

# Circuit Design Completion using Graph Neural Networks

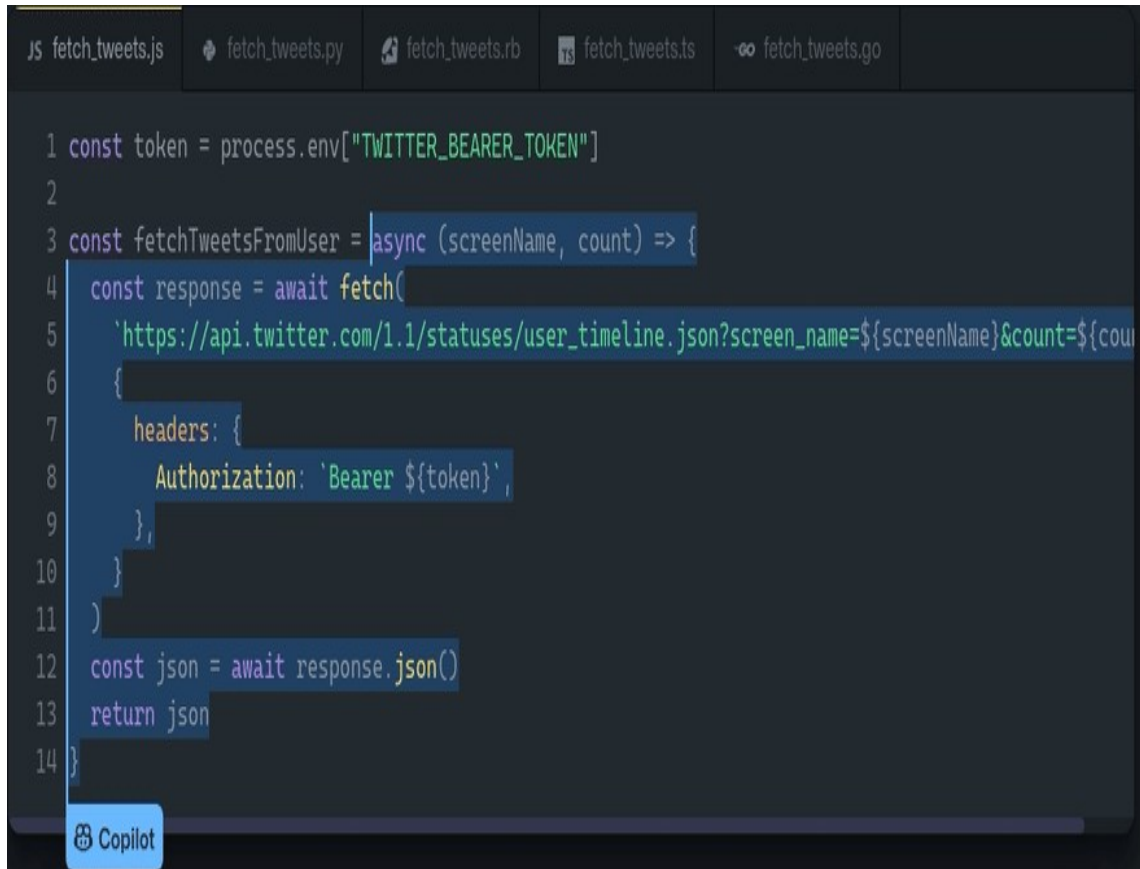
**Anwar Said, Mudassir Shabbir, Brian Broll, Waseem Abbas, Peter Volgyesi, Xenofon Koutsoukos**

# Agenda

- Motivation
- Problem formulation
- Dataset generation
- Proposed methodology
- Results

