International
Institute of Information
Technology Bangalore

Micron – IIITB
Bi-Weekly Presentation

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Project Schedule (Planned vs. Actual)

Planned:

- Clear on Input format
- Exploration of SPICE netlist, recommended to use Calibre LVS with LVS blackboxing option.
- Cadence Innovus to be explored by Surresh
- Explore more on Neo4J graph database, compare with Google circuit training.

Actual:

- Steps for Dataset generation using Virtuoso and Calibre.
- Explored WireMask Black Box Optimization.
- Explored and Applied graph embedding techniques to few example cases

Dataset Generation

Steps we intend to follow for Dataset generation:

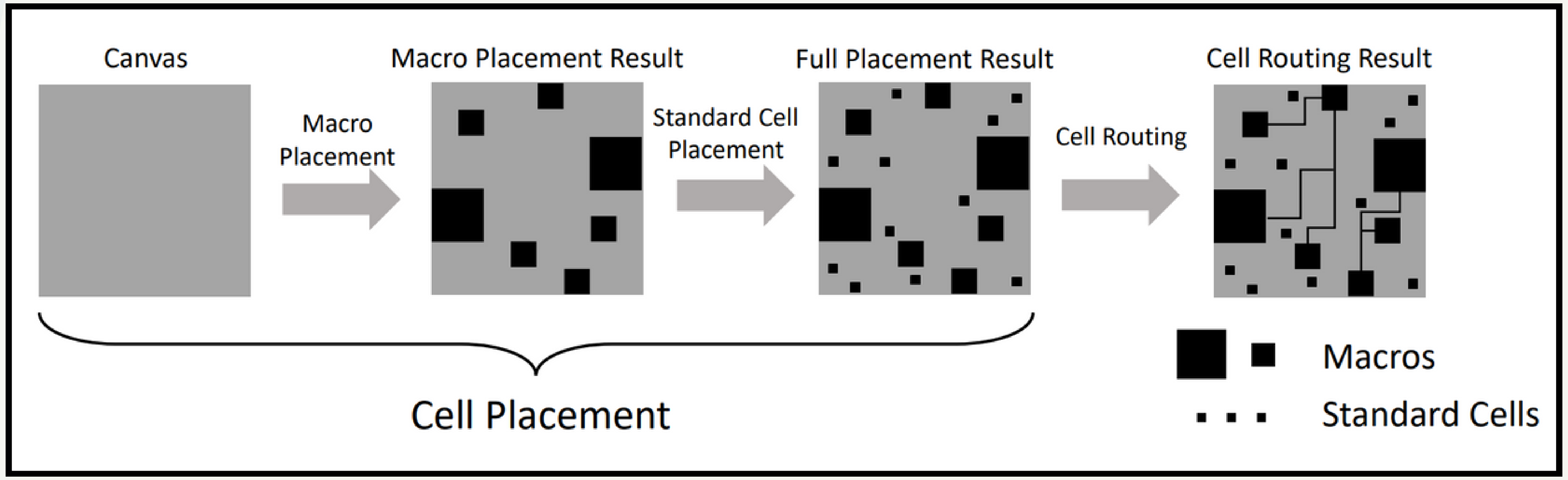
1. **Synthesize the Netlist in Genus and create a layout design of the Netlist in Virtuoso**
2. **Next, to perform the LVS check, Pass the design through Calibre using a plugin that can be integrated with Virtuoso.**
3. **We have chosen Virtuoso because the problem statement emphasizes the importance of analog circuit designs, which can be effectively simulated using Cadence Virtuoso.**
4. **Additionally, Calibre offers the option of Black Boxing during LVS Checks. A dummy circuit with the required number of ports can be defined as a Black Box and considered as a macro.**
5. **Once this is done these files can be sent to the ML model for Training and Inference.**

