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Sequence-based neural networks applied to denoising of single-cell RNAseq data

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2 Abstract

Single-cell RNA-sequencing(scRNAseq) offers many exciting analysis opportunities. Unlike bulk RNA-sequencing, scRNAseq gives an expression profile for each individual cell in a sample. This allows for identification of rare sample cell-subtypes, analysis of cell differentiation among other interesting analysis. The sequencing depth of each cell in scRNAseq is however very small, leading to many dropout events and general overdispersed data.

Several methods have been developed in order to denoise scRNAseq data, imputing the dropout events and correcting counts. In recent years, several neural network models have been developed in the field of scRNAseq denoising. Common for all current modelling approaches is that they only utilize the scRNAseq gene-counts themselves to denoise the counts.

In this thesis we argue that the inherent sequence context of each gene holds expression information, and that this could be utilized in inferring the denoised gene-counts. To that end we develop the Sequence- and Count-based Encoder and Linear Decoder(SCELD) model which utilizes sequence information in addition to the count-matrix. We also implement the Deep-CountAutoencoder(DCA) an existing scRNA-denoising model as a benchmark model.

In general the SCELD was slightly outperformed by DCA across the several denoising metrics. Especially when investigating the ability to retain the clustering of cells when trained on a corrupted dataset did SCELD perform poorly while DCA was able to reproduce the cell clusters.

The choice of benchmarking data and the model design may not have been optimal however, and we argue that further research is needed to properly evaluate the use of sequence information in scRNAseq denoising.