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GeniusRoute: A New Analog Routing Paradigm Using Generative Neural Network Guidance

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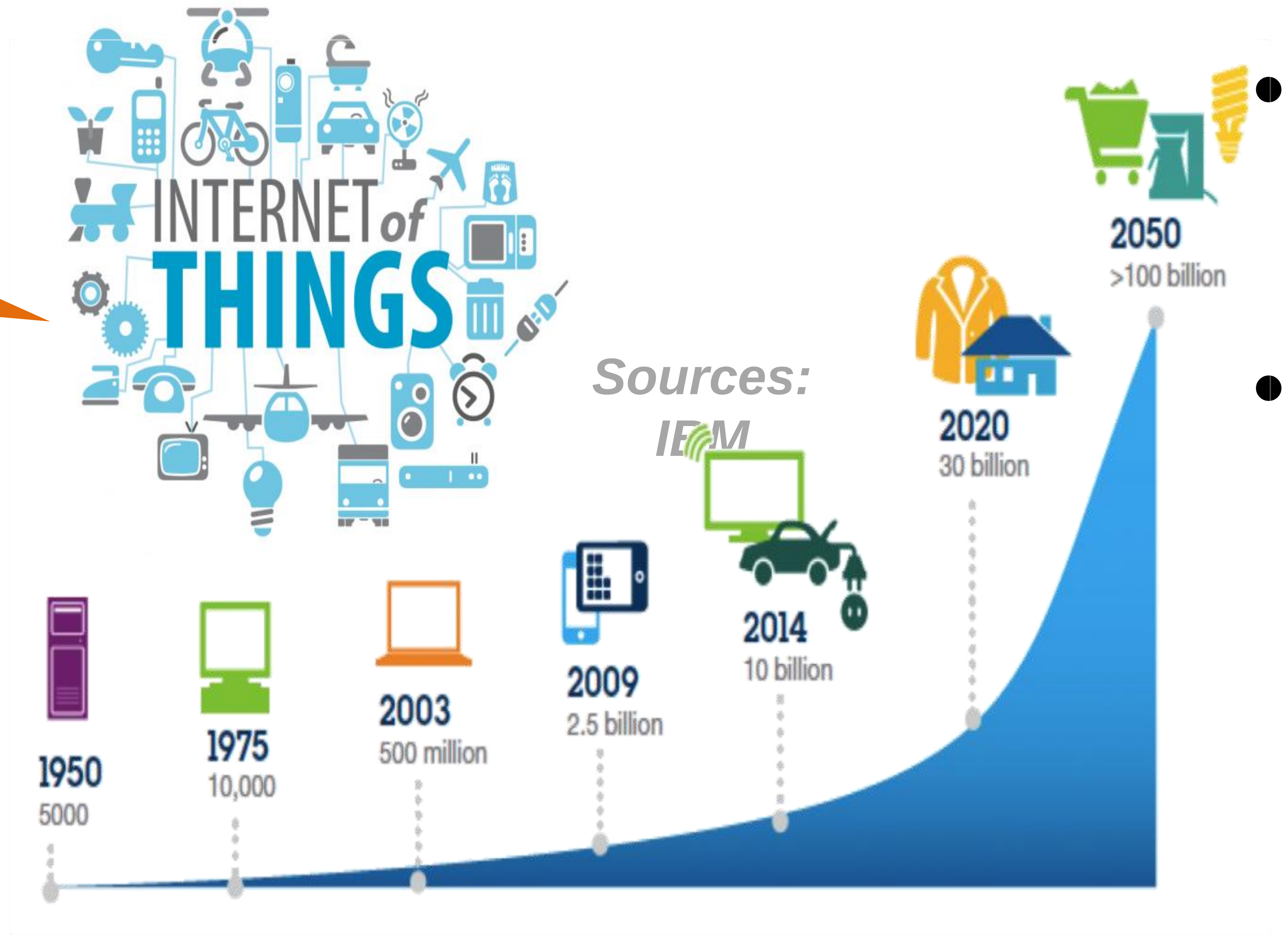
Outlines

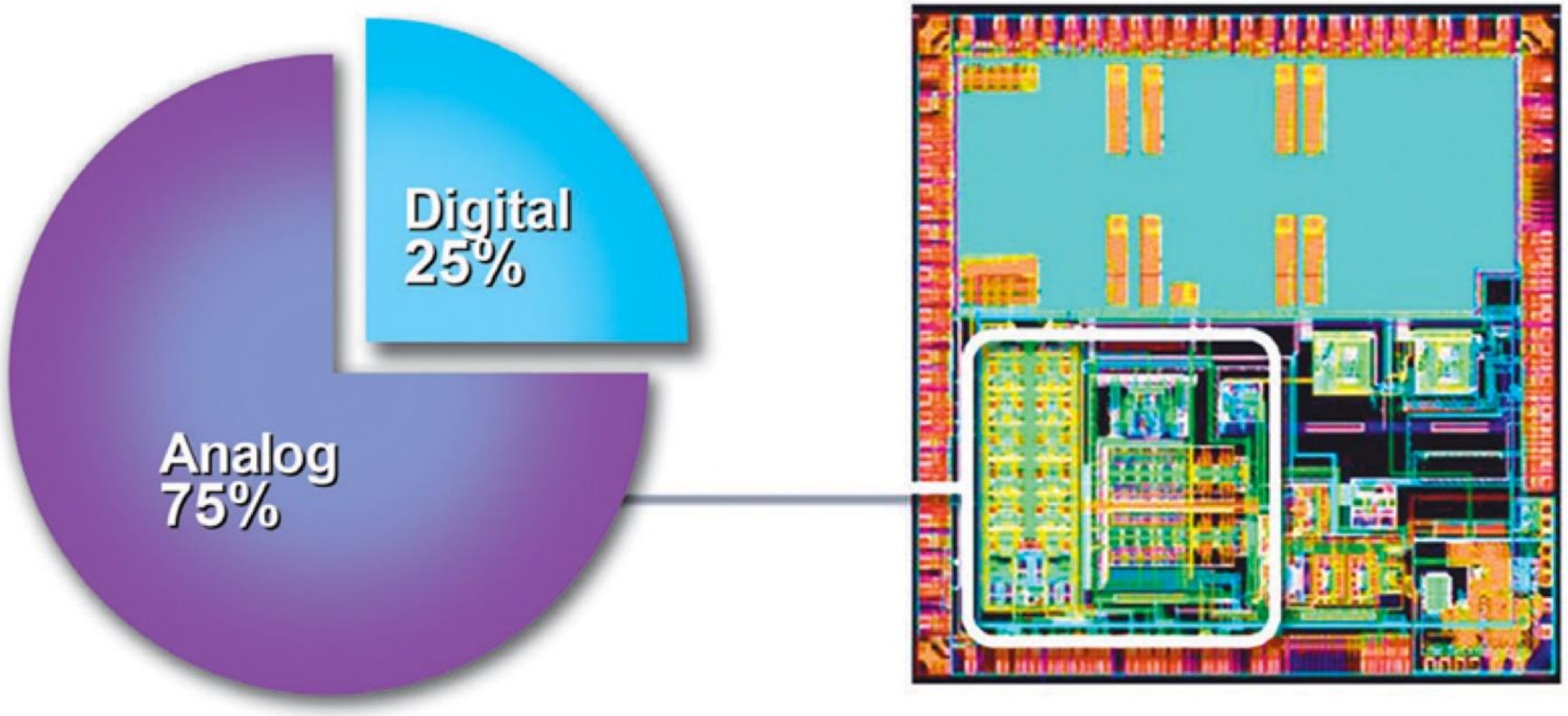
- Introduction and Problem Formulation
- GeniusRoute Framework
- Experimental Results
- Conclusion

High Demand of Analog/Mixed-Signal IC



- Anything related to sensors needs analog!
- Internet of Things (IoT), autonomous and electric vehicles, communication and 5G networks…