WireMask - Black Box Optimization

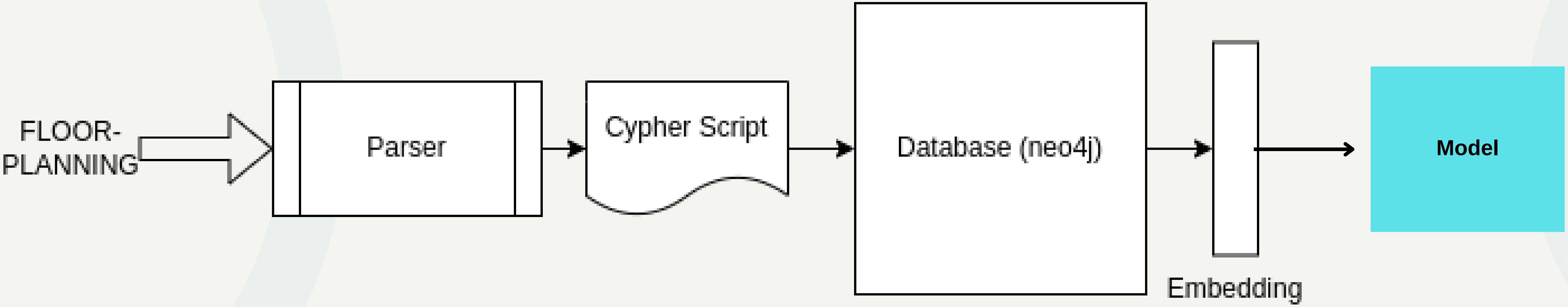
- A similar tool was explored that almost aligns with our problem statement. WireMask-BBO is a technique for Macro Placement. This approach uses the same constraints i.e., the Half Perimeter Wire Length (HPWL) and Congestion parameters for optimization.
- Analytical methods for simultaneous placement of MACROs and Standard Cells often cause overlapping and to fix this a simpler solution involved dividing the chip canvas into discrete grids and placing the MACROs step by step, checking for the most optimized results

WireMask - Black Box Optimization

- We can use the WireMask to record the increment if HPWL by moving a macro to each candidate grid on the chip canvas.
- The macros in the solution can be sequentially adjusted to the nearest solution.
- This algorithm can be further optimized with the prior knowledge of best datasets using ML techniques



Interfacing with DB



Interfacing with DB - Parser

- **Parser will take in the Spice Netlist as input and give the cypher script that will generate the same graph .**
- **Mainly reads connectivity information and any other features about each macro like size, shape, etc.**
- **This component is still a work in progress.**

Interfacing with DB - Cypher Script

- Cypher is a declarative graph query language that allows for expressive and efficient data querying in a property graph.
- It is the language that is primarily used in Neo4J to query the database.
- This will mainly contain connectivity and features of individual macros.
- Additionally, properties about the connections (wires) can also be added.

Interfacing with DB - Database

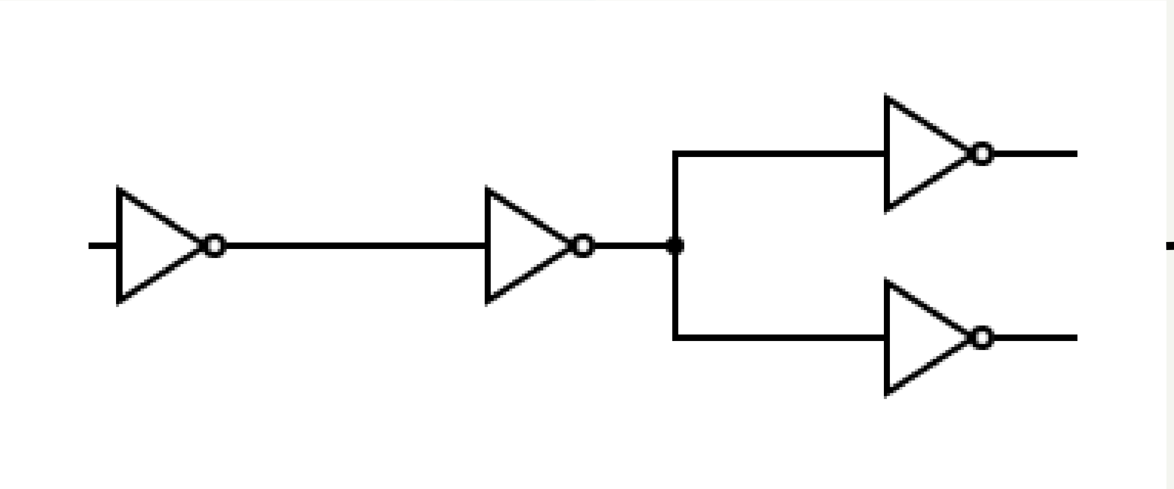
- Neo4J will be used as the database to store and query the graph data coming from the parser.
- Some of its useful features include:
  - Built and designed specifically for storing graph data
  - Easy to add properties to nodes and edges.
  - Good visualisation tools available (eg. Neo4J Bloom).
  - Has in-built Data-Science library for processing tasks.

Interfacing with DB - Embedding

- The graph data needs to be processed into form of vectors that the downstream ML models can understand.
- Similar to text-to-vector embedding used in NLP. (Graph-to-vector in this case)
- Several algorithms that could be used here.
    - Currently FastRP and GraphSAGE are explored.
    - Working on finding better algorithms.
- Gives output of n (embedding dimension) vectors of floats.