# Modern Innovative Tools

## GitHub Copilot: Coding suggestions

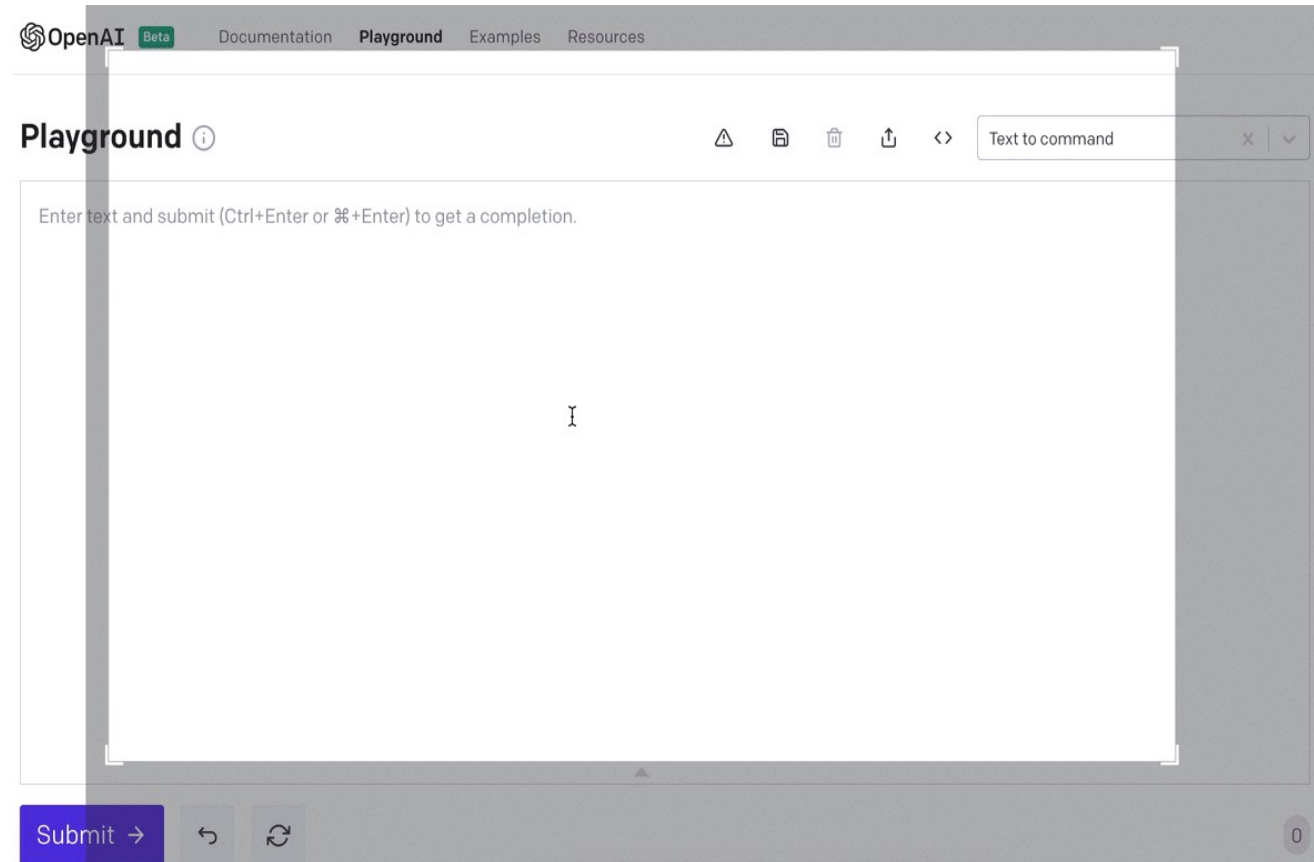


The screenshot shows the GitHub Copilot interface within a code editor. At the top, there are tabs for different file types: `js fetch_tweets.js`, `python fetch_tweets.py`, `ruby fetch_tweets.rb`, `typescript fetch_tweets.ts`, and `go fetch_tweets.go`. The main editor area displays a JavaScript code snippet for fetching tweets from a user's timeline. The code is as follows:

```
1 const token = process.env["TWITTER_BEARER_TOKEN"]
2
3 const fetchTweetsFromUser = async (screenName, count) => {
4   const response = await fetch(
5     `https://api.twitter.com/1.1/statuses/user_timeline.json?screen_name=${screenName}&count=${count}`
6   )
7   const headers = {
8     Authorization: `Bearer ${token}`,
9   }
10  const json = await response.json()
11  return json
12 }
13
14
```

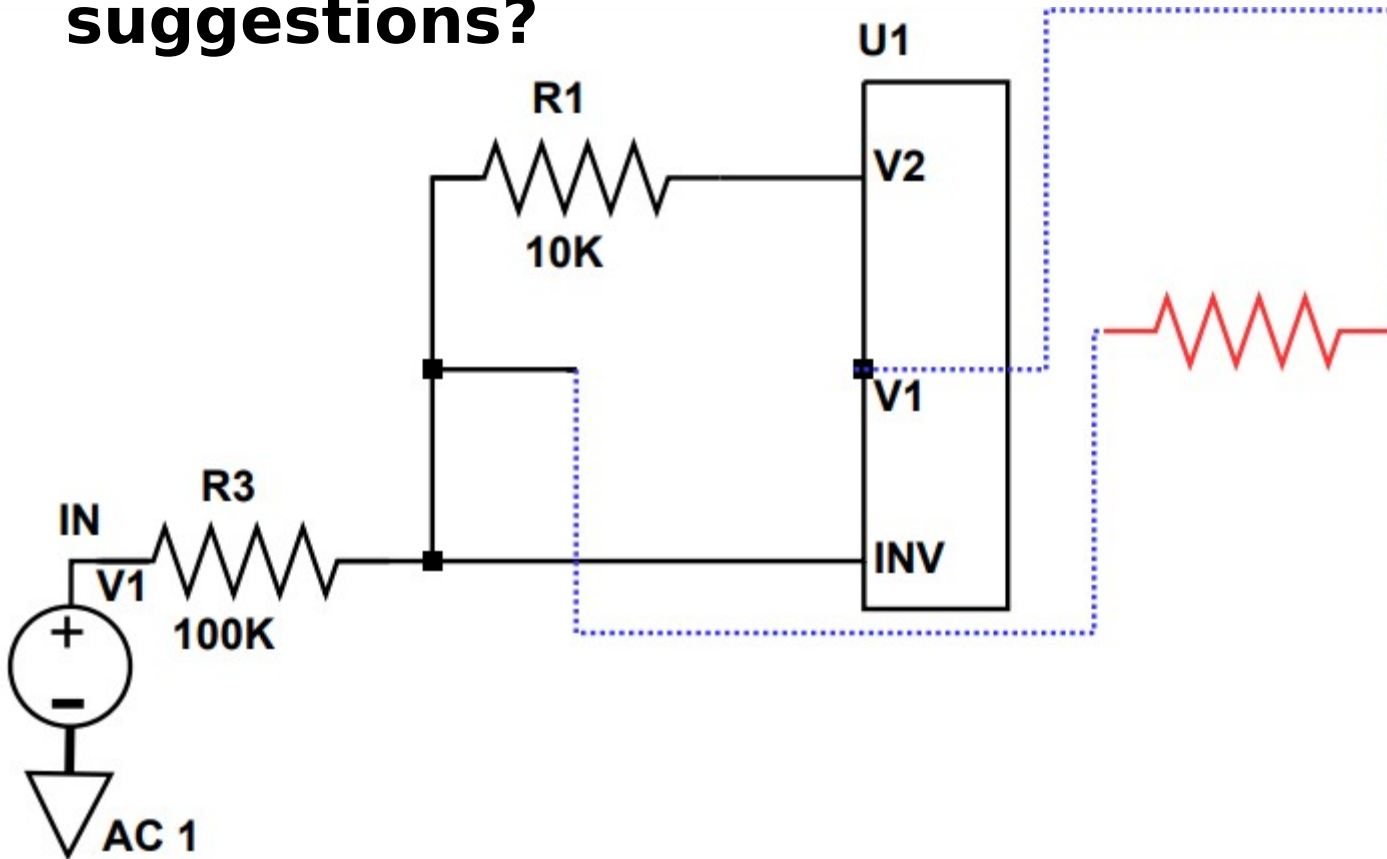
At the bottom left of the editor, there is a blue button with the GitHub logo and the text "Copilot".