A Bottleneck in IC Design: Analog/Mixed-Signal

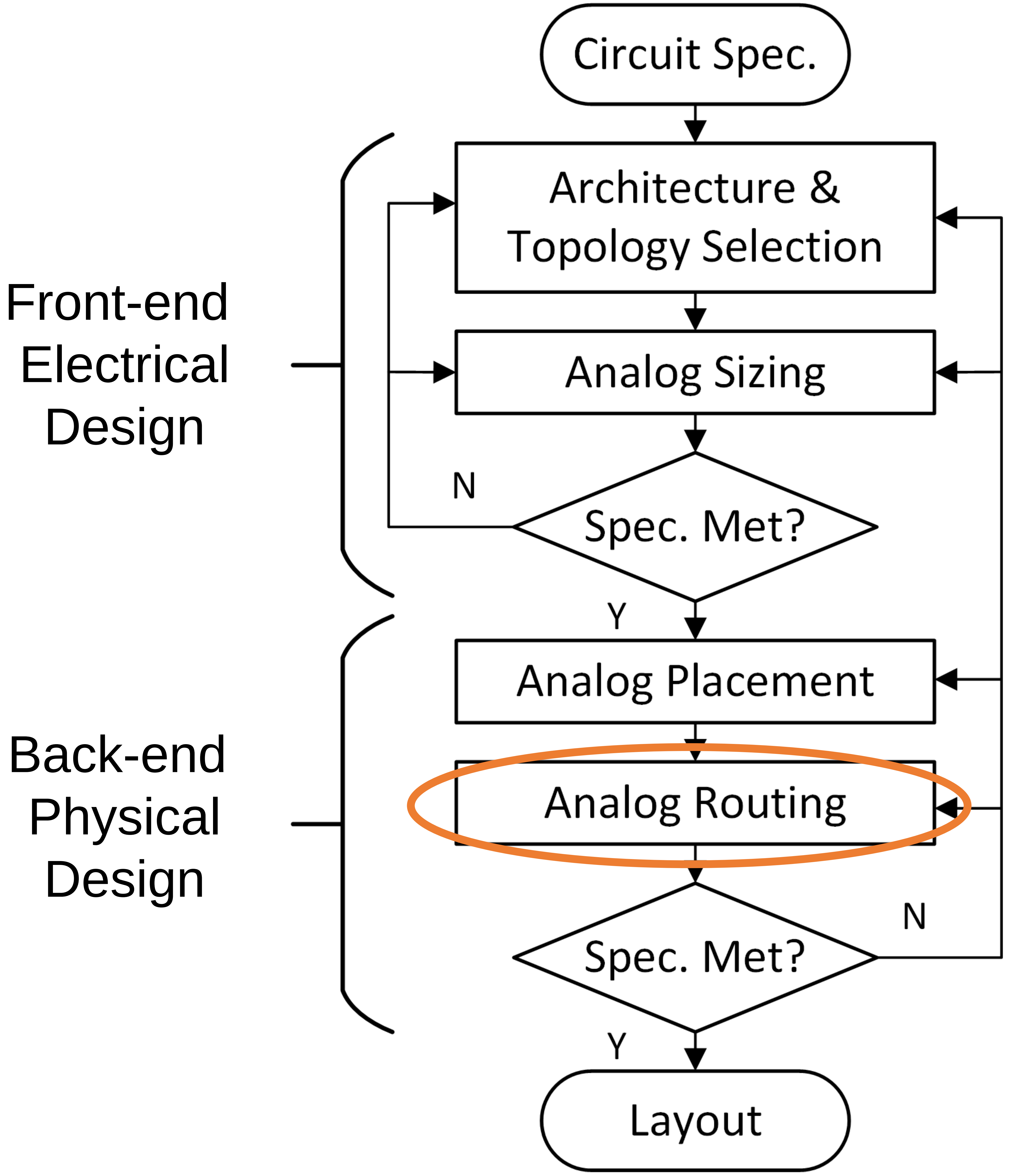


Analog parts of IC take large design efforts

A major reason: analog circuit layout is usually done manually

[IBS and Dr. Handel Jones, 2012]

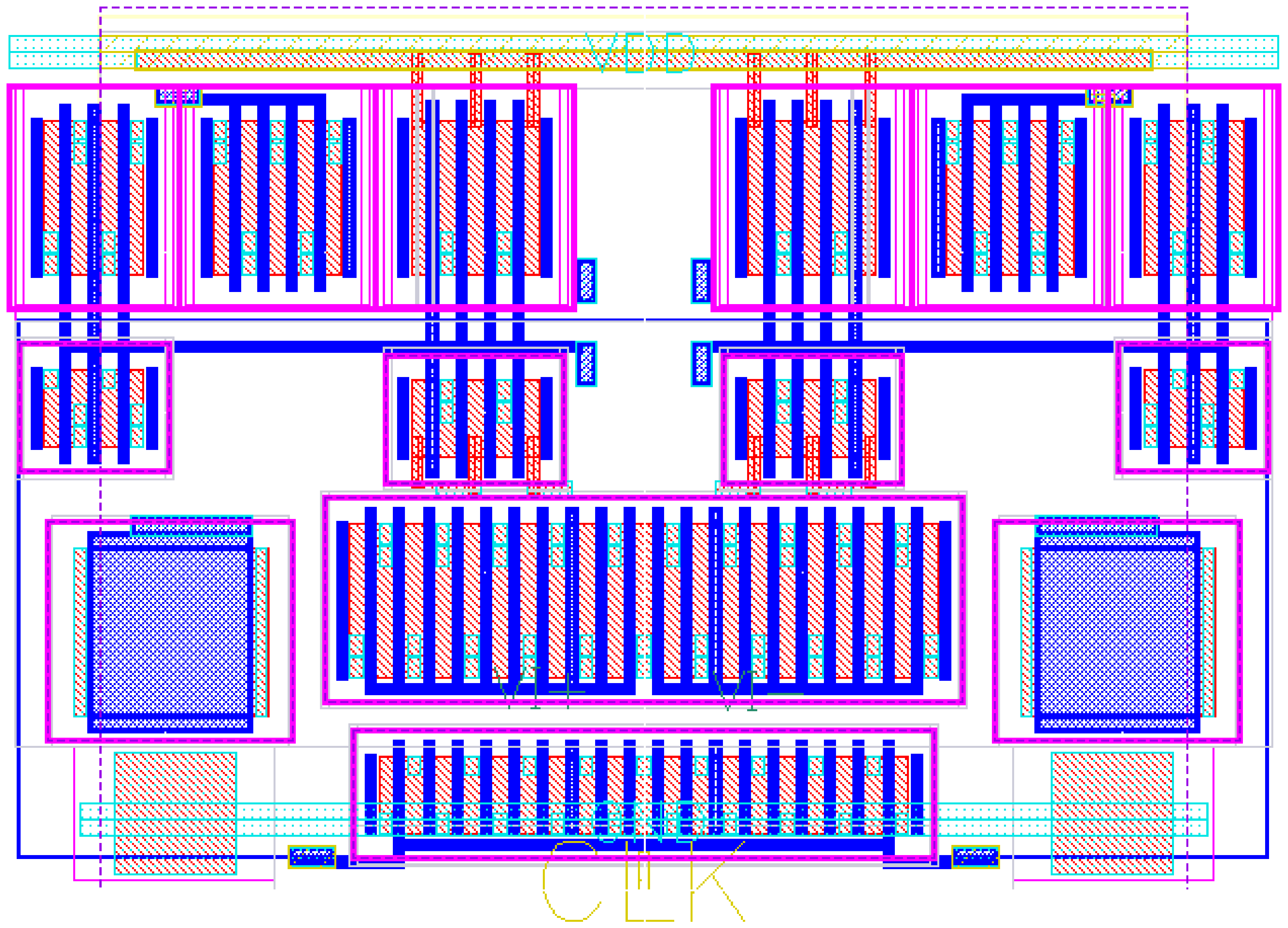
Typical Automatic Analog Circuit Design Flow



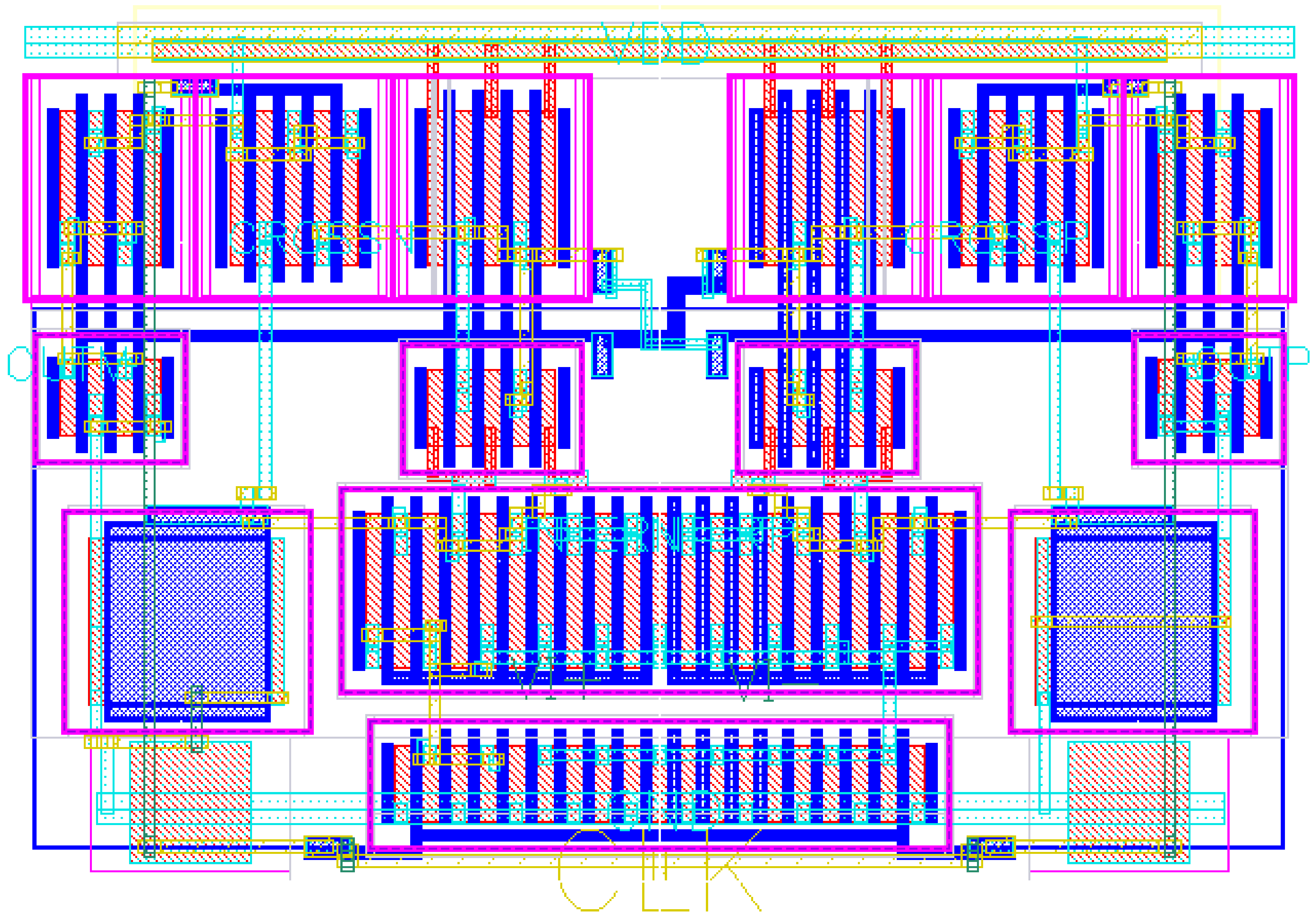
- Automated analog design often consists of front-end and back-end flows

