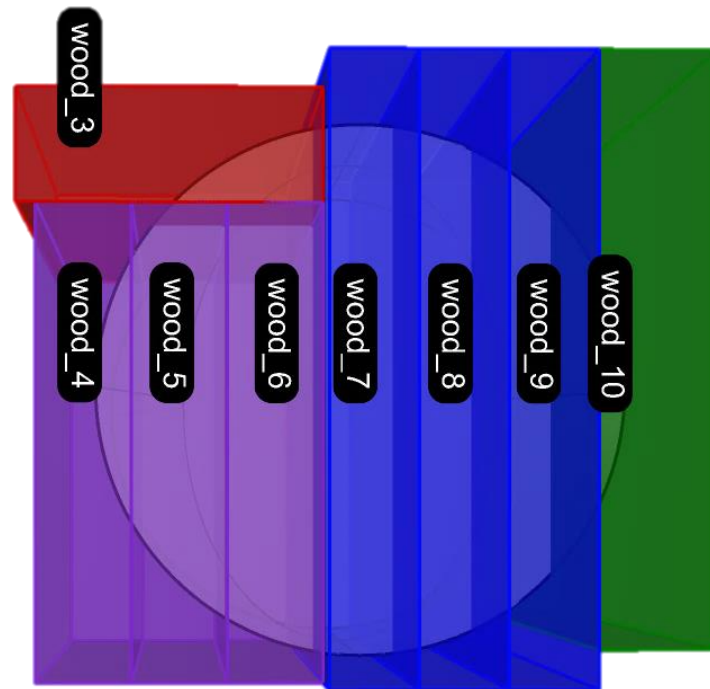
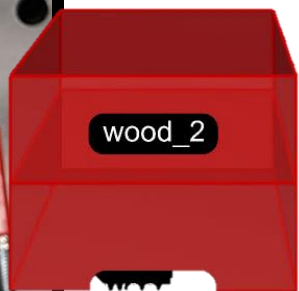