## GPT3: Text completion



# Circuit Design Completion

## Circuit design suggestions?



### Challenges:

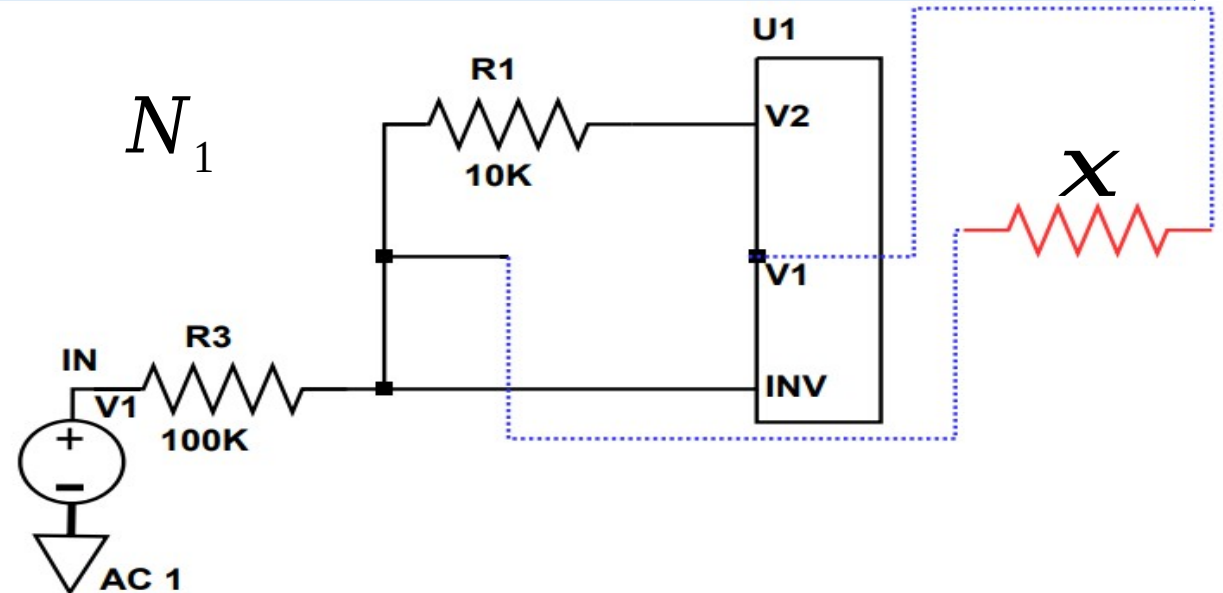
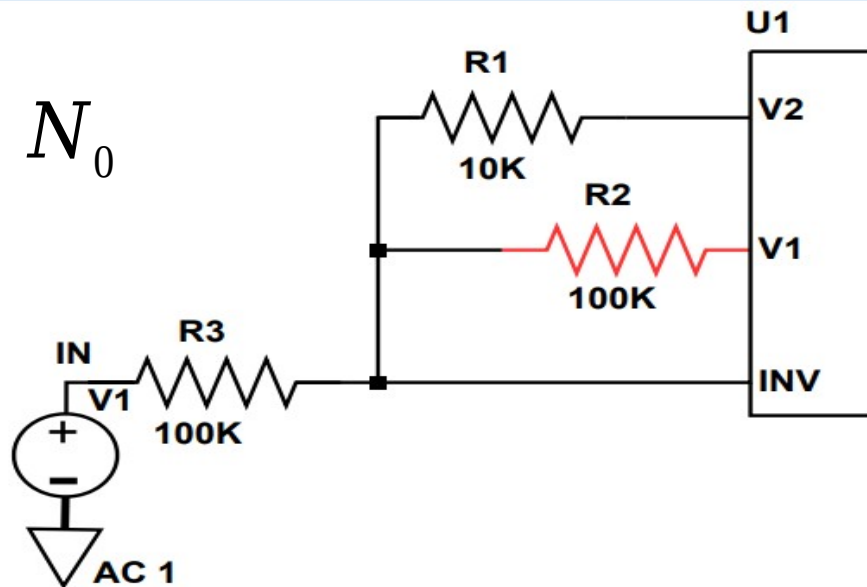
- Time consuming process due to very large search space
- Chance of errors in chips or boards after manufacturing