- Physical design (back-end) is separated in placement and routing

Analog Routing Problem

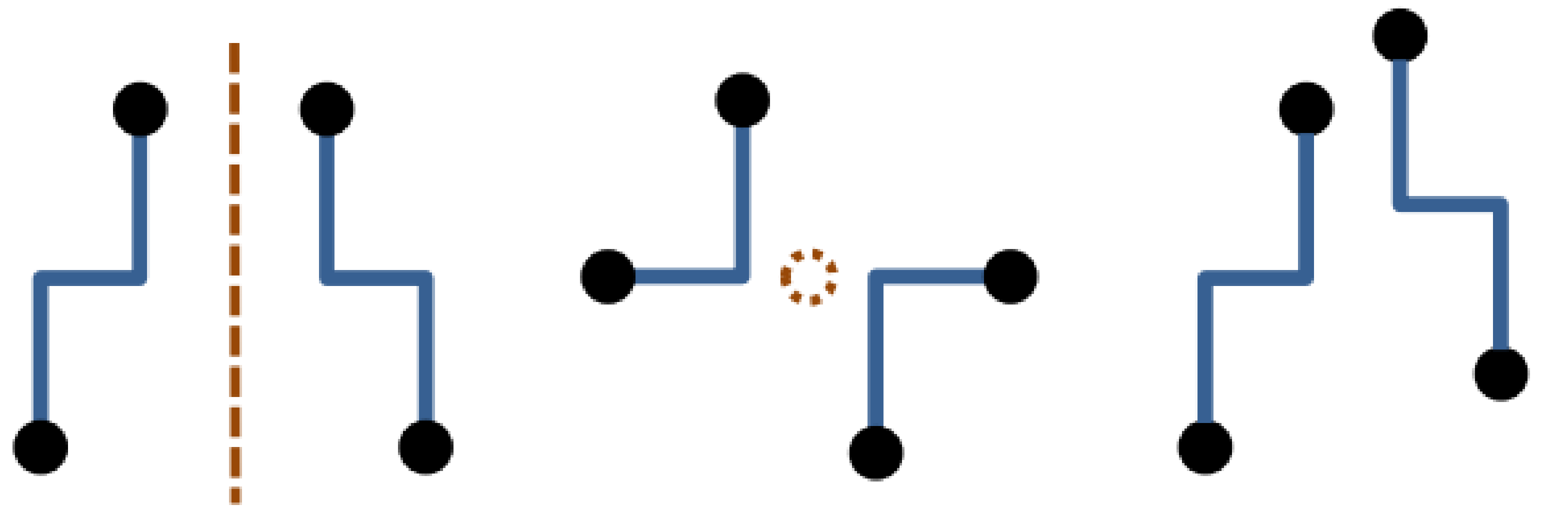


Placement



Routed Layout

Challenges in Formulating Analog Routing Problem



[Ou et al., 2014]

Shielding,
Avoid active region,
…

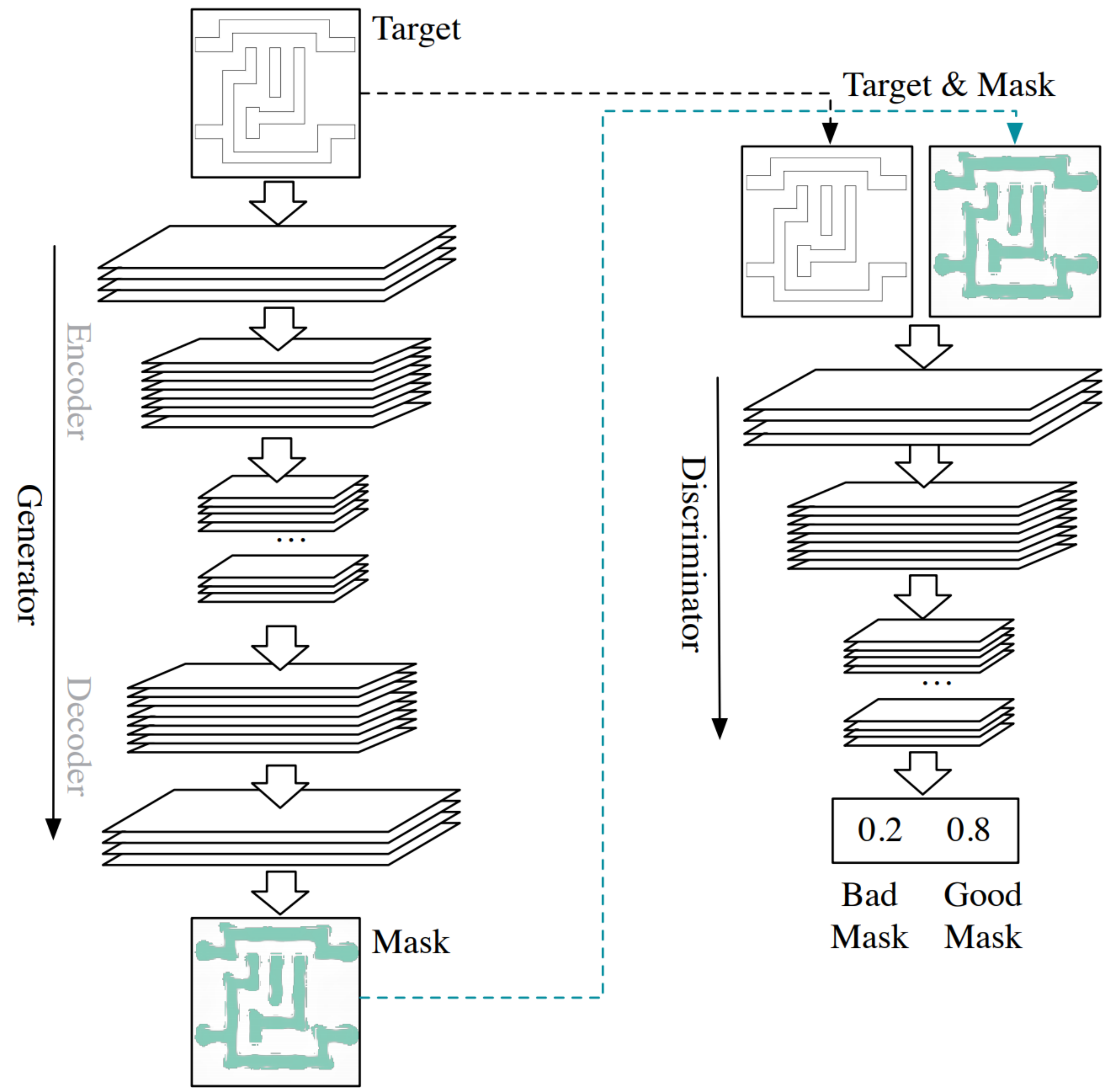
Symmetry constraints are widely accepted

No standard rule for additional constraints. Design-dependent.

Automatically learn from human layouts?

