Barcode Layout Optimization in Spatial Transcriptomics: Theory and Experiments

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Motivation Problem Related Work Contribution

Introduction

• Application: Spatial transcriptomics with high-resolution microarrays of DNA-barcodes



Motivation Problem Related Work Contribution

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- **Application**: Spatial transcriptomics with high-resolution microarrays of DNA-barcodes
- **Problem**: High error rates during barcode synthesis by photolithography (10 20% per base)



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- **Application**: Spatial transcriptomics with high-resolution microarrays of DNA-barcodes
- **Problem**: High error rates during barcode synthesis by photolithography (10 20% per base)
- Goal: Reduce errors during synthesis
- Approach: Barcode selection and placement



Motivation Problem Related Work Contribution

Barcode Synthesis



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BARCODE-LAYOUT Problem

Objective: Minimize situations, in which only one of two adjacent barcodes is illuminated.

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• Select barcodes from a large set of candidates



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Task:

- Select barcodes from a large set of candidates
- Assign barcodes to locations



Motivation Problem Related Work Contribution

Related Work

Border Length Minimization Problem

- Discussed by Hannenhalli et al. 2002, Kahng et al. 2004 and Carvalho Jr. and Rahmann 2008
- Main difference: no selection of probes
- Application: diagnostics

Motivation Problem Related Work Contribution

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Quadratic Assignment Problem

• Assign n facilities to n locations minimizing a distance-dependent cost function

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 \bullet Proof for maxSNP-hardness \Rightarrow hard to approximate

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- Proof for maxSNP-hardness \Rightarrow hard to approximate
- Study of lower bounds for layout cost

Motivation Problem Related Work Contribution

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- \bullet Proof for maxSNP-hardness \Rightarrow hard to approximate
- Study of lower bounds for layout cost
- Development and assessment of heuristics

Layout Generating Layout Improving

Layout Generating

Greedy Algorithms

• Iteratively fill positions by choosing the best remaining candidate



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- Previously used with limited lookahead (Kahng et al. 2004)



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Greedy Algorithms

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- Previously used with limited lookahead (Kahng et al. 2004)
- $\bullet~{\rm GPU}$ parallelization \Rightarrow all remaining barcodes can be searched



Layout Generating Layout Improving

Layout Improving

Local search (2-OPT)

- Swap barcodes if it improves layout cost
- Stop when local minimum is reached



Layout Generating Layout Improving

Layout Improving Algorithms

Genetic Algorithm (GA)

- Population of 1024 layouts
- Simulates natural evolution



Lower Bounds Experimental Comparison Further Improvements

Lower Bounds for Layout Cost

- Bound from Kahng et al. 2004 (modified):
 - Each barcode selects 8 closest neighbors
 - Discard surplus of neighborhood relationships



Lower Bounds Experimental Comparison Further Improvements

Lower Bounds for Layout Cost

- Bound from Kahng et al. 2004 (modified):
 - Each barcode selects 8 closest neighbors
 - Discard surplus of neighborhood relationships
- 2 LP relaxation of Integer Linear Programming formulation
- Gilmore Lawler Bound
- Bound based on b-matching



Lower Bounds Experimental Comparison Further Improvements

Comparison of the algorithms

- $768 \times 1024~{\rm array}$
- 768, 432 barcodes
- Gain: improvement over a random layout
- Gap: optimality gap to the lower bound

Algorithm | Gain (%) | Gap (%)

Lower Bounds Experimental Comparison Further Improvements

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Lower Bounds Experimental Comparison Further Improvements

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Lower Bounds Experimental Comparison Further Improvements

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768,432 barcodes	Greedy (unlimited)	37.16	34.16
Gain: improvement over a	Random + 2-OPT	28.56	52.51
random layout	Greedy + 2-OPT	37.18	34.12
Gap: optimality gap to the	Random + GA	20.13	70.50
lower bound	Greedy + GA	35.70	37.31

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Lower Bounds Experimental Comparison Further Improvements

Local Costs in Greedy Results



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Lower Bounds Experimental Comparison Further Improvements

Providing Excess Barcodes



Lower Bounds Experimental Comparison Further Improvements

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• Steep deterioration disappears

Lower Bounds Experimental Comparison Further Improvements

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- $\bullet~{\rm Gain}$ increased from 37.18% to 43.42%

Lower Bounds Experimental Comparison Further Improvements

Providing Excess Barcodes



- Steep deterioration disappears
- $\bullet~{\rm Gain}$ increased from 37.18% to 43.42%
- Runtime increased linearly

Conclusions

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- Parallel greedy algorithm shows promising results

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• Experiments with alternative barcode sets

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- Improved error models

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Outlook

- Experiments with alternative barcode sets
- Improved error models
- Experimental validation of error reduction

