









Micron – IIITB Presentation

Date: February 27th, 2024

By:

- Prof. Madhav Rao
- Saket Gurjar (iMTech)
- Anshul M (iMTech)



Agenda

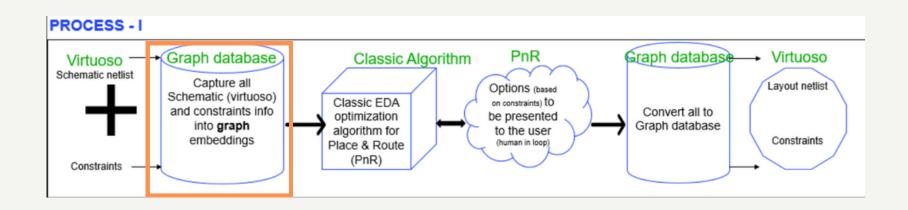
- Interface for verifying graph DB
- Database to GA Pipeline
- Macro Placement using GA Visualiser
- Macro Placement using GA Possible Improvement
- MacroRank overview







Interface for verifying graph DB



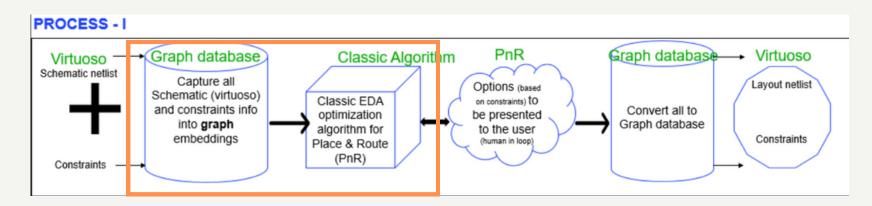
- Python Interfaces ready for probing nodes, edges and their properties from Neo4J.
- In form of a python function, so it can be used under an automation flow for verification.
- Code available on GitHub.



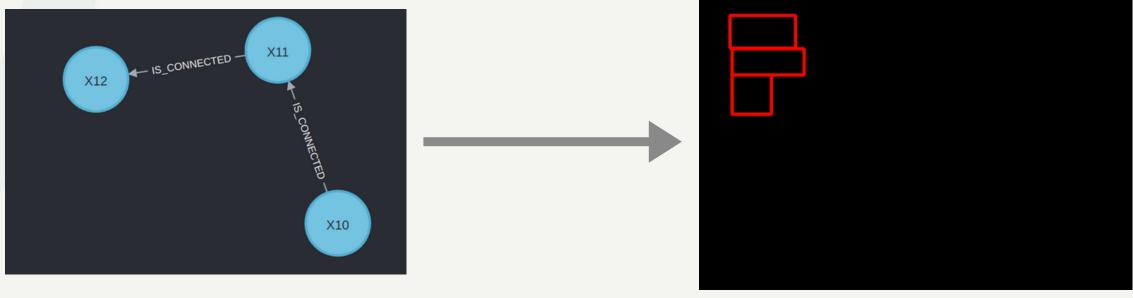




Database to GA Pipeline



• Pipeline from the graph database to producing results from Placement algorithm working and tested.









Macro Placement using GA - Constraints

- Function F changes in our case.
 - For now, negative of HPWL taken as F
- Overall objective function is:
 - F(X) = HPWL(X) (K * OverlapArea(X))
 - We aim to maximise this function F(X)
- To add constraints,
 - F(X) = HPWL(X) (K1 * OverlapArea(X)) (K2 * Penalty)

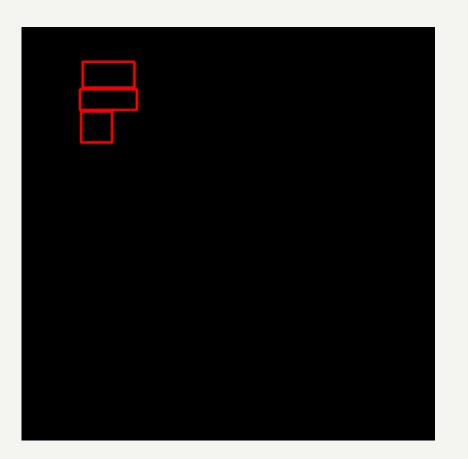






Macro Placement using GA - Visualiser

- Created basic visualiser for the genetic algorithm using OpenCV.
- Generates video based on where the macros are placed