### Solution

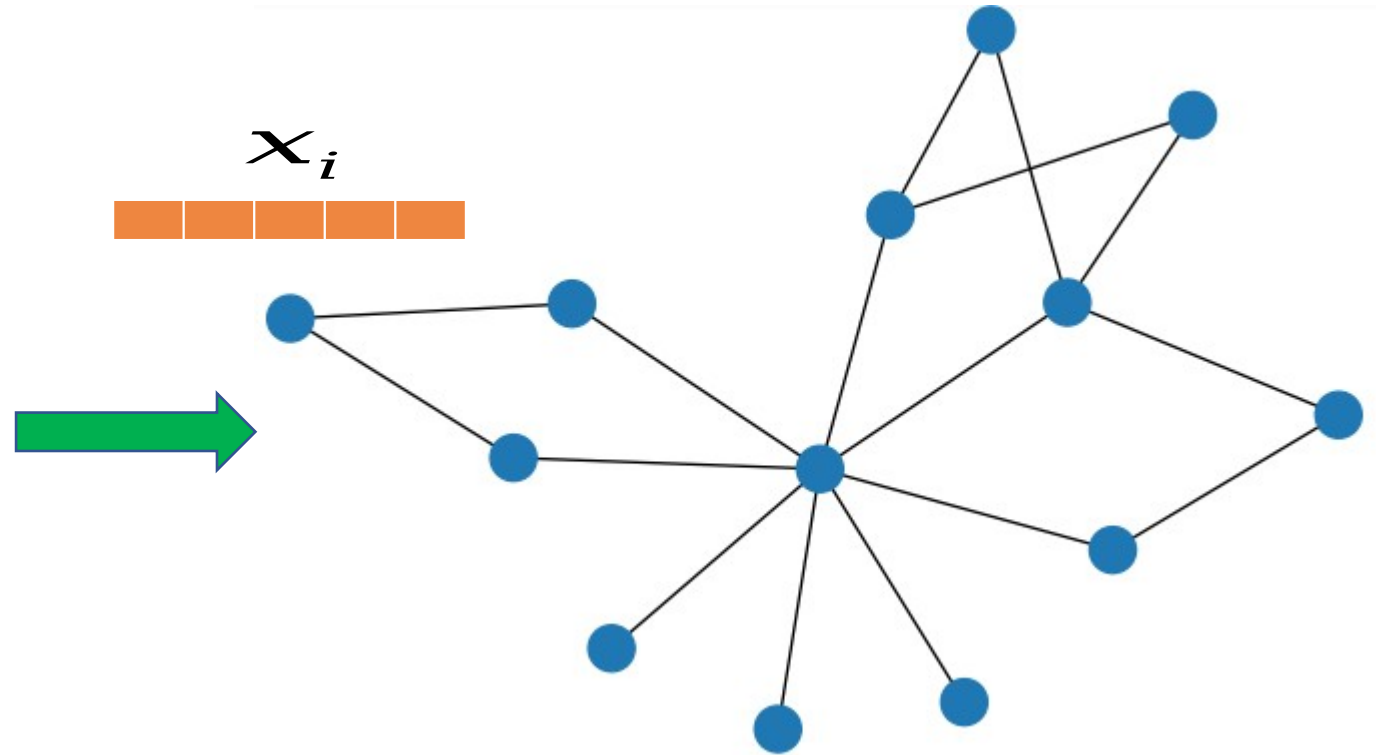
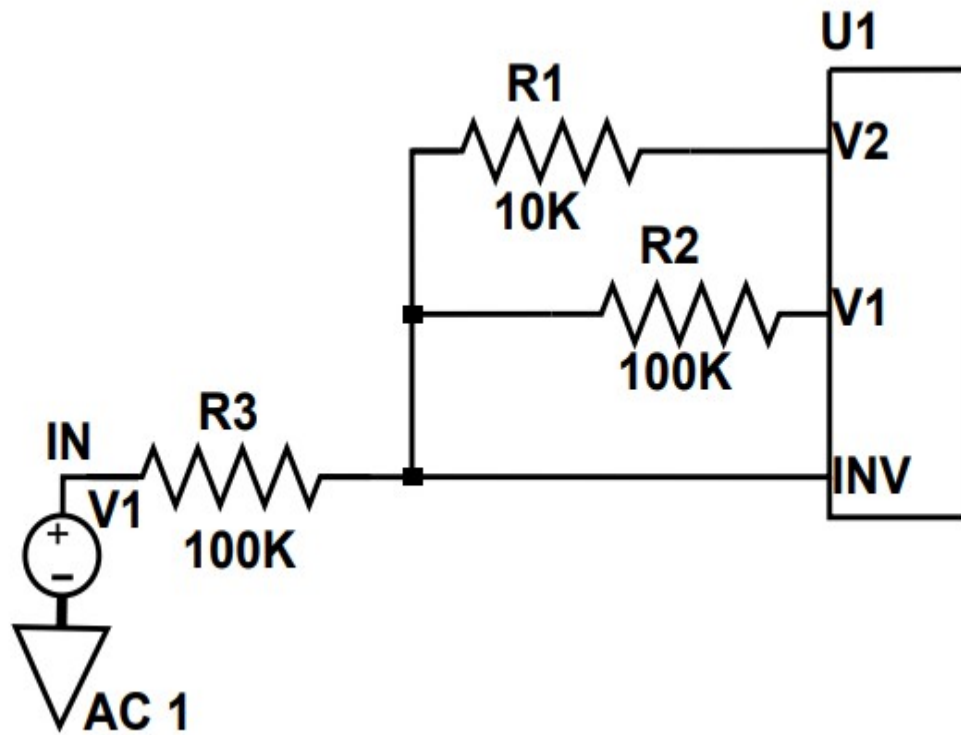
- ML in Circuit Design

# Circuit Completion Problem (CCP)

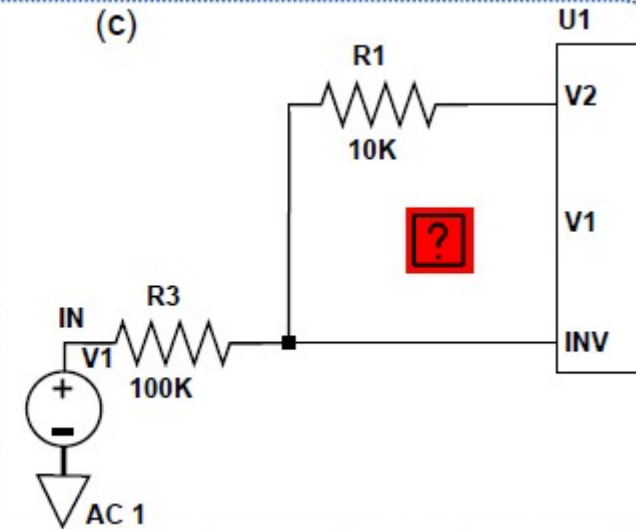
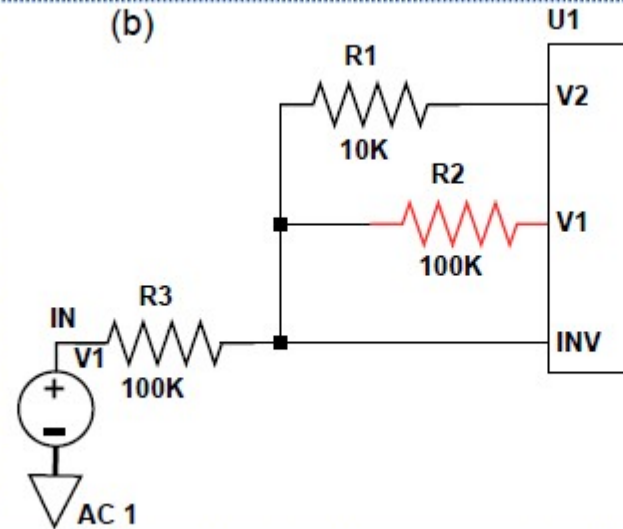
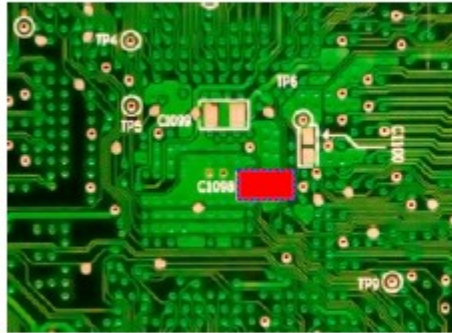
Let  $N_0$  and  $N_1$  be the netlists of two circuit schematics where  $N_0$  is an original circuit while  $N_1$  is a copy of  $N_0$  that is missing a component and all its connections that are present in  $N_0$ . The circuit completion problem is to predict the type of component and all its missing connections.