Graph Embedding and Interfacing with DB - Example

- Sample graph tested for embedding.



Parser (SPICE Netlist to Cypher)

*

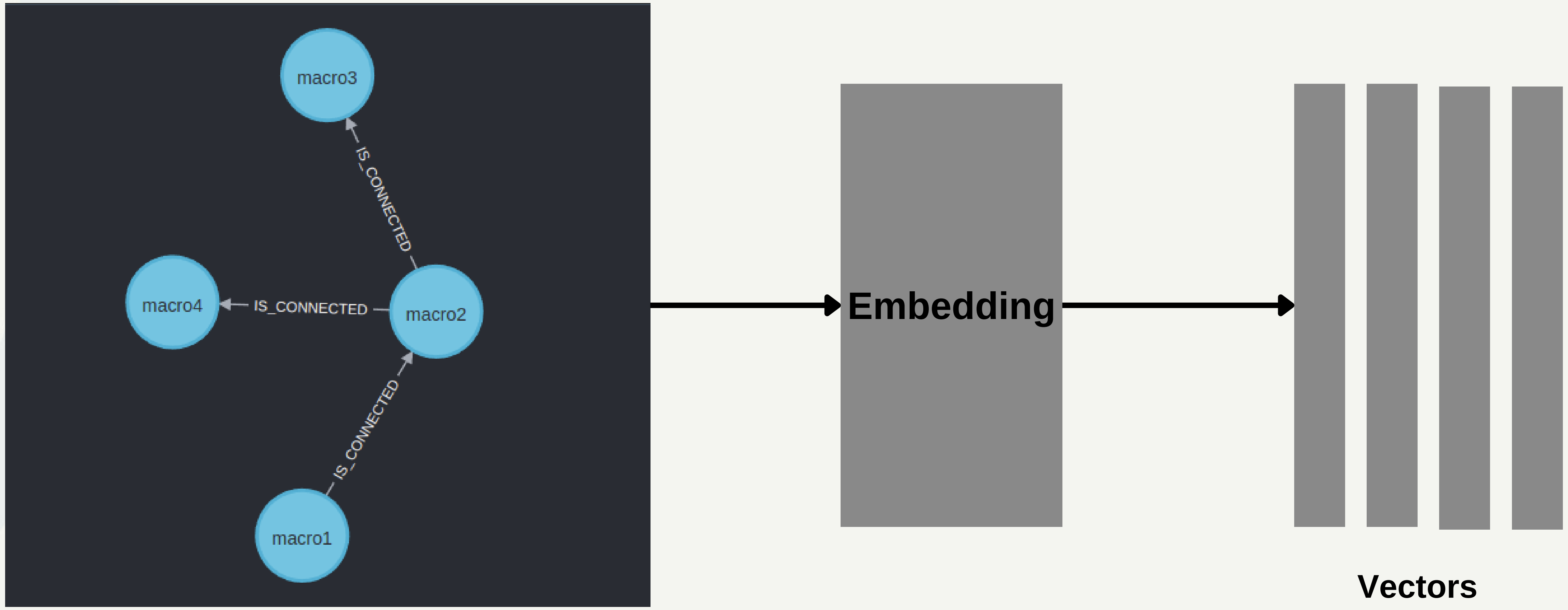
```
CREATE (macro1: Macro {name:'macro1' , type:'rectangle', x1: 0.1, y1: 0.2, x2: 0.4, y2: 0.6})
CREATE (macro2: Macro {name:'macro2' , type:'rectangle', x1: 0.8, y1: 0.8, x2: 0.9, y2: 0.9})
CREATE (macro3: Macro {name:'macro3' , type:'rectangle', x1: 0.7, y1: 0.1, x2: 0.9, y2: 0.3})
CREATE (macro4: Macro {name:'macro4' , type:'rectangle', x1: 0.6, y1: 0.5, x2: 0.7, y2: 0.6})

CREATE (macro1)-[w1:IS_CONNECTED]->(macro2)
CREATE (macro2)-[w2:IS_CONNECTED]->(macro3)
CREATE (macro2)-[w2:IS_CONNECTED]->(macro4)
```

*Cypher Script uploaded on GitHub

Graph Embedding and Interfacing with DB - Example

- Neo4J Bloom used for graph visual



*Cypher Script uploaded on GitHub

Graph Embedding

- Two algorithms explored yet: FastRP, GraphSAGE
- FastRP only considers relative positioning of nodes, hence not so useful.
- GraphSAGE uses the feature vectors as initial embeddings.