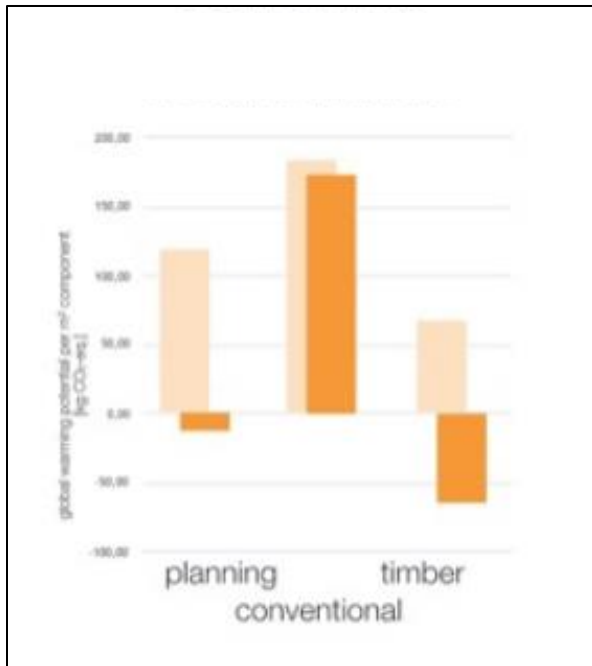
2

Componential Data

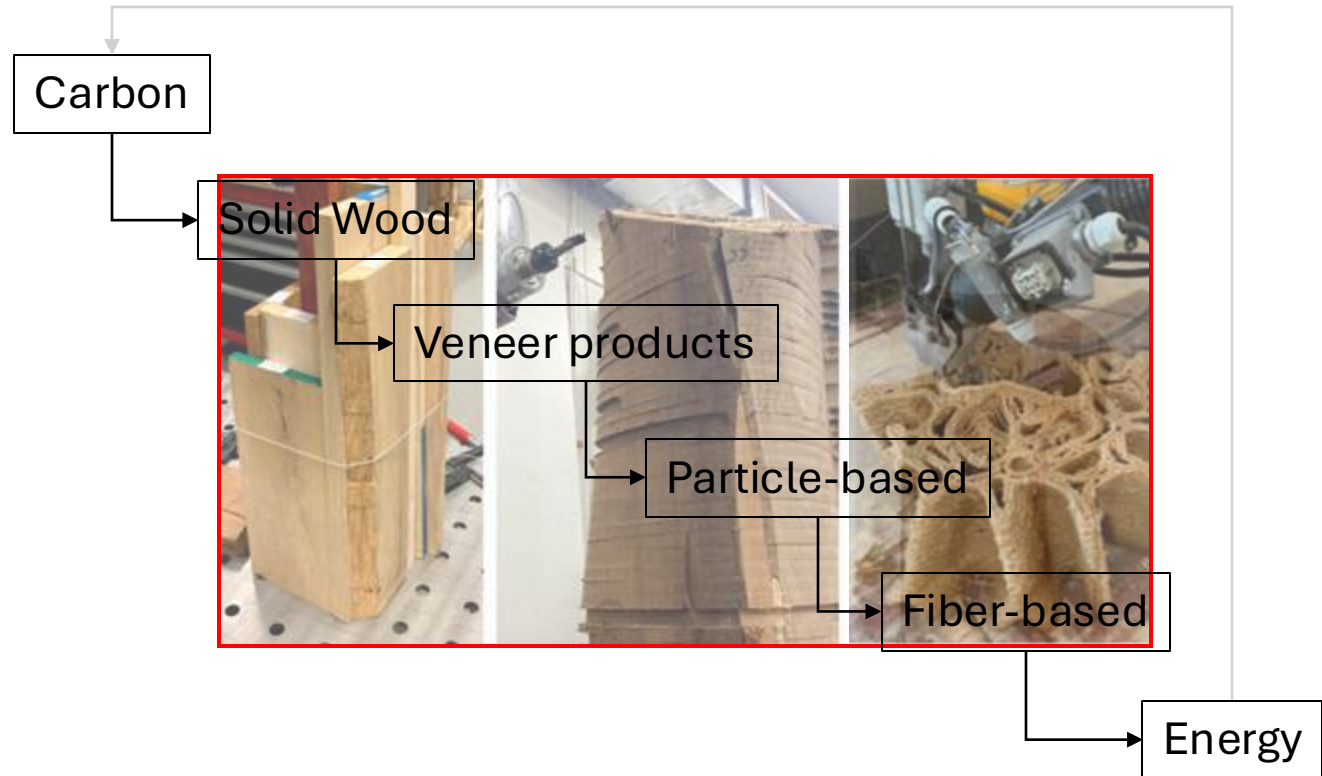
Research/on-going



Digital representation of wood packing



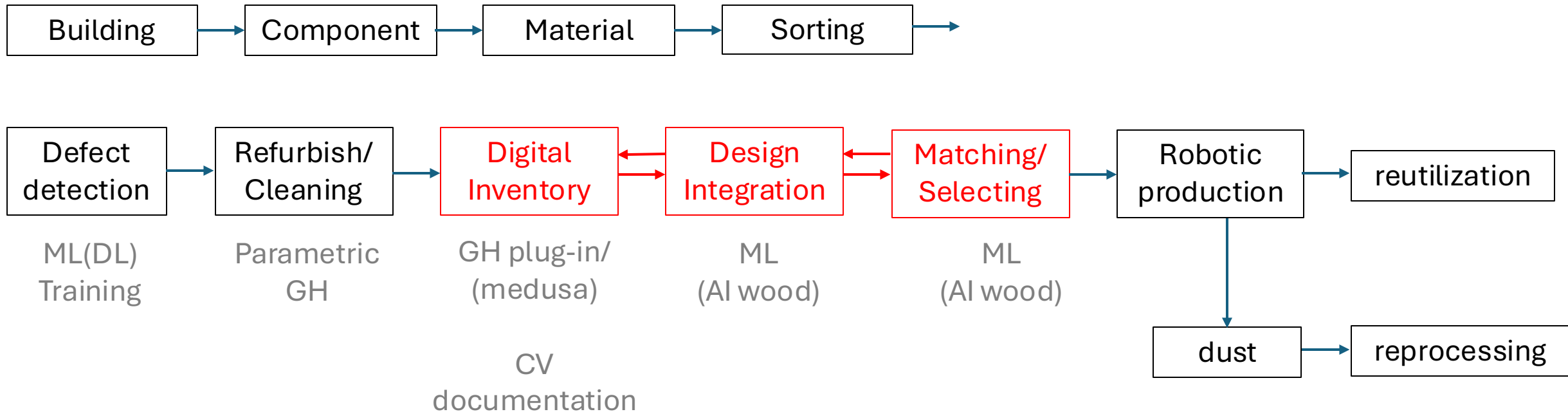
Planning: timber-concrete mix
 Conventional: concrete
 Timber: timber structure
 Light orange: release of carbon in 50 yrs
 Orange: embodied carbon