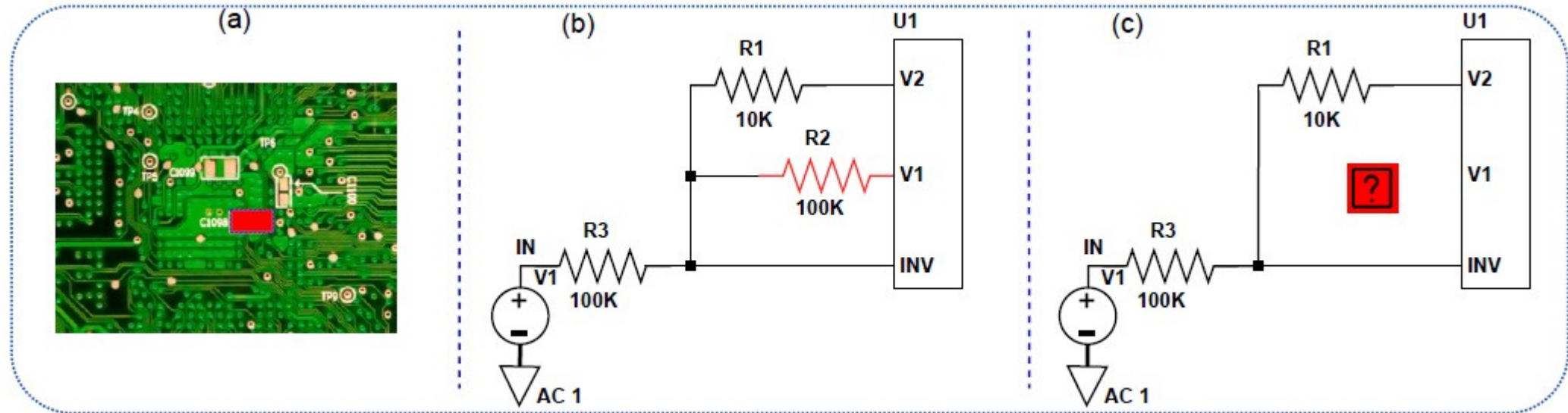
# Circuit Completion using networked representation



# Missing Component Identification (Problem 1)



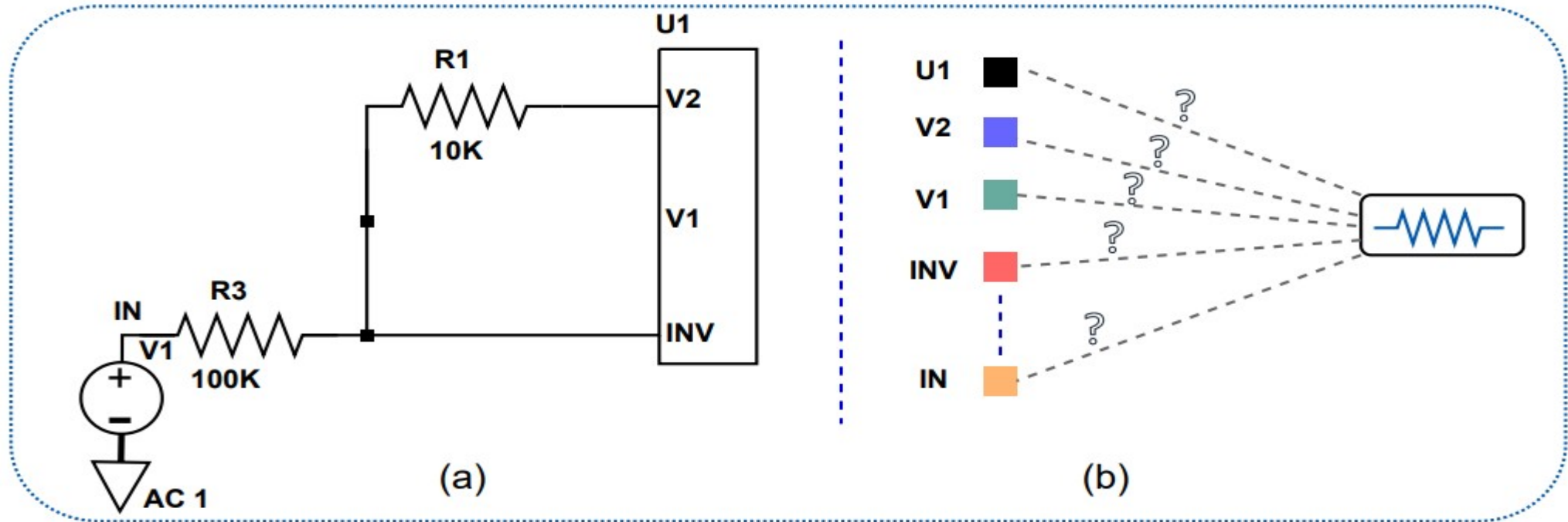
# Missing Component Identification (Problem 1)