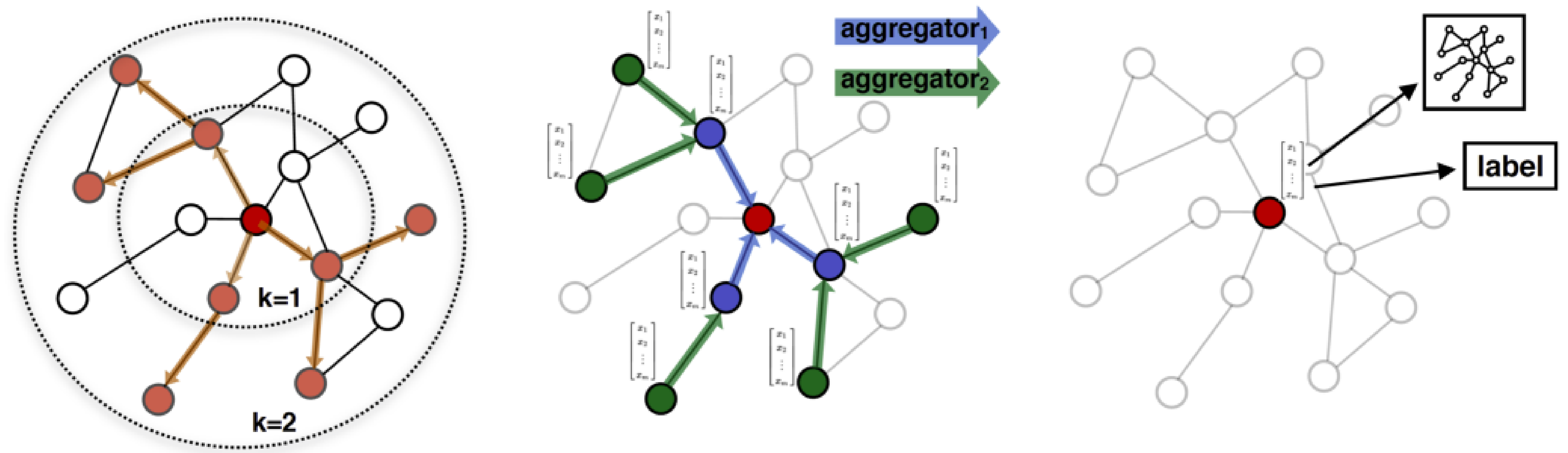
```
neo4j$ CALL gds.beta.graphSage.stream( 'macros', { modelName: 'multiLabelModel' } ) YIELD nodeId, embedding
```

	nodeId	embedding
1	0	[0.10447923938615808, 0.12800022533210947, 0.11753087955850602, 0.12081487968211563, 0.13869151731781898, 0.12073753233817763, 0.09756668149012274, 0.11485334368583841, 0.15333129094696213, 0.1273366358164664, 0.1357949068269213, 0.11825444466846305, 0.1296732810688213, 0.1471818784547465, 0.12705270436384436, 0.122
2	1	[0.10452544484479376, 0.12801723445133542, 0.11790880701187403, 0.12101939821307058, 0.1387432860128747, 0.12067584838310204, 0.0973808677089801, 0.11461474839083607, 0.15303156106823884, 0.12747132477975917, 0.1358998493678267, 0.11799076553164016, 0.12976309900110783, 0.1471281037635331, 0.12723014991121068, 0.1227
3	2	[0.10457039868891084, 0.12779141802561006, 0.11779857375415806, 0.12094260992929178, 0.13857694460616843, 0.12064224707505128, 0.09750741237194678, 0.11486816590609478, 0.15335315329500354, 0.1274545453396251, 0.1357296165986284, 0.11820183841053085, 0.12961891899841244, 0.14723681269298167, 0.12703077508876384, 0.1
4	3	[0.10452552332438639, 0.12803884935144988, 0.11802001849400985, 0.12107285738795655, 0.13877840276066447, 0.12066824090169768, 0.09731925146949218, 0.11452976709343193, 0.1529136220596627, 0.12748886413973007, 0.13595098326031463, 0.11790571501683256, 0.12980538088811273, 0.14711014028091018, 0.12729357057925286, 0.1

GraphSAGE paper : https://arxiv.org/pdf/1706.02216.pdf

Graph Embedding - GraphSAGE

- Inductive Algorithm that uses the node feature information.
- Trains Aggregate functions and set of weights via supervised and unsupervised methods.