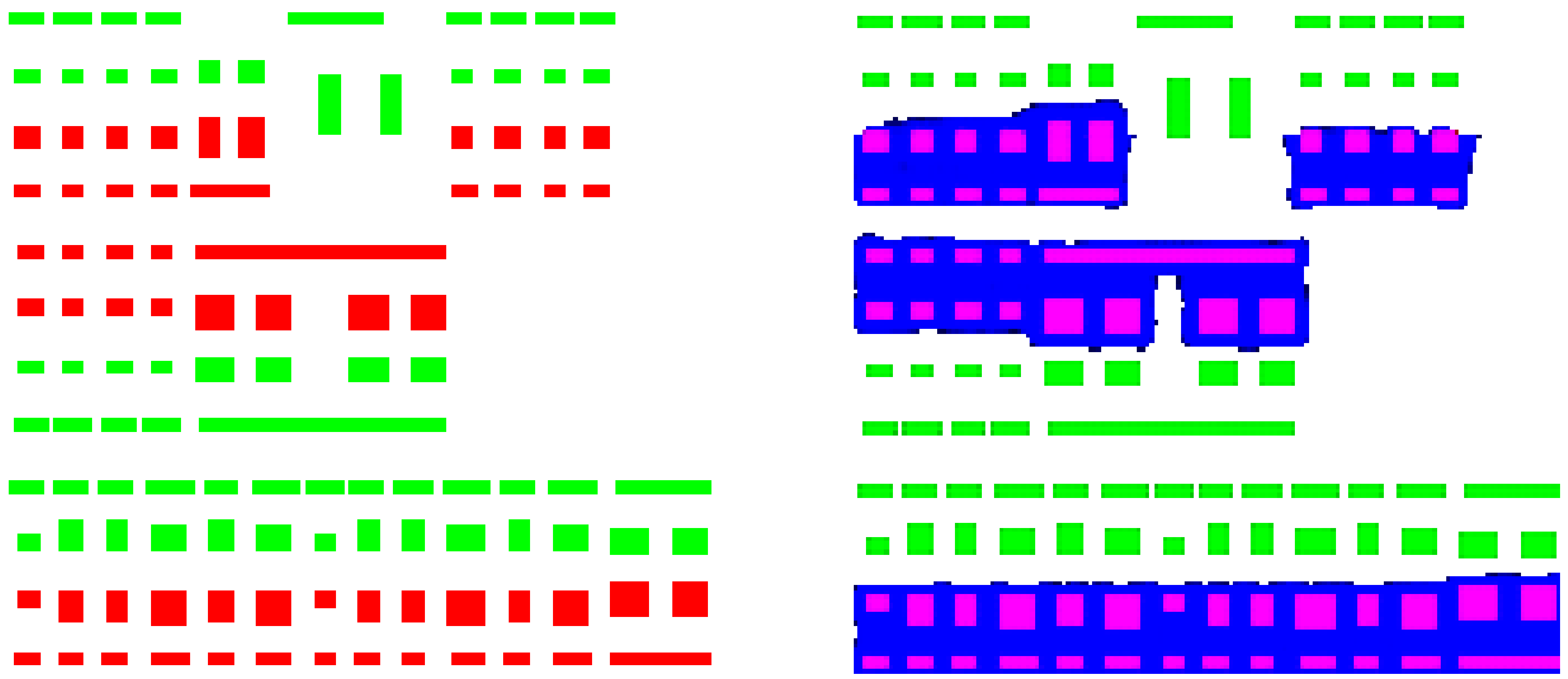
Emerging Machine Learning Applications

Lithography: GAN-OPC



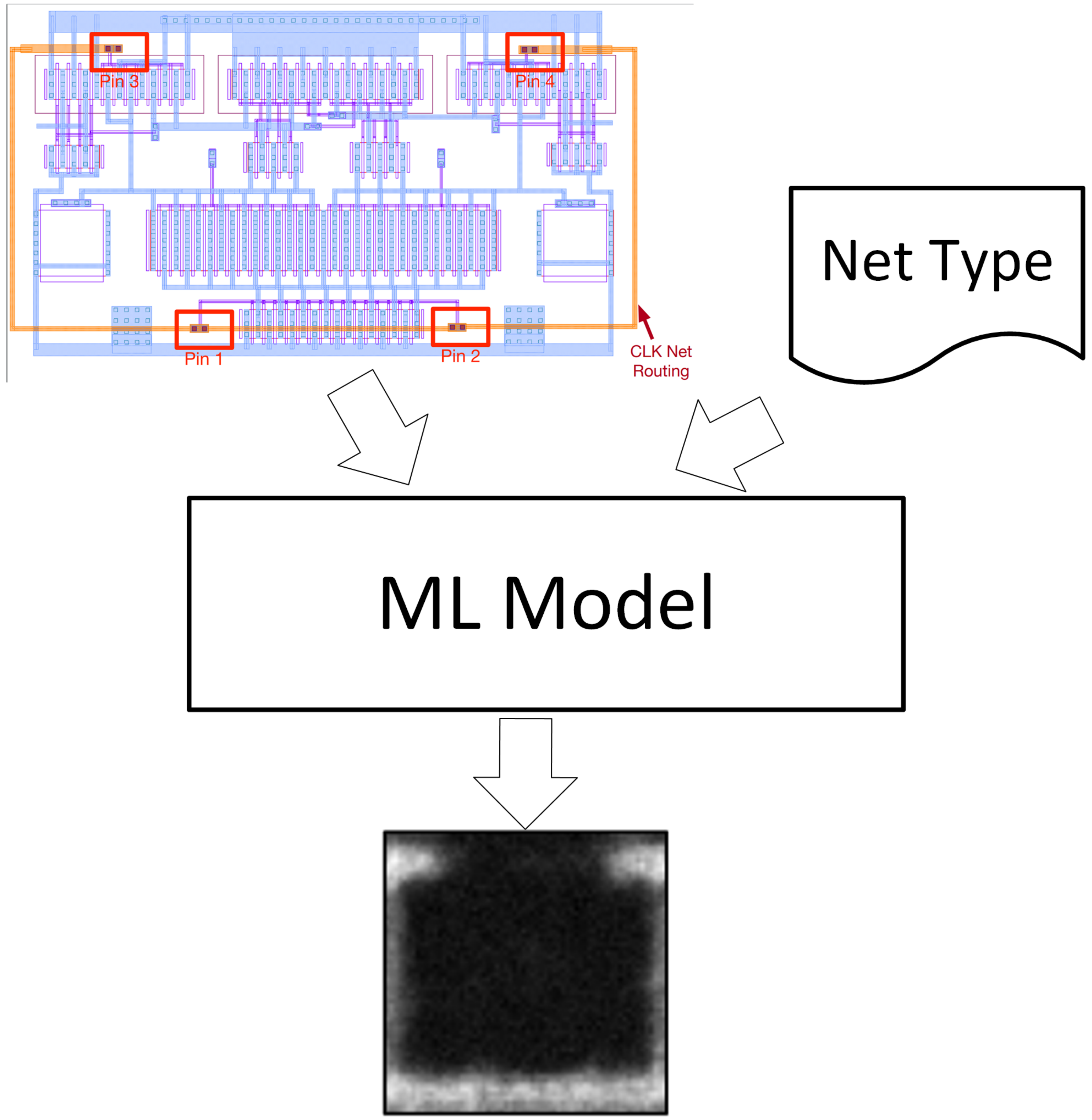
[Yang et al., 2018]

Physical Design: WellGAN



[Xu et al., 2019]

Automatically Learn Guidance from Human Layouts



- Learn routing guidance
  - Where the human would likely to route the nets
- Extract training data from labeled layouts
- Apply learned model to automatic routing as guidance