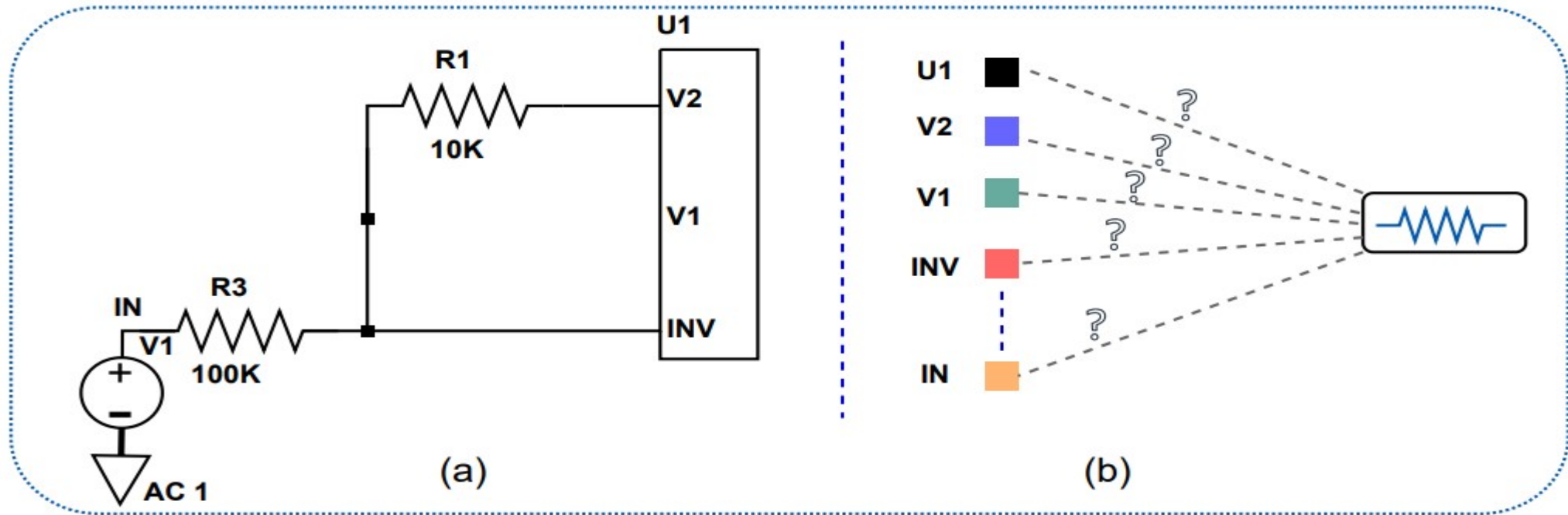
Let  $G$  be a graph of a netlist with  $n$  vertices. Let  $G'$  be a graph obtained by removing an arbitrary vertex from  $G$ . Compute the value of  $\chi(G')$  from  $\chi(G)$ .



## Link Completion (Problem 2)



## Link Completion (Problem 2)



Let  $G$  be a graph of a netlist with  $V$  where  $V$  is a graph obtained by removing an arbitrary vertex  $v$  from  $G$ . Given the value of  $v$  and the  $G$ , predict the set of neighbors of  $v$  in  $G$ .

# Proposed Framework

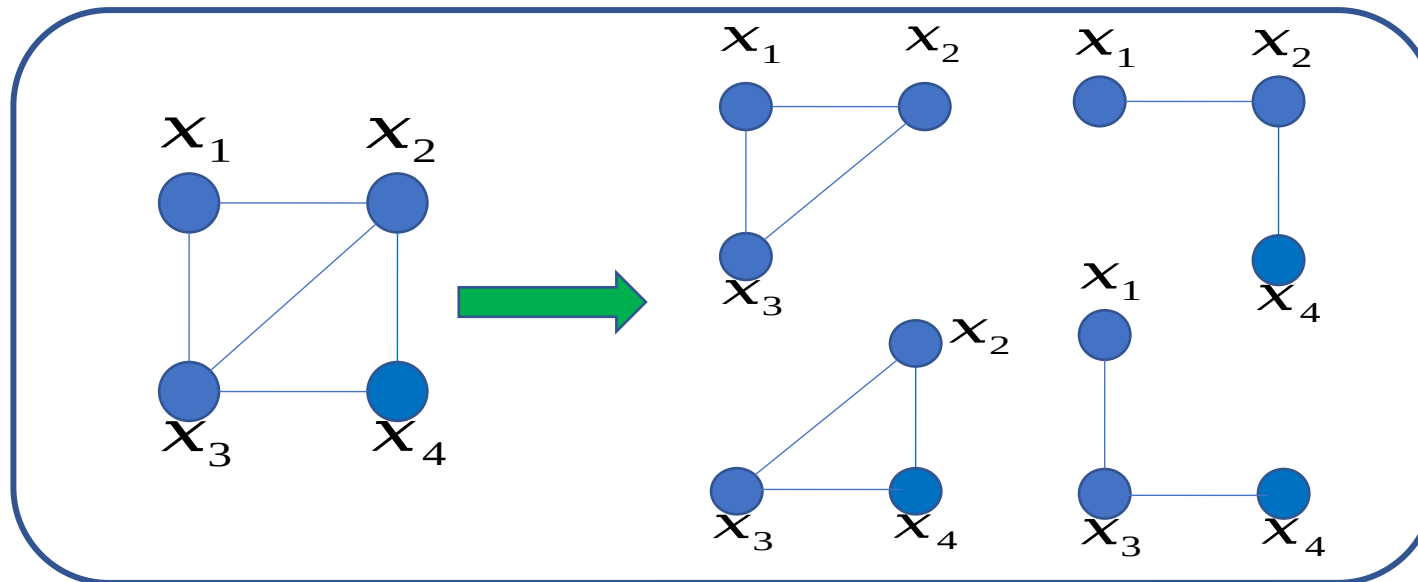
- Two ingredients:
  - Leverage Graph Neural Networks (GNNs) framework in a graph classification setting to predict missing component (problem 1)
  - Adapted GNNs based link prediction approach to predict edges for the missing components (problem 2)

# Datasets

Dataset	Valid netlists	Total comp	Max comp per class	Min comp per class
Ltspice Examples	1505-377	19-18	1505-377	[1,1,6,6,8,9]
Ltspice Demos	235-59	17-12	235-59	[1,2,3,3,4,7]
Kicad Github	553-139	22-20	553-153	[2,3,3,4,12,13]

