Enhancing Hi-C contact map resolution with neural network

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1 Introduction

Recently, the high-throughput chromoseome comformation capture(Hi-C) technique has become a powerful tool for studying the three-dimensional structure of chromosomes. Hi-C data is usually expressed as a $n \times n$ matrix. The resolution of Hi-C data is defined as the bin size of each cell of the matrix. Hi-C data at kilobase level are requisite for future genome 3D structure studies. Rao et al.(2014) generated Hi-C data with 1 kilobase resolution. However, millions of sequenced reads are required to archive this resolution with a huge amount of money and time consumption.
Zhang et al. presented a approach to enhance the resolution of Hi-C data called HiCPlus. Which generated low-resolution data by down-sampling the number of sequenced reads and then a neural network was used to create the mapping between high-resolution contact map and low-resolution contact map.
[1]

2 Methods

Let D be a set of paired ends reads of a Hi-C experiment. We make a low and high contact maps from D, denoted by M_ℓ and M_h. Let S_ℓ and S_h be the size of M_ℓ and M_h. Let R be the ratio of M_ℓ to M_h, which can be represented by $R = \frac{M_h}{M_\ell}$. And O be the number of overlapping pixels between adjacent sub-maps.

% Divide matrices M_ℓ and M_h
To M_ℓ :

for i = 1, 1+$40 - O$, 1+2$\times(40 - O)$, ...
    for j = 1, 1+$40 - O$, 1+2$\times(40 - O)$, ...
        IF $i + 40$ > M_ℓ || $j + 40$ > M_ℓ, BREAK
        ELSE extract 40 $\times$ 40 sub-maps whose left-top coordinate is (i, j) from M_ℓ.

Do the same process to M_h :

for i = 1, 1+$(40-O)$ $\times$ R, 1+2$\times(40-O)$ $\times$ R, ...
    for j = 1, 1+$(40-O)$ $\times$ R, 1+2$\times(40-O)$ $\times$ R, ...
        IF $i+40$ $\times$ R > M_h || $j+40$ $\times$ R > M_h, BREAK
        ELSE extract $(40 \times R) \times (40 \times R)$ sub-maps whose left-top coordinate is (i, j) from M_h.

Let C_ℓ and C_h be a collection of the resulting sub-maps. Train a neural network using C_ℓ and C_h. Mean square error is used as loss function in the training process.

$$MSE[C_\ell, C_h] = \frac{1}{40\times 40}\sum_{i=1}^{40\times 40}(C_{\ell_i} - C_{h_i})^2$$

We can use (f,n) to represent the parameters of each layer. Parameter f means the size of the filter and n means the number of filter.
Layer1(Pattern extraction) Base on every 40×40 sub-matrix, using $f \times f$(13×13 in HiCPlus) filters to extract patterns of each sub-contact-map. Which can represented by following formula:

$$F_1(X) = ReLU(w_1 * X + b_1)$$

Where $*$ represent the convolution process. w represents $n \times f \times f$ filters. b is the bias.

Layer2(Low-res mapping to high-res) Layer3(Predicted contact maps generation)

Use other chromosome.

Do the same dividing process like M_ℓ and M_h

Calculate the Pearson's correlation between the output and M_h.

Step 1 Data preparation and processing

Since this experiment is to validate the algorithm for mapping low-resolution data to high-resolution data, high-resolution data are required.

In order to compare to some state-of-the-art approaches (HiCPlus and HiCNN), we use data sets (such as GM12878 from GSE63525) which are also used in other approaches. We start from generating a 10kb resolution contact map using Hi-C Pro. Then we perform down-sampling on high-resolution data. We use BAM files to generate low-resolution contact maps by changing the bin size bigger. We generate three contact maps with bin sizes are 20kb, 30kb and 40kb, respectively. We use chromosome 1-8 as training sets, and chromosome 17 as test set.

Step 2 Learning by Neural network

We separate the low-resolution contact map into many 40×40 sub-matrices. Those sub-matrices are used as inputs.

2.1 Layer Structure

We consider the

References

[1] Mizushima, N., and Komatsu, M. Autophagy: renovation of cells and tissues. *Cell 147* (2011), 728–741.