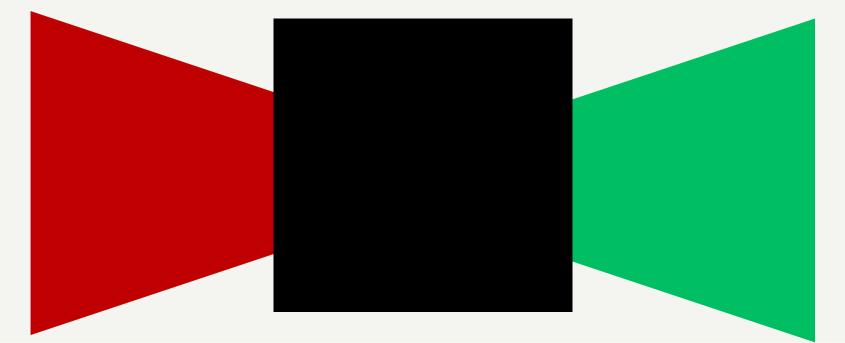




Macro Placement using GA - Possible Improvement



- Possible strategy for improving GA's time to converge:
 - Time complexity for GA : O(g(nm + nm + n))
 - Using an auto-encoder around the GA block to reduce the number of genes(m).
 - Further using the time to converge for a small sample of data points, as a part of the loss function.
 - eg. L = MSE + T









MacroRank

- MACRORANK is a macro placement ranking framework, that works at predicting routing quality metrics like wire length, number of vias, shorts, etc. at the early macro placement stage
- It majorly uses <u>EHNN</u> and <u>Learning to Rank</u> (LTR) Technique for accurately predicting the routing quality metrics.
- It uses a translation <u>Equivariant Hypergraph Neural Network</u> (EHNN) to capture interconnect and geometric information from netlist and macro locations.
- The LTR technique takes into account the relative relationship of solution quality, this approach helps focus on relative ranking instead of actual metric prediction hence opening room for the algorithm to explore and learn the best solutions.







Impact of Translation and Rotation

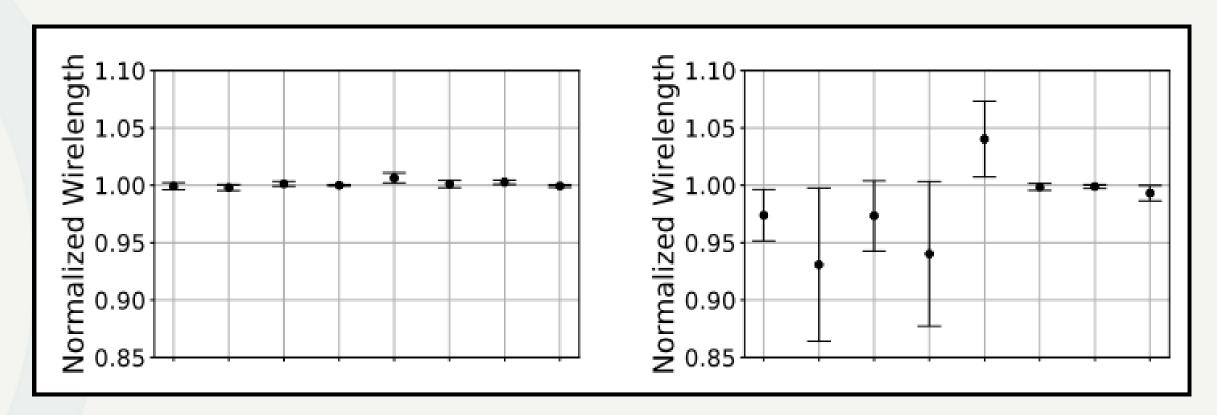
- Supposing the layout is homogeneous, a rigid transformation like translation and rotation on the whole layout (including the instances, wires, and boundaries) will not affect the optimal solutions of placement and routing.
- But in practice these datasets when fed to the auto place and route algorithms, the paper explains that significant variances in optimized results were observed when the layout was either flipped or rotated.
- Thus a positive aspect of this would be to train the Neural Network with the same layout in different orientations to capture the transformation invariant knowledge and generalize our model to translation equivariant inputs.







Impact of Translation and Rotation



Variation when (a) Translated (left) and (b) Rotation and flipping (right) for different datasets

Thus a positive aspect of this would be to train the Neural Network with the same layout in different orientations to capture the transformation invariant knowledge and generalize our model to translation equivariant inputs.







Learning to Rank (LTR)

- To select the best macro placement solution, the relative relationship between them is noteworthy instead of the absolute value of each candidate. By absolute value here we refer to the routing quality metrics and the candidate refers to each unique placement solution
- A well-known LTR method is called the pairwise method, which approximates the ranking problem to a binary classification problem aiming to distinguish which candidate is better in the chosen pair.
- For example, a classical pairwise method RankNet adopts a probability model and defines the estimated probability of the candidate X1 having higher quality than X2 as

$$Prob(X_1 > X_2) = \frac{1}{1 + \exp\{f(X_2) - f(X_1)\}}.$$







Summary of overall Progress

- The paper about the MacroRank algorithm was discussed and transformation invariant dataset generation was explored.
- We will use the learnings of EHNN, i.e., pin offset, pin location, and sparsity of location information in the netlist.
- Currently, we are still exploring our method to implement this so that we can easily use the benefits of the classification techniques to identify which macro rank placement solution is better than the other and try to implement it in the current workflow.





Any specific request to Micron

None for now