# Dataset Generation (Graph Classification)

- For each graph (netlist), we remove a node for  $G$  and label the resulting graph as
- We can have as many training or testing instances as there are types of components in a netlist
- We consider only five most common component types in a given dataset

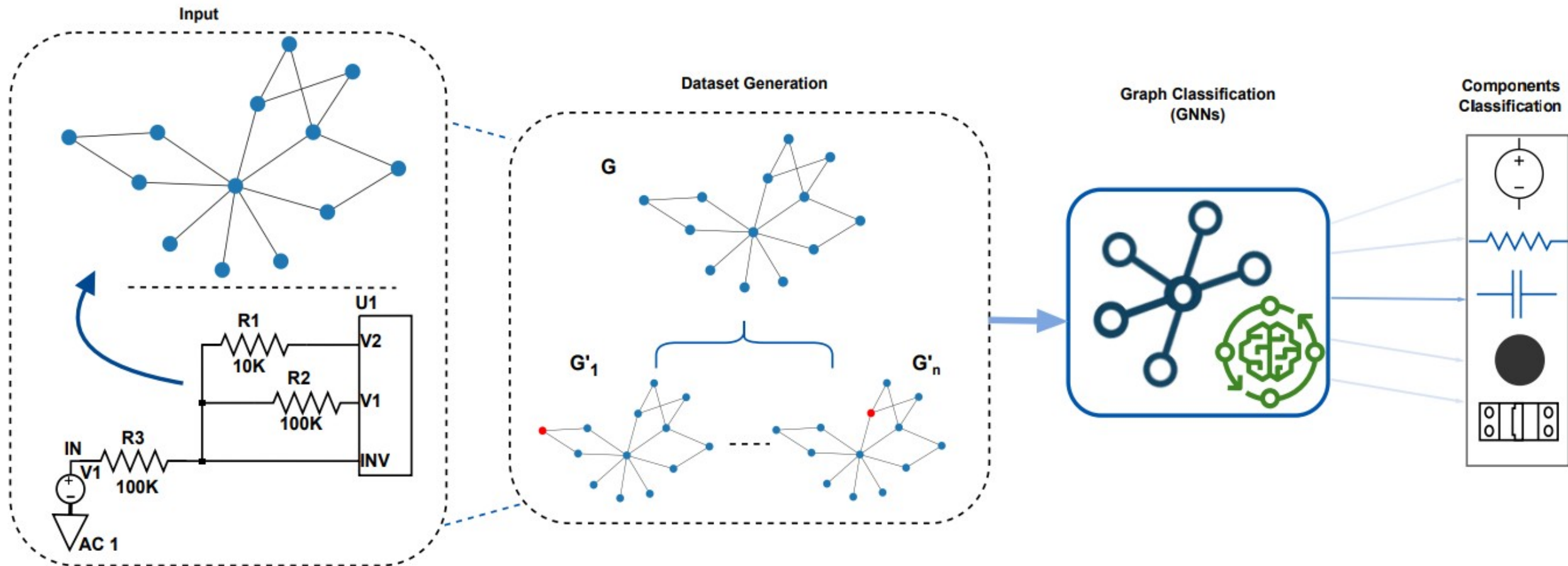


# Dataset Stats

**Table 2** Datasets' class-wise stats for component classification task.

	Ltspice Examples		Ltspice Demos		Kicad Github	
Component Class	Train	Test	Train	Test	Train	Test
Voltage_source	1238	303	142	38	N/A	N/A
Sub_element	1224	300	142	38	N/A	N/A
Junction-node	1243	305	142	38	254	72
Resistor	1107	272	142	38	135	38
BehavioralCap	835	189	124	37	114	32
UnifDistRCLine	N/A	N/A	N/A	N/A	142	43
JunFETrans	N/A	N/A	N/A	N/A	86	25

# Component Classification using GNNs



# Graph Neural Networks

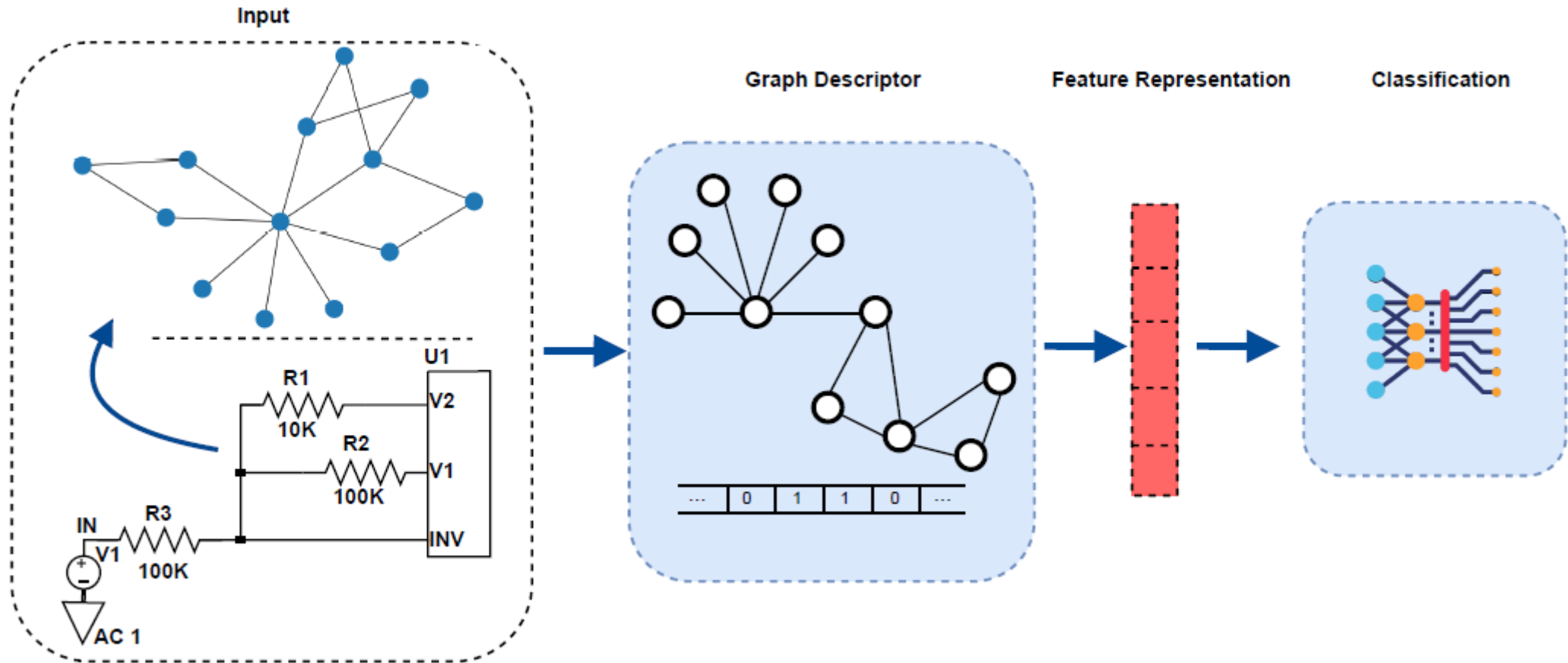
- Graph Convolutional Network (GCN)
- GraphSAGE
- Graph Attention Network (GAT)
- Graph Isomorphism Network (GIN)
- Nested Graph Neural Networks (NGNNs)
  - Nested GCN (NGCN)
  - Nested GAT (NGAT)
  - Nested GraphSAGE (NGraphSAGE)
  - Nested GIN (NGIN)