Lower Bounds Expected Cost of a Random Layout Experiments

Lower Bounds

LP relaxation

- Lawler's linearization(Lawler 1963)
- $\mathcal{O}(wh|B|^2)$ variables

Lower Bounds Expected Cost of a Random Layout Experiments

ILP formulation

$$\begin{array}{ll} \min & 2 \cdot \left(\sum_{x=1}^{w} \sum_{y=1}^{h} \sum_{b \in B} \sum_{b' \in B, b' \neq b} \sum_{(x',y') \in N(x,y)} y_{(xyb),(x'y'b')} \cdot d(b,b') \right) \\ \text{s. t.} & \sum_{x=1}^{w} \sum_{y=1}^{h} x_{xyb} = 1 & \forall b \in B \\ & \sum_{b \in B} x_{xyb} = 1 & \forall x \in \{1,...,w\}, \forall y \in \{1,...,h\} \\ & x_{xyb} x_{x'y'b'} - 2 \cdot y_{(xyb)(x'y'b')} \ge 0 & \forall b \neq b' \in B, (x',y') \in N(x,y) \\ & \sum_{x=1}^{w} \sum_{y=1}^{h} \sum_{b \in B} \sum_{(x',y') \in N(x,y)} \sum_{b' \in B, b \neq b'} y_{(xyb),(x'y'b')} = m & m \text{ edge count in a grid} \\ & x_{xyb} \in \{0,1\}, y_{(xyb),(x'y'b')} \in \{0,1\} & \forall 1 \le x \le w, 1 \le y \le h, b \neq b' \in B, \\ & (x'y',) \in N(x,y) \end{array}$$

Lower Bounds Expected Cost of a Random Layout Experiments

Gilmore Lawler Bound

Gilmore Lawler Bound

- For each barcode, choose the best 3, 5, and 8 neighbors (parallelized computation)
- For each barcode, decide if it is best to be placed in a corner, border or middle position (ILP)
- Take into account the required corner, border and middle positions

Lower Bounds Expected Cost of a Random Layout Experiments

Gilmore Lawler Bound: ILP Formulation

$$\begin{array}{ll} \min & 2 \cdot \sum_{b \in B} \left(I_{b,3nb} \cdot x_{b,3nb} + I_{b,5nb} \cdot x_{b,5nb} + I_{b,8nb} \cdot x_{b,8nb} \right) \\ \text{s. t.} & \sum_{b \in B} x_{b,3nb} = 4 \\ & \sum_{b \in B} x_{b,5nb} = 2 \cdot (\dim X - 2) + 2 \cdot (\dim Y - 2) \\ & \sum_{b \in B} x_{b,8nb} = (\dim X - 2) \cdot (\dim Y - 2) \\ & x_{b,3nb} + x_{b,5nb} + x_{b,8nb} = 1 \qquad b \in B \\ & x_{b,3nb}, x_{b,5nb}, x_{b,8nb} \in \{0,1\}, b \in B \end{array}$$

Lower Bounds Expected Cost of a Random Layout Experiments

b-matching bound

b-matching bound

- Consider a complete undirected graph over the barcode set
- $\bullet\,$ Choose the required number of edges such that each node has degree $3 \leq \textit{deg} \leq 8$

Lower Bounds Expected Cost of a Random Layout Experiments

b-matching bound (ILP Formulation)

$$\min 2 \cdot \sum_{b \in B} \sum_{c \neq b \in B} d_{synth}(b, c) \cdot x_{bc}$$

s. t.
$$\sum_{b \in B} \sum_{c \neq b \in B} x_{bc} = m$$
$$\sum_{c \neq b \in B} x_{bc} \le 8 \qquad b \in B$$
$$\sum_{c \neq b \in B} x_{bc} \ge 3 \qquad b \in B$$
$$x_{b,c} \in \{0,1\}, b \neq c \in B$$

Lower Bounds Expected Cost of a Random Layout Experiments

Experiment for lower bounds

Table: Lower bounds for different array sizes and barcode sets of size $w \cdot h$. Entries with NA stand for instances which we could not solve within reasonable time and memory.

method	10×10	15×15	20×20	100×100	1024×768
LP	13,216	30,120	NA	NA	NA
GLB	21,344	48,202	84,988	1,881,900	119,211,464
Kahng	20,964	47,744	84,376	1,884,112	119,215,966
<i>b</i> -matching	21,032	47,852	84,676	1,884,904	NA

Lower Bounds Expected Cost of a Random Layout Experiments

Calculation of expected cost of a random layout

Expected Layout Cost

- Calculate the expected synthesis distance $E(d_{synth})$ between two barcodes sampled uniformly at randomly from B
- Expected layout cost for $w \times h$ -array $E(cost) = 2m \cdot E(d_{synth})$ with $m := 2 \cdot (w 1) \cdot (h 1) + w \cdot (h 1) + (w 1) \cdot h$

Computed Layout Cost

- For set B with $|B| = 768 \cdot 1024$ and a 1024×768 array
- E(cost) = 254, 498, 050
- \bullet Empirically: 254,485,241.6 with a standard deviation of 14,378.1

Lower Bounds Expected Cost of a Random Layout **Experiments**

Performance of 2-OPT



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Lower Bounds Expected Cost of a Random Layout Experiments

Objective value for different barcode set sizes





Figure: Average local cost of every column in the layout for each barcode set size used.

Figure: The average cost value for each barcode set size used.

Lower Bounds Expected Cost of a Random Layout **Experiments**

Objective value for different barcode sets



Figure: Average local cost of every column in the layout for each barcode set type used.

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