Decarbonization and circular wood: a cascading approach

State-of-the-Art

(Inter Höglmeier et al., 2017; Klinge et al., 2023; Kuzman et al., 2024)

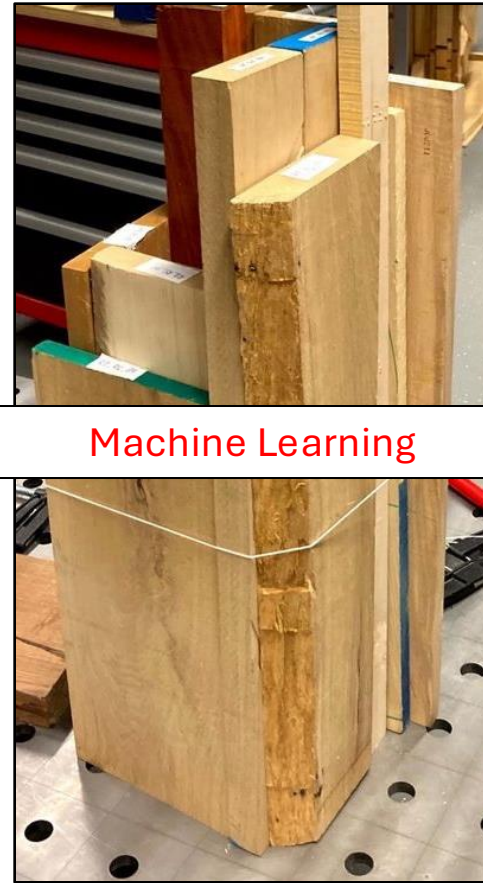


Digital workflow for circular design

State-of-the-Art



Wood Stock Inventory



Assemblies

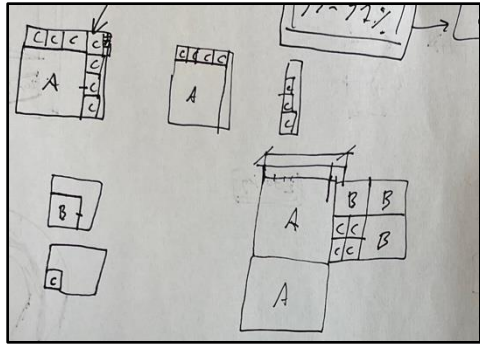


Target

AI-supported Design-to-Construction Workflow: Circular Wood In The Neighborhood

Approach

(@Robotic Building, 2022)

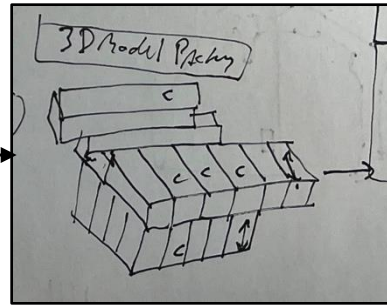


Size: 1, 2, 3

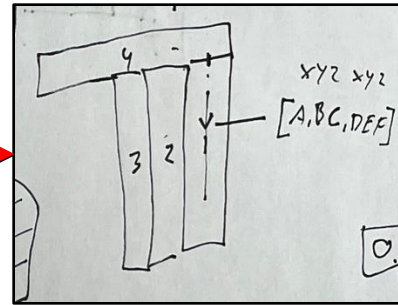


Color/type: 1, 2, 3

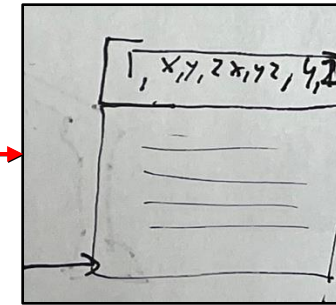
Expected Findings:



