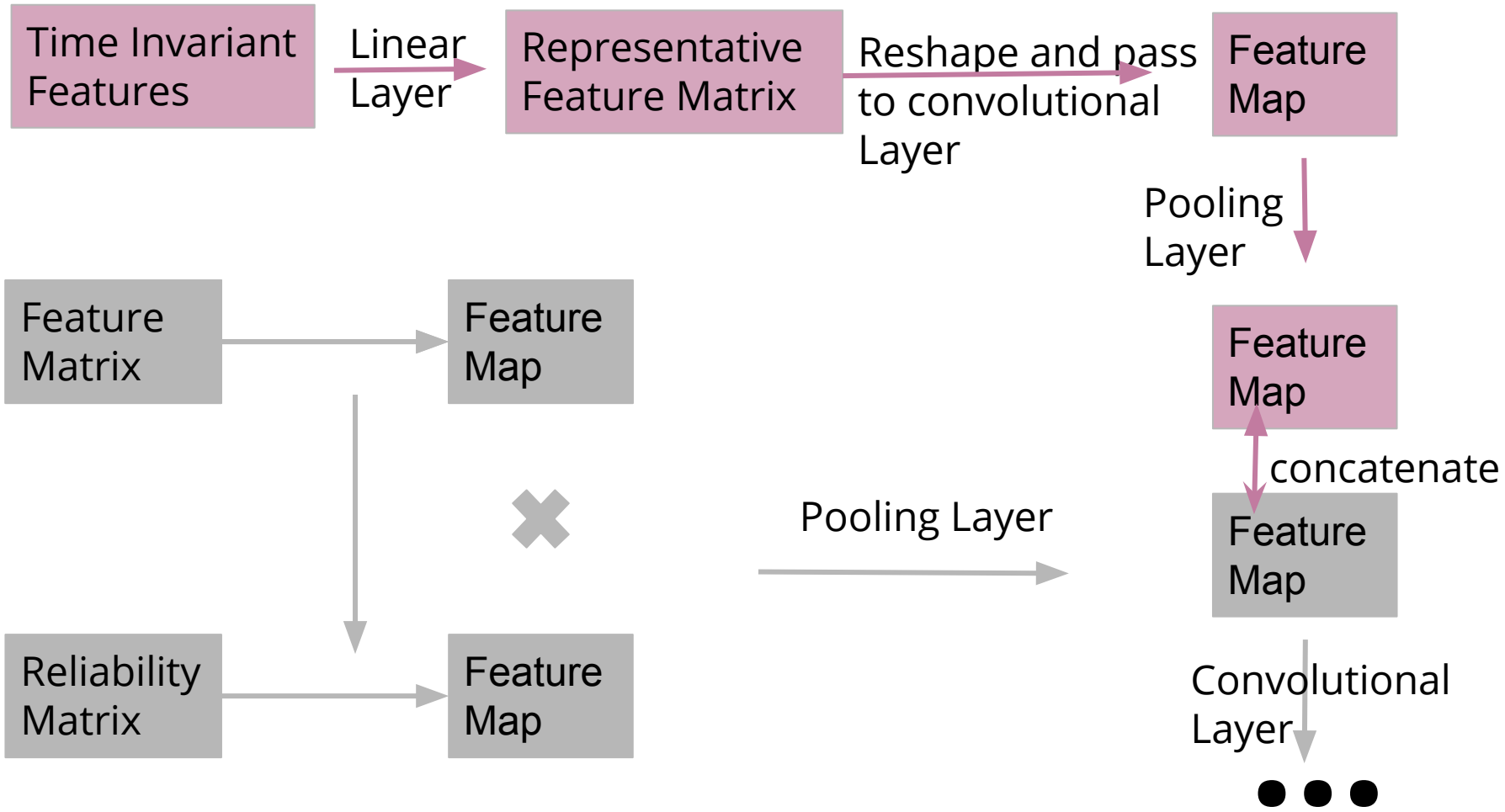

Model Evaluation

Model	AUROC Confidence Interval	Loss Confidence Interval
Baseline CNN	[0.823, 0.847]	[0.312, 0.327]
Proposed CNN	[0.835, 0.858]	[0.293, 0.367]

Conclusion

- The proposed model modestly improves prediction performance

- **Clinical Relevance:** Approach can be applied to irregularly sampled clinical time-series data

- **Technical Relevance:** Approach can be generalized to irregularly sampled time-series data in different domains, provided that the irregularities in the sampling rate are non-random and non-uniform across features

Q&A

Thank You.