1. Sample neighborhood
2. Aggregate feature information from neighbors
3. Predict graph context and label using aggregated information

GraphSAGE paper : https://arxiv.org/pdf/1706.02216.pdf

Graph Embedding - GraphSAGE

$\mathbf{h}_v^0 \leftarrow \mathbf{x}_v, \forall v \in \mathcal{V}$;

for $k = 1...K$ **do**

  for $v \in \mathcal{V}$ **do**

    $\mathbf{h}_{\mathcal{N}(v)}^k \leftarrow \text{AGGREGATE}_k(\{\mathbf{h}_u^{k-1}, \forall u \in \mathcal{N}(v)\})$;

    $\mathbf{h}_v^k \leftarrow \sigma\left(\mathbf{W}^k \cdot \text{CONCAT}(\mathbf{h}_v^{k-1}, \mathbf{h}_{\mathcal{N}(v)}^k)\right)$

  end

  $\mathbf{h}_v^k \leftarrow \mathbf{h}_v^k / \|\mathbf{h}_v^k\|_2, \forall v \in \mathcal{V}$

end

$\mathbf{z}_v \leftarrow \mathbf{h}_v^K, \forall v \in \mathcal{V}$

- **Forward Propagation (after training)**
  - Embedding vectors initialised to feature vectors of each nodes.
  - Vector computed from aggregation of neighbours. This is concatenated with vector at the current node.
  - Forward Pass through non-linearity.
  - Normalisation

GraphSAGE paper : https://arxiv.org/pdf/1706.02216.pdf

Graph Embedding - GraphSAGE

- **Training Phase**
  - Can be done in supervised or unsupervised manner
  - Nodes would be labelled and cross-entropy loss can be computed in supervised learning
  - Similarity measure used as loss function in case of unsupervised learning.
  - We plan to modify this to suit our needs. (i.e. include parameters that would apply constraints)

$$J_{\mathcal{G}}(\mathbf{z}_u) = -\log\left(\sigma(\mathbf{z}_u^\top \mathbf{z}_v)\right) - Q \cdot \mathbb{E}_{v_n \sim P_n(v)} \log\left(\sigma(-\mathbf{z}_u^\top \mathbf{z}_{v_n})\right)$$

GraphSAGE paper : https://arxiv.org/pdf/1706.02216.pdf

Graph Embedding - GraphSAGE

```
+------------------------------------------------------------------------------------------------------------------------------------+
| nodeId | embedding                                                                                                                 |
+------------------------------------------------------------------------------------------------------------------------------------+
| 0      | [0.10447923938615808, 0.12800022533210947, 0.11753087955850602, 0.12081487968211563, 0.13869151731781898, 0.12073753233817763, 0.09756668149012274, 0.11485334368583841, 0.15333129094696213, 0.1273366358164664, 0.1357949068269213, 0.11825444466846305, 0.1296732810688213,
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| 1      | [0.10452544484479376, 0.12801723445133542, 0.11790880701187403, 0.12101939821307058, 0.1387432860128747, 0.12067584838310204, 0.0973808677089801, 0.11461474839083607, 0.15303156106823884, 0.12747132477975917, 0.1358998493678267, 0.11799076553164016, 0.12976309900110783,
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| 2      | [0.10457039868891084, 0.12779141802561006, 0.11779857375415806, 0.12094260992929178, 0.13857694460616843, 0.12064224707505128, 0.09750741237194678, 0.11486816590609478, 0.15335315329500354, 0.1274545453396251, 0.1357296165986284, 0.11820183841053085, 0.12961891899841244
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| 3      | [0.10452552332438639, 0.12803884935144988, 0.11802001849400985, 0.12107285738795655, 0.13877840276066447, 0.12066824090169768, 0.09731925146949218, 0.11452976709343193, 0.1529136220596627, 0.12748886413973007, 0.13595098326031463, 0.11790571501683256, 0.1298053808811273
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+------------------------------------------------------------------------------------------------------------------------------------+

4 rows
```

GraphSAGE paper : https://arxiv.org/pdf/1706.02216.pdf

Summary of overall Progress

- Steps for Dataset generation using Virtuoso and Calibre were explored.
- WireMask Black Box Optimization was surveyed.
- FastRP and GraphSAGE embedding technique.
- Better Embedding techniques to be explored.
- Working on developing parser for the cypher script to feed data into neo4j database.

Any specific request to Micron

- Confirmation is needed whether the extracted spice netlist format suffices our need at this point of time.
- What all parameters of the macros (nodes) and the wires (edges) need to be considered during embedding? Currently working with shape and size (in form of coordinates of vertices).