Design Variants
3d models



Spatial relation
Sequence/proximity

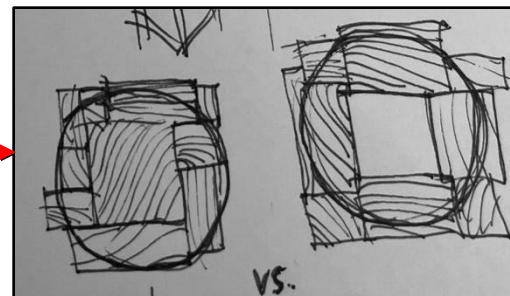


Training input
3D >> 2D

(1)
Output

(2)

Evaluation



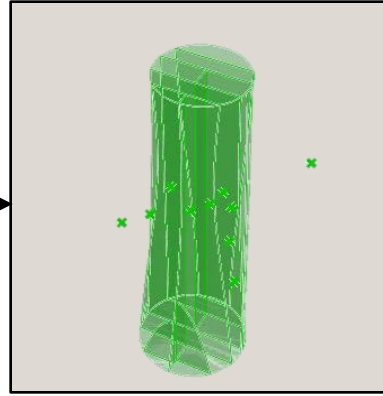
Feedback/rewards



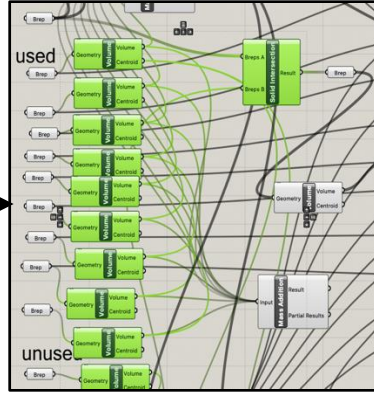
Research Design and Objective



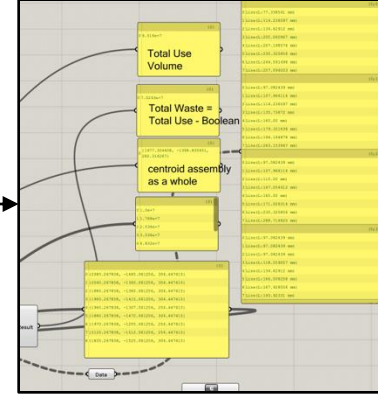
Physical design outcome



Digital 3D representation



Transcoding: geometrical relation



Panels: flattened structured data

```
df_summary
```

assembly_ID	target_ID	visual_score	hitting_feasibility	circularity_score	used_wood_count
0	A001	T001	0.25	1	NAN
1	A002	T001	0.25	1	NAN
2	A003	T001	0.75	1	NAN
3	A004	T001	0.75	1	NAN
4	A005	T001	0.90	0	NAN

5 rows x 21 columns

```
df_details
```

AssemblyID	TargetID	WoodID	Used	CenterX	CenterY	CenterZ	RelX	RelZ	Width	Depth	
0	A2	structure_01	wood_001	1	120	80	0	20	10	0	30
1	A2	structure_01	wood_002	1	150	90	0	80	20	0	25
2	A3	structure_01	wood_003	1	100	70	0	-10	-20	0	20
3	A3	structure_01	wood_004	1	130	100	0	30	10	0	30

```
Inv
```