A ML-Guided Routing Problem

Heuristic constraints: use a set of detailed heuristics as routing constraints

Placement → **Explicated Constraints** → **Routing**

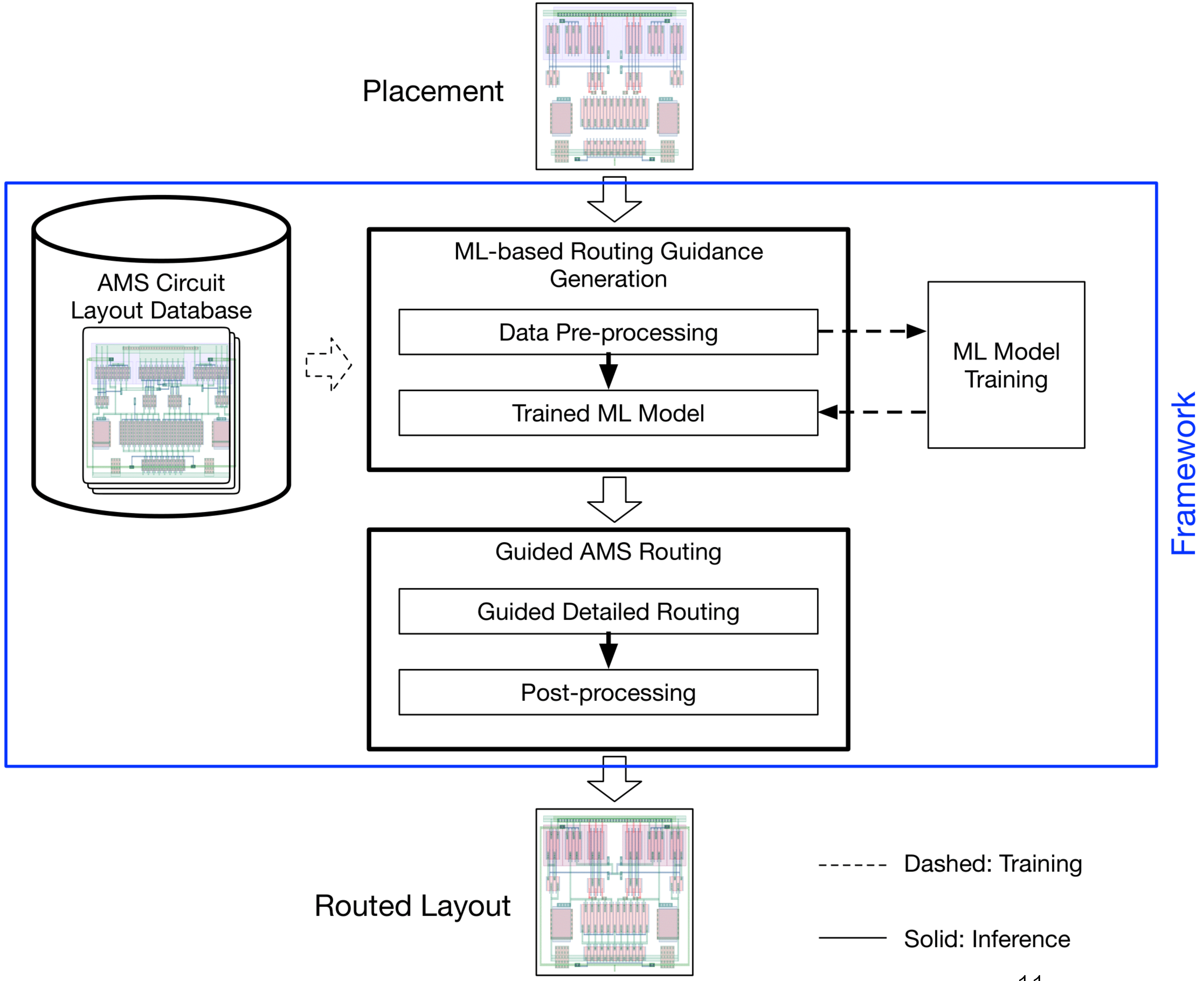
Conventional Approach

Routing guide: routing strategies learned from human

Placement → **Symmetric Constraints + ML-based Routing Guide** → **Routing**

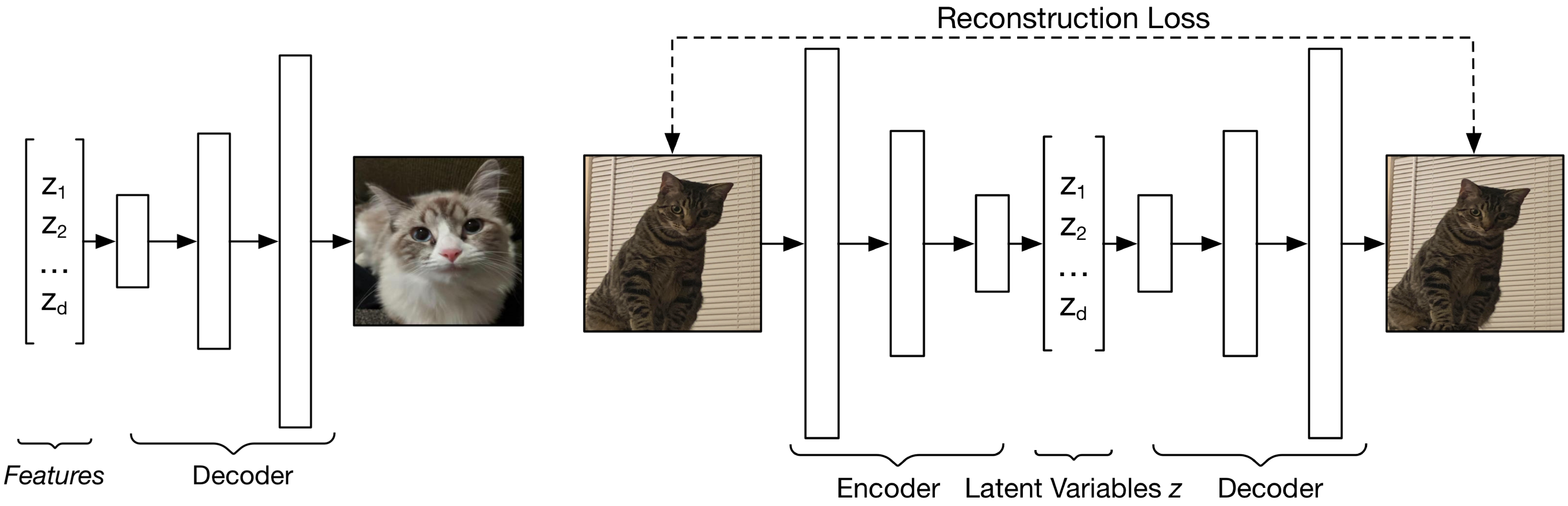
GeniusRoute Approach

The GeniusRoute Flow

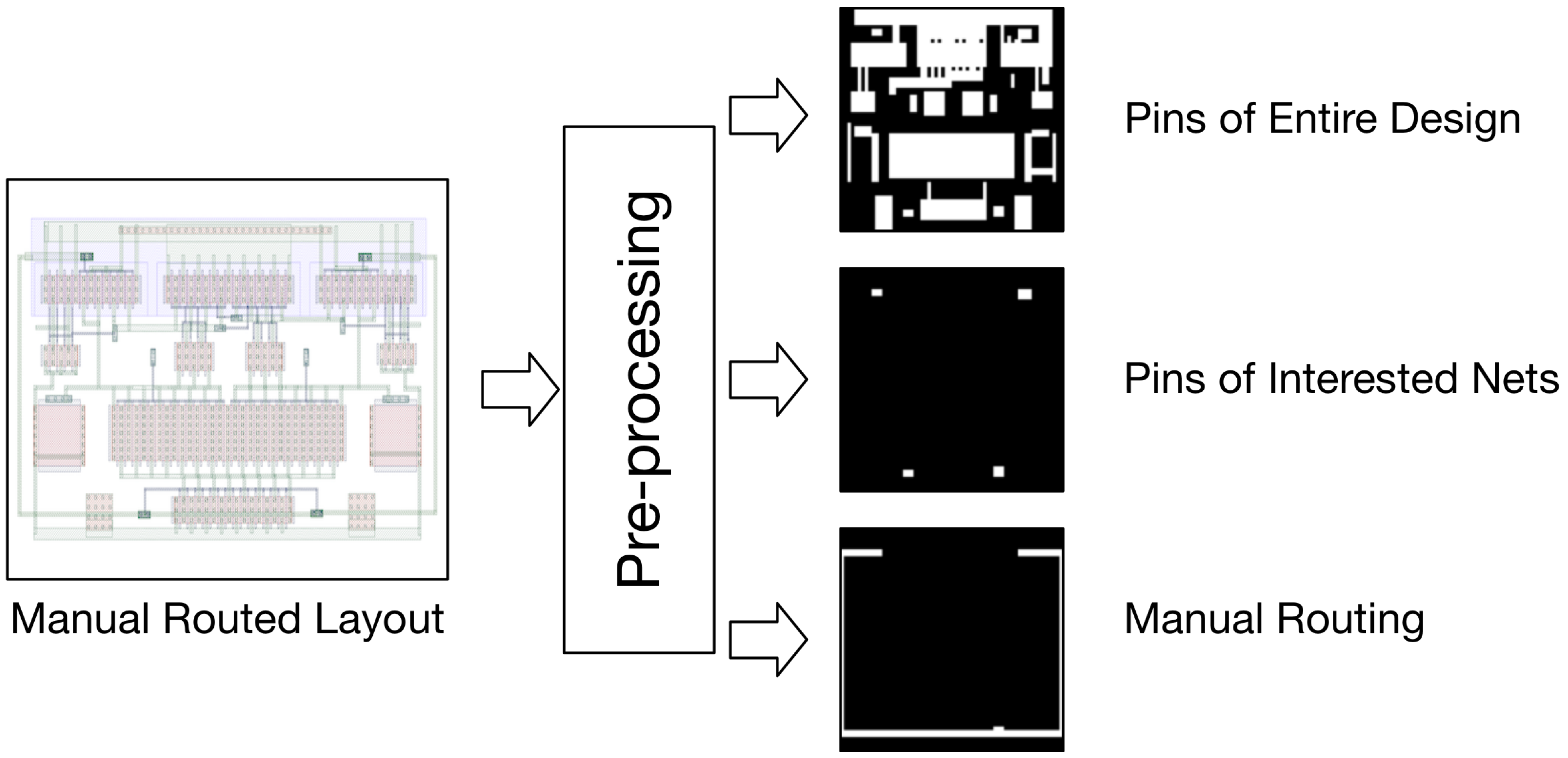


- Learn from GDS layouts
- Pre-process layouts into images
- Predict routing probability using autoencoder
- Use prediction as detailed routing guidance

Generating Images with Generative Neural Network



Data-Preprocessing: Extracting Routing from Layouts

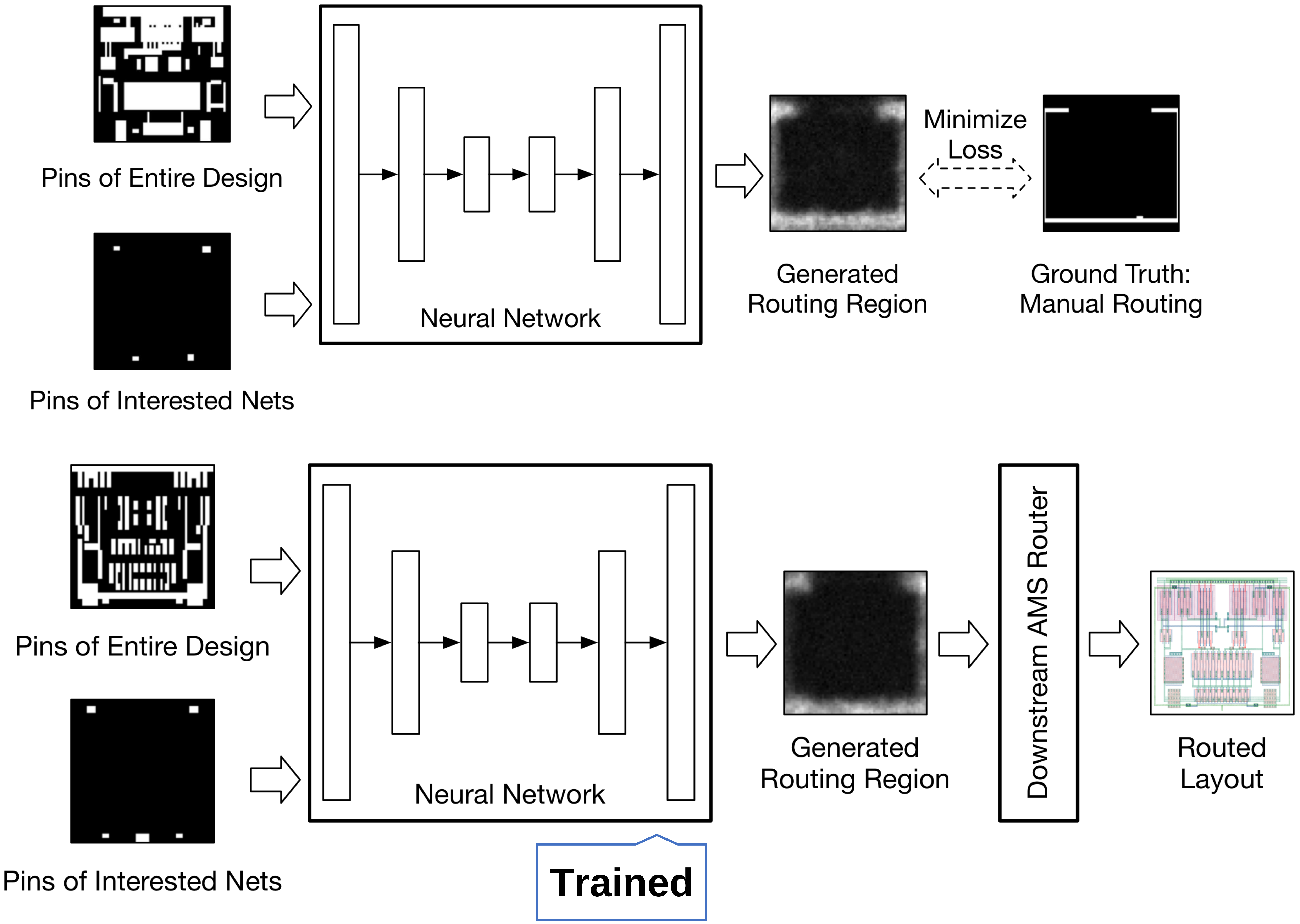


Extract “pins” and routing of nets

Three categories of models:

- Symmetric nets
- Clocks
- Power and Ground

GeniusRoute: Learning Routing Patterns from Human

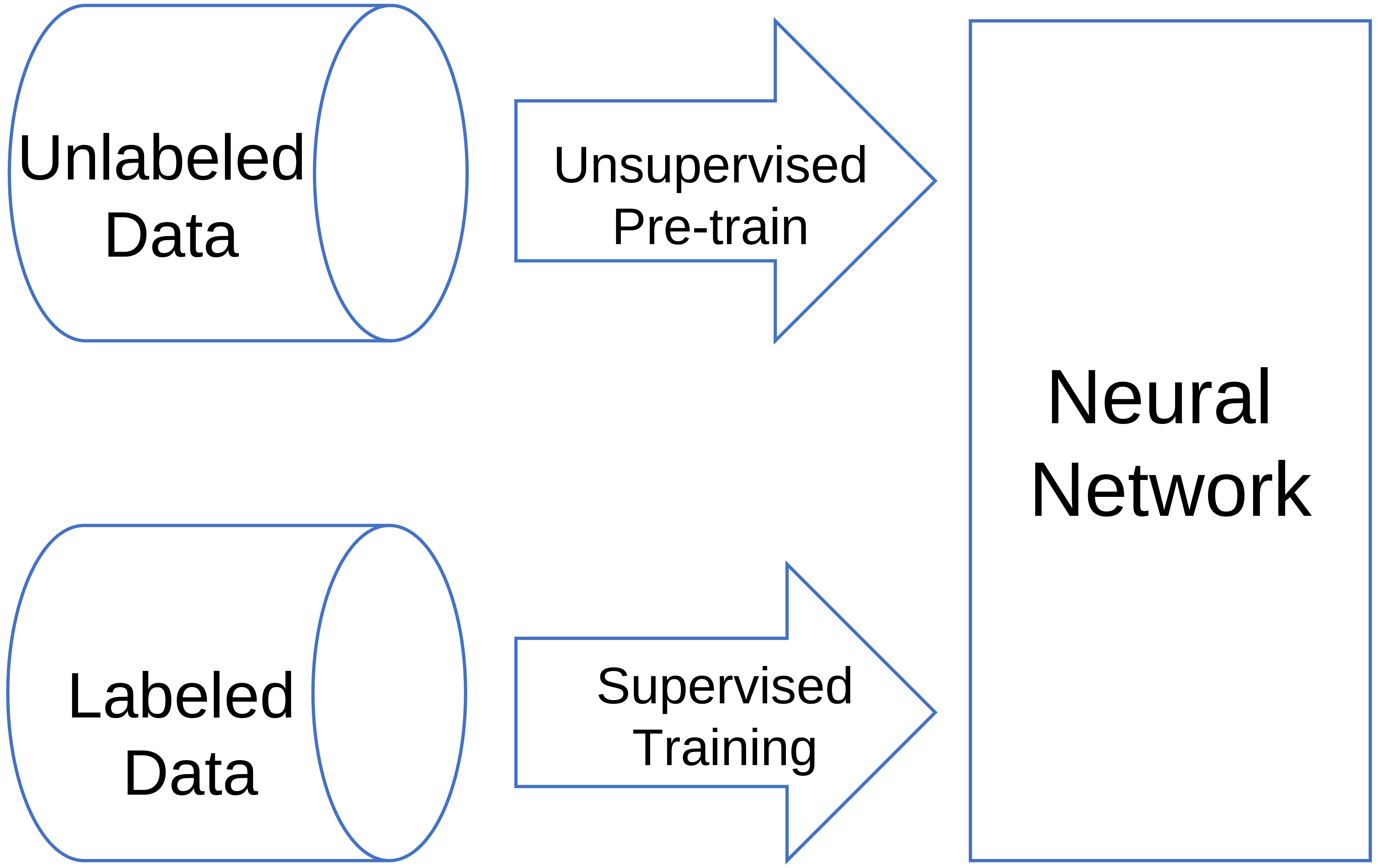


Training Phase

Do we have enough data?

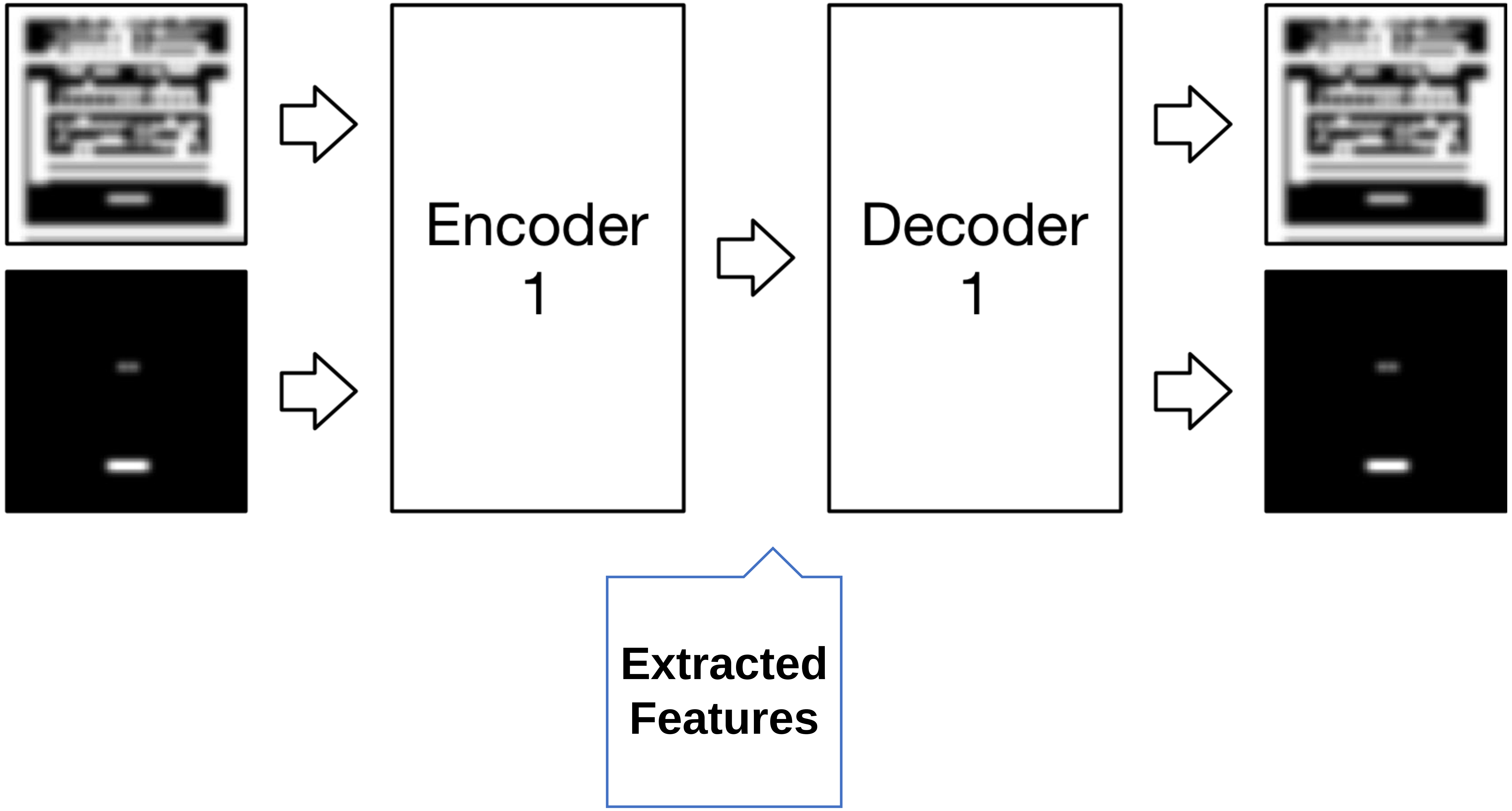
Inference Phase

3-Stage Semi-supervised Training Algorithm



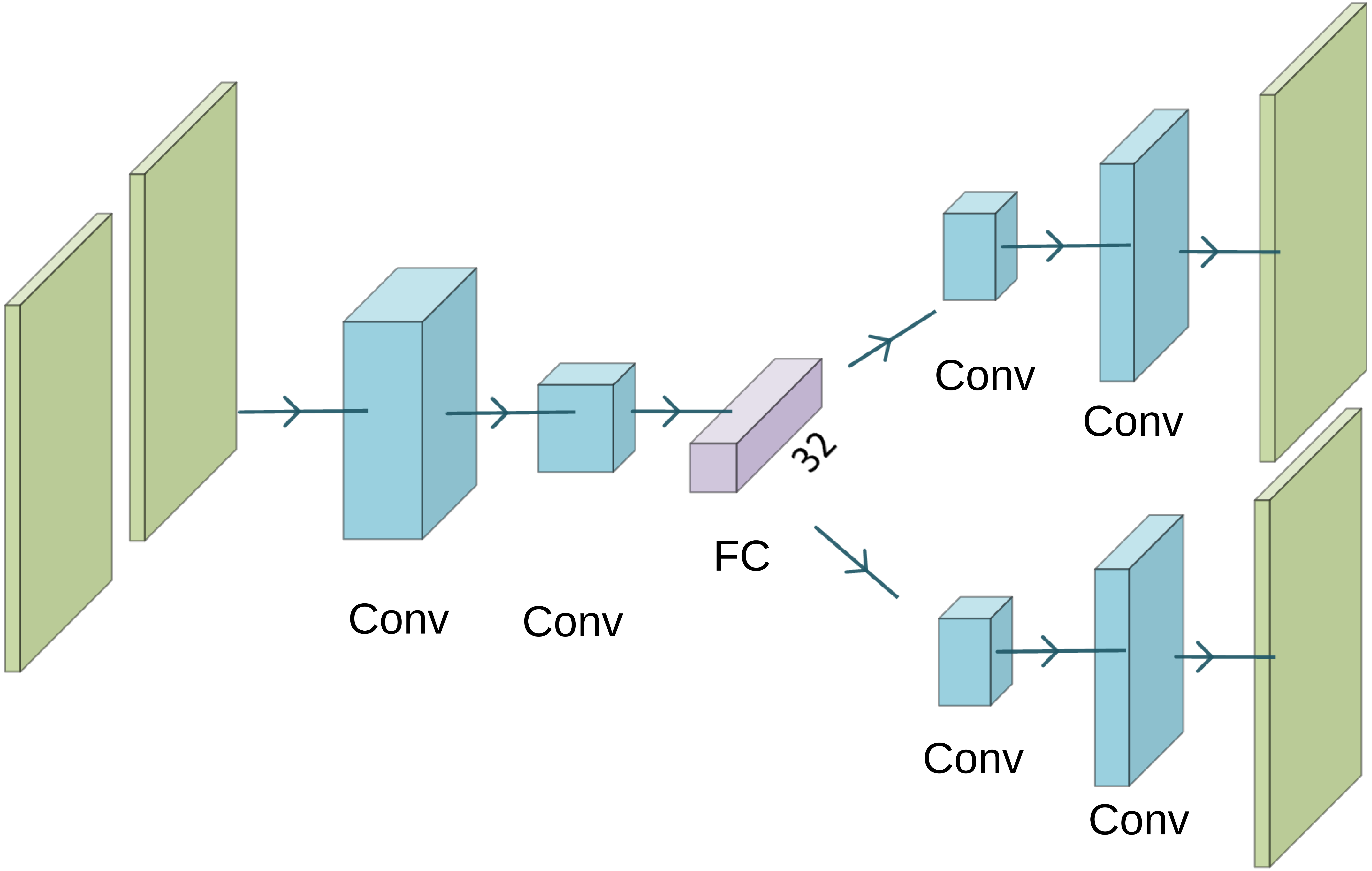
- Labeled layouts are hard to get
- Could rely on unlabeled data to help train the model