**Evaluation measure:**



# Graph Descriptors

- FGSD, NetLSD, DGSD, NetSimile, WL and Shortest Path



# Results

Dataset	GCN	GIN	GAT	GraphSAGE	NGCN	NGIN	NGAT	NGraphSAGE
Ltspice Examples	$79.5 \pm 0.01$	<b><math>89.8 \pm 0.01</math></b>	$78.1 \pm 0.04$	$78.6 \pm 0.03$	$81.9 \pm 1.04$	$88.9 \pm 0.01$	$82.7 \pm 0.03$	$82.2 \pm 0.03$
Ltspice Demos	$61.8 \pm 0.01$	<b><math>85.0 \pm 0.02</math></b>	$58.5 \pm 0.03$	$59.0 \pm 0.04$	$52.6 \pm 0.08$	$82.4 \pm 0.03$	$53.8 \pm 0.09$	$53.7 \pm 0.06$
Kicad Github	$51.7 \pm 0.03$	<b><math>67.4 \pm 0.02</math></b>	$56.7 \pm 0.04$	$46.6 \pm 0.02$	$58.1 \pm 0.01$	$62.5 \pm 0.02$	$56.8 \pm 0.03$	$57.0 \pm 0.02$

Dataset	DGSD	NetLSD	WL	FGSD	NetSimile	Shortest Path
Ltspice Examples	77.63	77.22	77.21	48.88	<b>85.11</b>	77.21
Ltspice Demos	57.60	52.07	48.27	33.03	<b>70.86</b>	48.26
Kicad Github	47.89	47.77	49.35	51.52	<b>59.27</b>	49.35

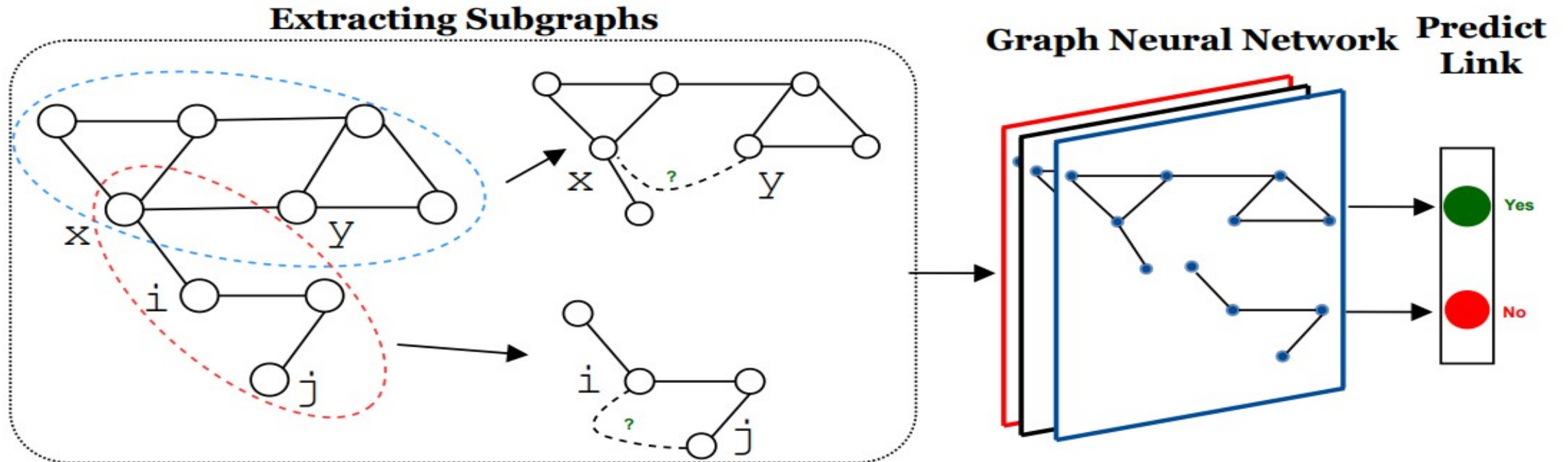
# Link Completion (problem 2)

- Data preparation
  - Stack graphs and node features

$$\mathcal{A} = \begin{bmatrix} \mathbf{A}_1 & & \\ & \ddots & \\ & & \mathbf{A}_n \end{bmatrix}, \mathbf{X} = \begin{bmatrix} \mathbf{X}_1 \\ \vdots \\ \mathbf{X}_n \end{bmatrix}$$

# Link Completion using SEAL

- SEAL:
  - Link prediction model based GNNs
  - Extracts enclosing subgraphs around the links to extract training and testing data.



# Results

<b>Dataset</b>	<b>SEAL</b>
Ltspice Examples	74.74
Ltspice Demos	61.39
Kicad Github	75.09

Thank you