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Mitigating Distribution Shift for Congestion Optimization in Global Placement

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Outline

1. Introduction
2. Proposed Method
3. Experiments
4. Conclusion
Introduction
Placement and Congestion Modeling

- Placement is crucial but time-consuming
- Congestion modeling and optimization is important
- Congestion optimization techniques
  - Trial global routing\(^1\)
  - Analytical model\(^2\)

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Congestion Modeling via Deep Learning

- Fully Convolutional Networks\(^3\)
- Generative Adversarial Networks\(^4\)
- Graph Neural Networks\(^5\)

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Observations: prediction only, useless in placement
Problems of Existing Methods

- Observations: **distribution shift** during placement
Solutions

- Congestion-driven Placement with DNN

(a) Congestion-driven Placement with DNN

(b) Congestion-driven Placement with DNN
• Look-ahead via Cell Flow Prediction
Proposed Method
Cell Flow Prediction

- Cell flow measures the motions of the cells
  - \( \mathbf{c}'_{i}(x_{i,j}, y_{i,j}) = (x_{i,j} - x_{i-K,j}, y_{i,j} - y_{i-K,j}) \)
  - \((x_{i,j}, y_{i,j})\) is cell \(j\)'s location at \(i\)-th iteration, \(K\) is the step size
  - Inspired by optical flow

![Diagram of cell flow prediction](image-url)
Grid-cell $b_{k,l}$ contains multiple cells, we need downsampling

- **Sampling:** $c_i(k, l) = s_j c'_i(x_j, y_j), \quad \hat{j} = \arg \max_j s_j, (x_{i,j}, y_{i,j}) \in b_{k,l}$.
- **Averaging:** $c_i(k, l) = \frac{1}{N_{k,l}} \sum_{(x_{i,j}, y_{i,j}) \in b_{k,l}} c'_i(x_{i,j}, y_{i,j})$.
- **Weighted-sum:** $c_i(k, l) = \sum_{(x_{i,j}, y_{i,j}) \in b_{k,l}} \frac{s_j}{N_{k,l}} \times c'_i(x_{i,j}, y_{i,j})$. ✓

**Quasi-voxelization**

(a) Grid Cell

(b) Diagram
Invariant feature space learning
- Cell flow prediction + invariant feature space learning

![Diagram showing the complete flow process with components like Conv2D, GroupNorm, LeakyReLU, Encoder, Middle Net, Decoder, VAE-like Structure, and Loss Function with Prediction Loss, KL Divergence Loss, and Reconstruction Loss.]
DREAMPlace$^6$ + Look-ahead Congestion Optimization

Experiments
Experimental Settings

- Placement Platform: DREAMPlace\(^7\)
- Baseline: DREAM-Cong\(^8\)
- Congestion Prediction Metrics:

\[
\text{NRMS}(\bar{Y}, Y) = \frac{\|\bar{Y} - Y\|_2}{(Y_{\text{max}} - Y_{\text{min}}) \sqrt{N_Y}},
\]

\[
\text{SSIM}(\bar{Y}, Y) = \frac{(2\mu_\bar{Y}\mu_Y + C_1)(2\sigma_{\bar{Y}, Y} + C_2)}{\left(\mu_\bar{Y}^2 + \mu_Y^2 + C_1\right)\left(\sigma_{\bar{Y}}^2 + \sigma_Y^2 + C_2\right)}.
\]

- Placement Metrics: (Given by Innovus)
  - Wire Length (WL)
  - Worst Congestion Score (WCS)


\(^8\)S. Liu et al., “Global placement with deep learning-enabled explicit routability optimization”, in Proc. DATE, 2021.
Comparison on Congestion Prediction

(a) NRMS

(b) SSIM

- DREAM-Cong
- Look-ahead-only
- Cell-flow
- Cell-flow-KL
## Comparison on Congestion Optimization

<table>
<thead>
<tr>
<th>Benchmark</th>
<th>#Cells</th>
<th>#Nets</th>
<th>DREAMPlace</th>
<th>DREAM-Cong</th>
<th>LACO</th>
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<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>$W_{CS_H}$</td>
<td>$W_{CS_V}$</td>
<td>$WL(10^5,\mu m)$</td>
<td>$W_{CS_H}$</td>
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<tr>
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<td>32k</td>
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<td>0.56</td>
<td>10.56</td>
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<tr>
<td><strong>Average</strong></td>
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<tr>
<td><strong>Ratio</strong></td>
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<td>1.00</td>
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<td>0.99</td>
</tr>
</tbody>
</table>

Note: The table provides a comparison of DREAMPlace, DREAM-Cong, and LACO in terms of cells (#Cells), nets (#Nets), and various metrics such as $W_{CS_H}$, $W_{CS_V}$, and $WL(10^5\,\mu m)$. The metrics include the area of the cells and nets, as well as the congestion optimization results. The ratios indicate the performance improvement or degradation relative to the baseline.
• Look-ahead, cell flow, invariant feature space learning bring better congestion prediction
• More accurate congestion prediction leads to better congestion optimization
• Up to 8% improvement in the maximum routing overflow
THANK YOU!