Stage 1: Unsupervised Feature Extraction using VAE

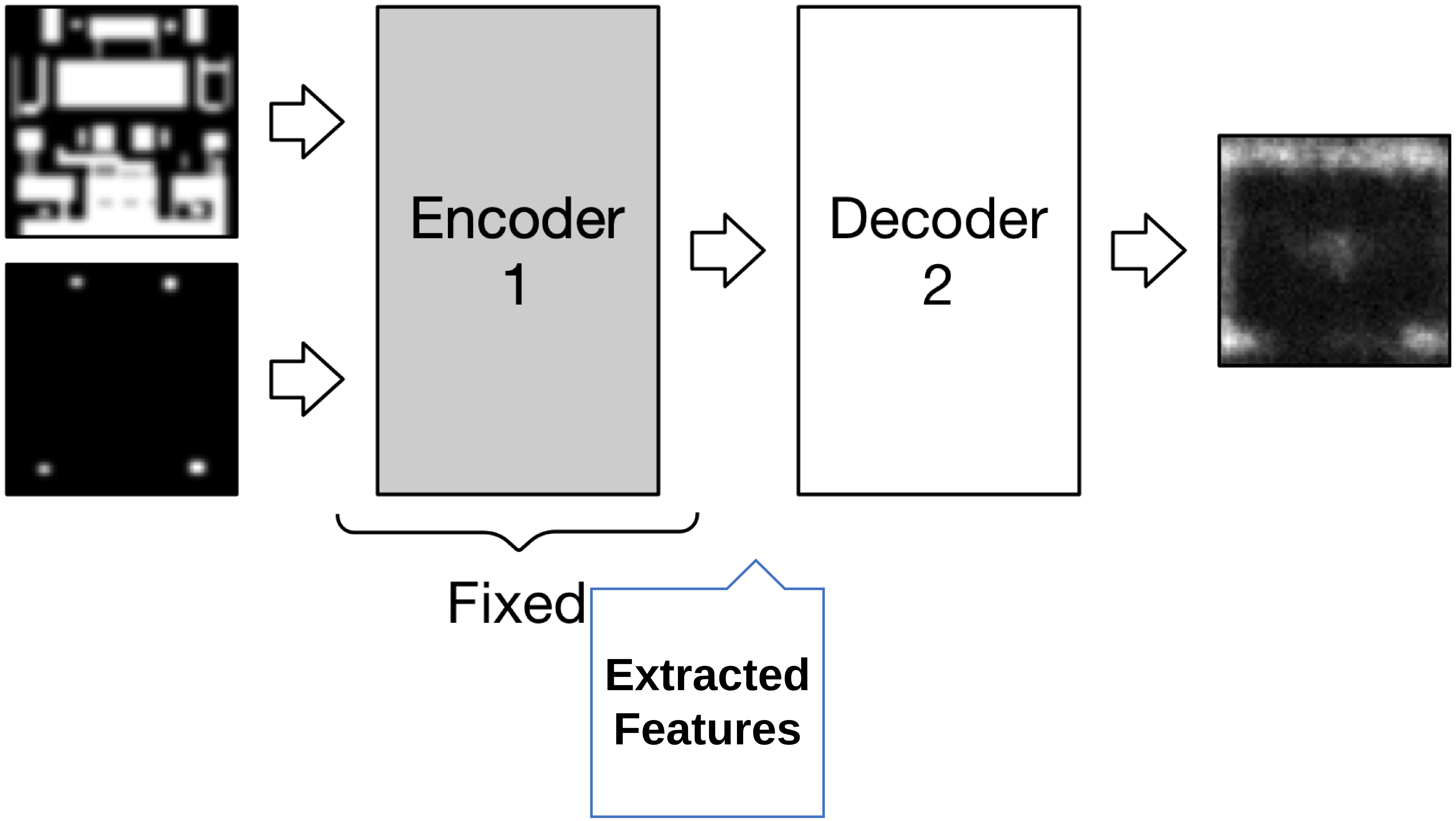


Use cheap unlabeled data to learn a general feature extraction

Network Architecture: Unsupervised for Stage 1

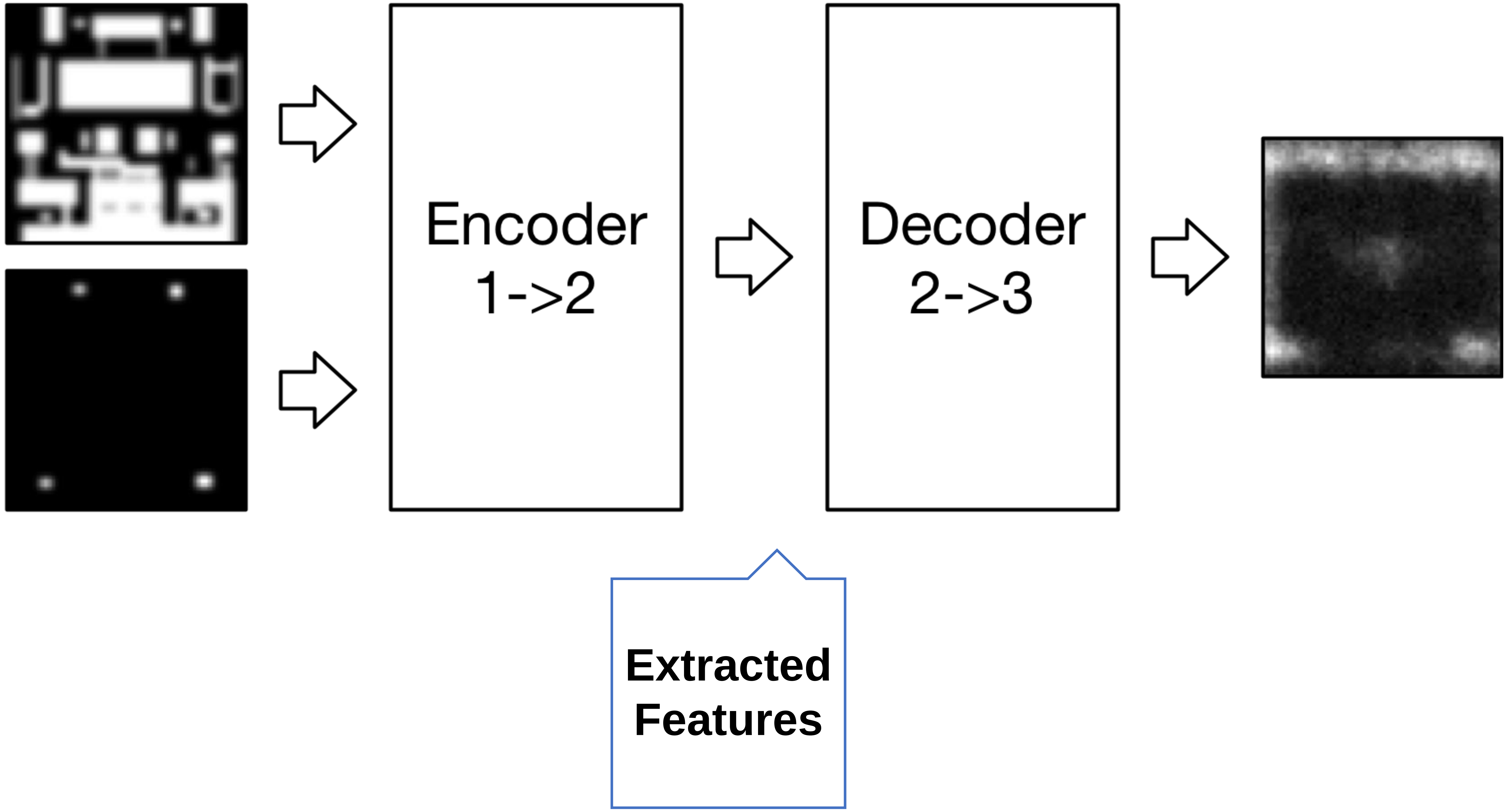


Stage 2: Supervised Decoder Training



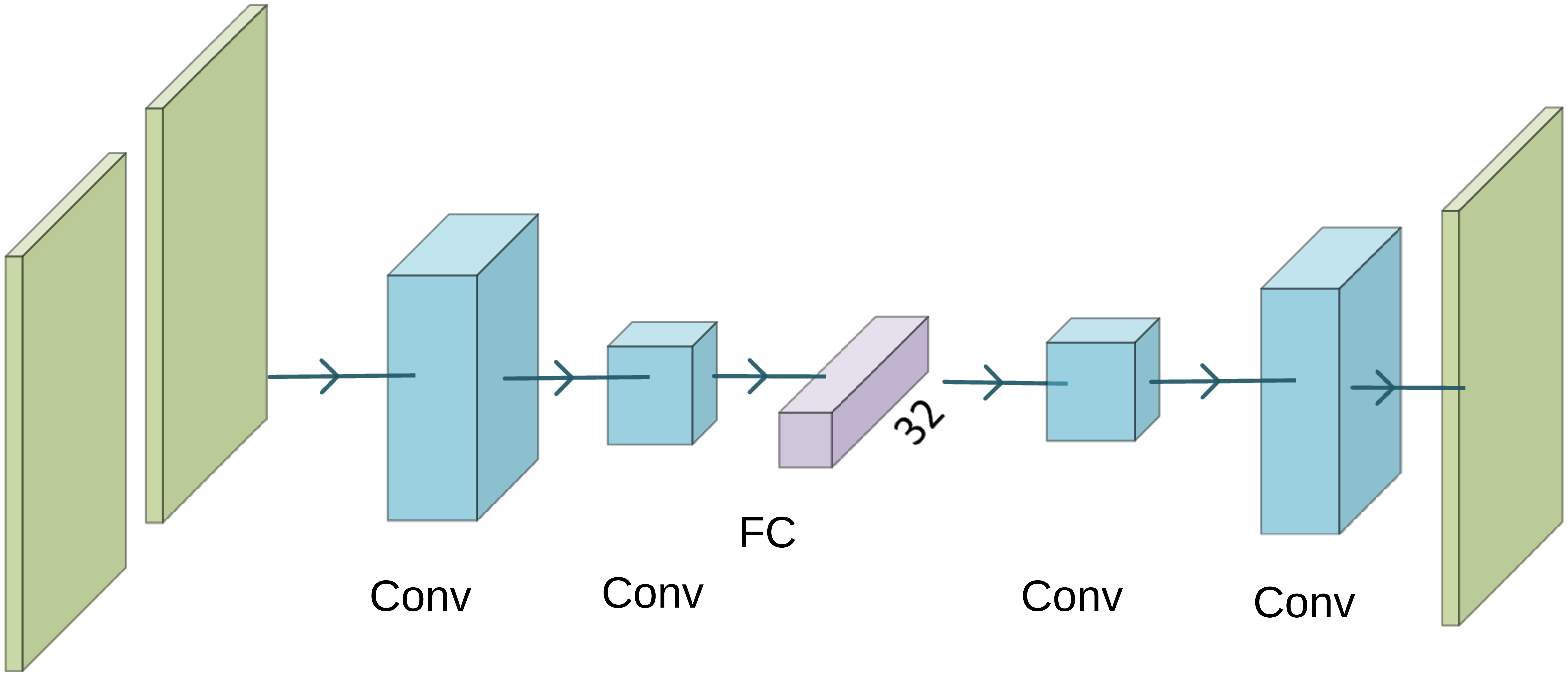
Fix the feature extraction to learn the generative model

Stage 3: Supervised Decoder Fine-Tune



Fine-tune the network for better accuracy with lower learning rate

Network Architecture: Supervised for Stage 2&3

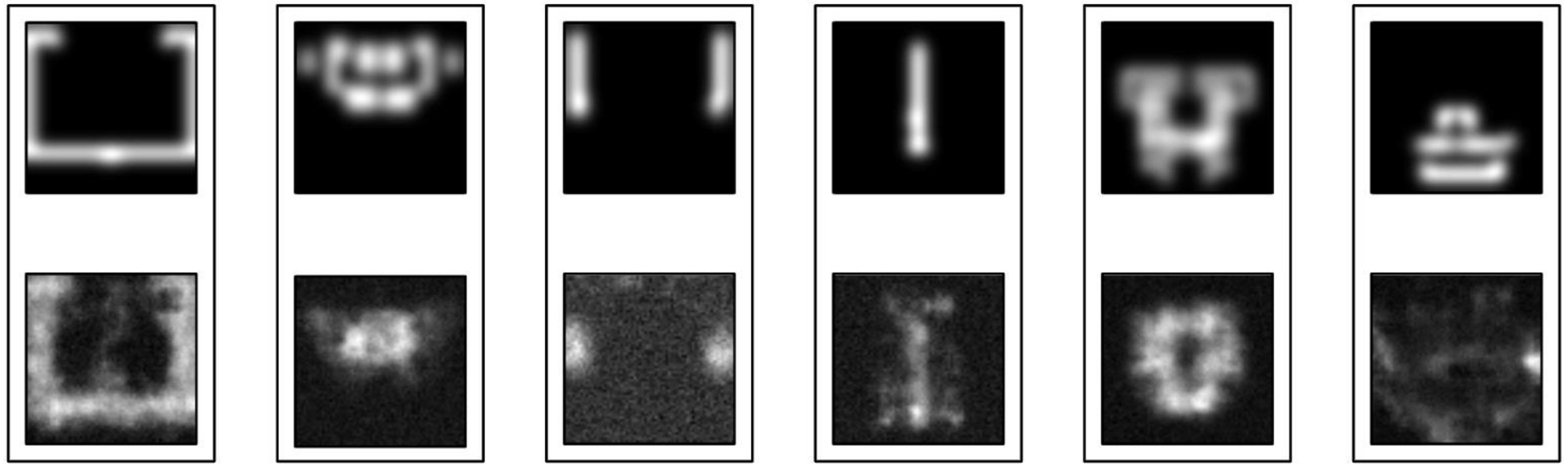


Framework Implementation and Environment Setup

- Data preprocessing: C++
- ML model: Python with Tensorflow
- Router: Modified maze routing in C++
- Simulation: Cadence ADE simulator with TSMC 40nm PDK

Experimental Result Examples

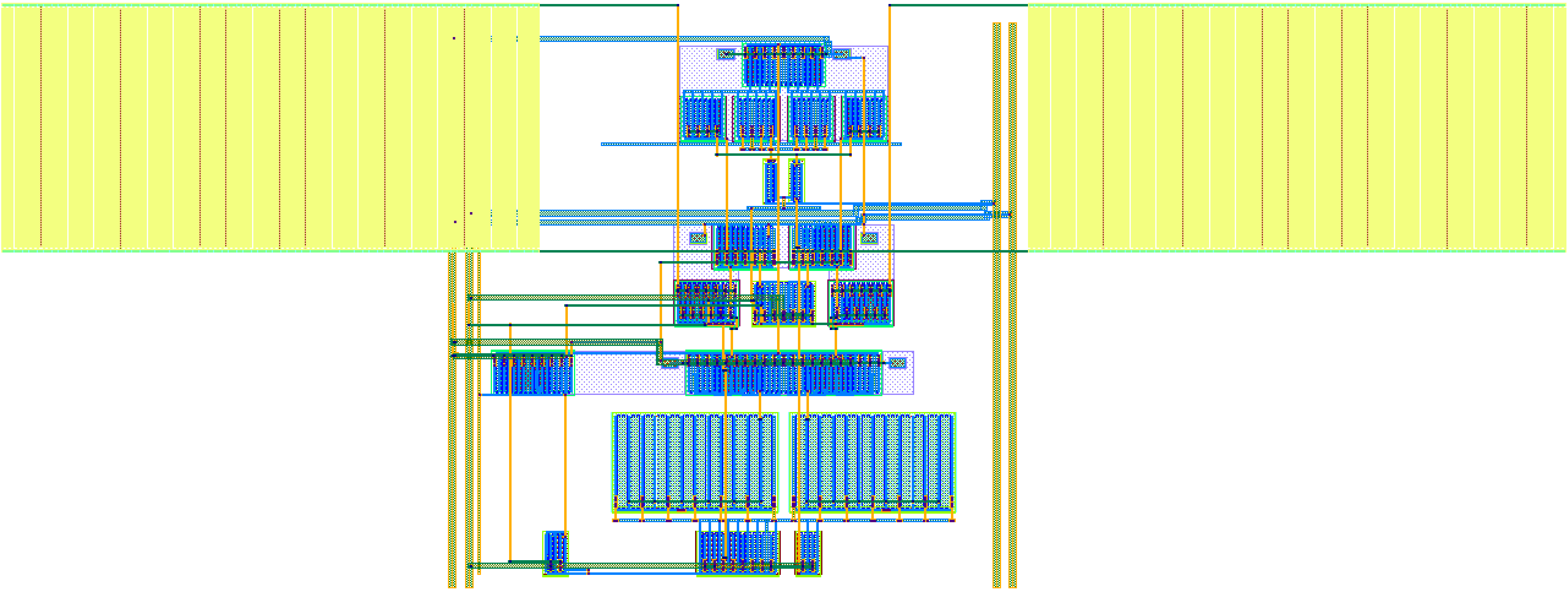
Model Output



Ground Truth

Prediction

Routed Layout



Experimental Results: Simulation Results

- Test on comparators and OTAs
- Evaluate with post layout simulation
- Compare with manual layout and previous methods

COMP1	Schematic	Manual	w/o guide	GeniusRoute
Offset (uV)	/	480	2530	830
Delay (ps)	102	170	164	163
Noise (uVrms)	439.8	406.6	439.7	420.7
Power (uW)	13.45	16.98	16.82	16.8

Closer results to the manual layout

Experimental Results: More Simulation Results

COMP1	Schematic	Manual	w/o guide	GeniusRoute
Offset (uV)	/	480	2530	830
Delay (ps)	102	170	164	163
Noise (uVrms)	439.8	406.6	439.7	420.7
Power (uW)	13.45	16.98	16.82	16.8

COMP2	Schematic	Manual	w/o guide	GeniusRoute
Offset (uV)	/	550	1180	280
Delay (ps)	102	196	235	241
Noise (uVrms)	439.8	380.0	369.6	367.8
Power (uW)	13.45	20.28	20.23	20.15

OTA	Schematic	Manual	wo/ guide	GeniusRoute
Gain (dB)	38.20	37.47	36.61	37.36
PM (degree)	64.66	72.46	94.68	76.40
Noise (uVrms)	222.0	223.7	292.7	224.8
Offset (mV)	/	0.88	3.21	0.39
CMRR (dB)	/	59.61	58.52	59.15
BW (MHz)	110.5	102.5	232.1	107.3
Power (uW)	776.93	757.35	715.11	787.82

Conclusion

GeniusRoute

- A new methodology to automatic learn from human layout and apply in automatic flow
- Semi-supervised learning algorithm for data-efficiency
- Experimental results show closed-to-human post layout simulation

Future directions

- How to overcome the challenge of obtaining human layouts for labeled data

Thank you!

Backup

TABLE I: Network configurations.

Stage 1 Configuration	
Input ($2 \times 64 \times 64$ image)	
conv/$5 \times 5 \times 64$	
conv/$5 \times 5 \times 128$	
FC/64	
Latent Variables (32)	
FC/$16 \times 16 \times 64$	FC/$16 \times 16 \times 64$
deconv/$4 \times 4 \times 32$	deconv/$4 \times 4 \times 32$
deconv/$4 \times 4 \times 1$	deconv/$4 \times 4 \times 1$
Output ($2 \times 64 \times 64$ image)	

Stage 2 & 3 Configuration
Input ($2 \times 64 \times 64$ image)
conv/$5 \times 5 \times 64$
conv/$5 \times 5 \times 128$
FC/64
Latent Variables (32)
FC/$16 \times 16 \times 64$
deconv/$4 \times 4 \times 32$
deconv/$4 \times 4 \times 1$
Output ($1 \times 64 \times 64$ image)

Backup

TABLE II: Runtime. (seconds)

	W/o guide	This work
COMP1	11.7	26.2
COMP2	2.3	21.3
OTA	49.6	55.4

TABLE III: Runtime breakdown. (seconds)

	PP	MI	DR
COMP1	<1	17.6	8.6
COMP2	<1	17.6	3.7
OTA	3.5	13.2	38.7