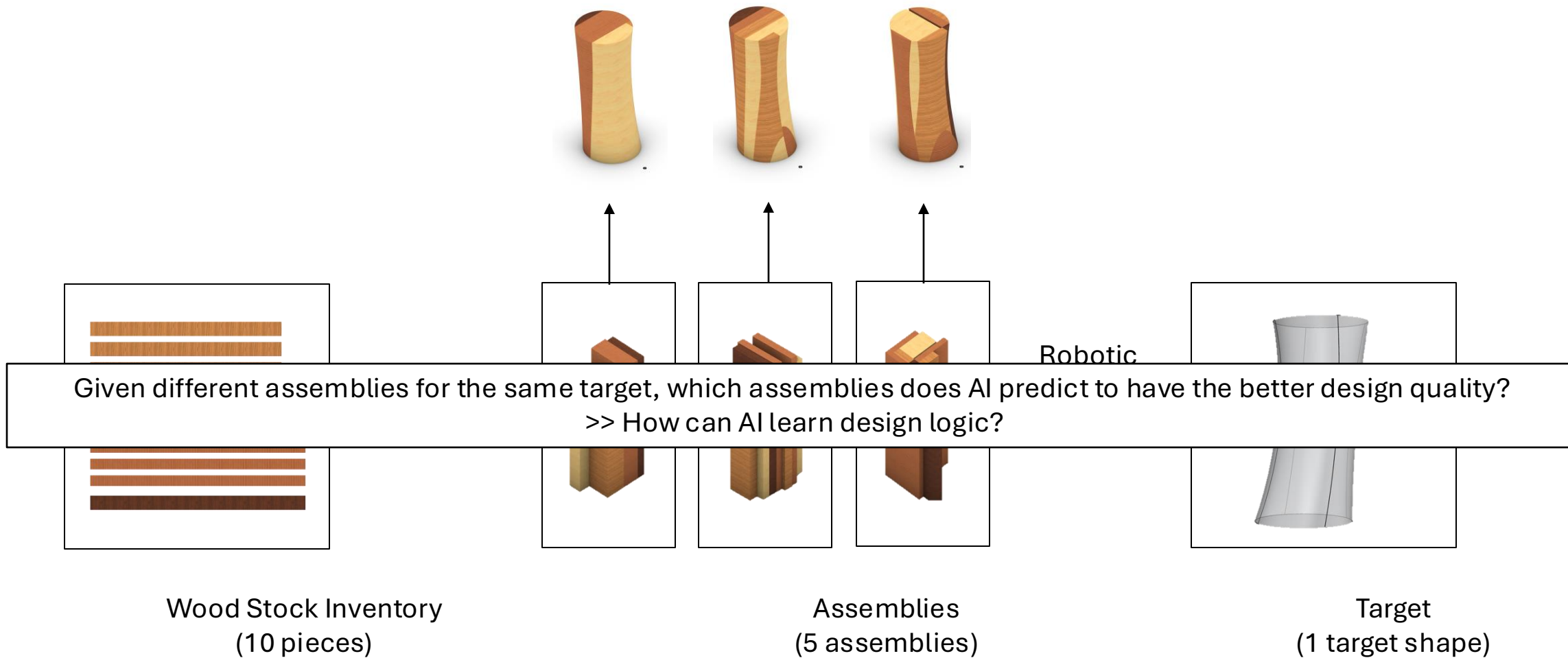
WoodID	Width	Depth	Length	Color	WoodType	CenterX	CenterY	CenterZ	WoodVolume
0	W001	180	60	800	brown	-1834.669227	-131.266220	400	7680000.0
1	W002	180	60	800	brown	-1834.669227	-131.266220	400	7680000.0
2	W003	180	60	800	brown	-1834.669227	-75.266220	400	7680000.0
3	W004	250	50	800	red	-1789.669227	8.745304	400	10000000.0
4	W005	250	50	800	red	-1789.669227	8.745304	400	10000000.0
5	W006	250	50	800	red	-1789.669227	108.745304	400	10000000.0
6	W007	300	45	900	yellow	-1754.669227	214.664652	450	12960000.0
7	W008	300	45	900	yellow	-1754.669227	259.664652	450	12960000.0

CSVs: input for python/AI

Visual/Spatial (Rhino/Grasshopper) → Text-based (ChatGPT/Google Collab)

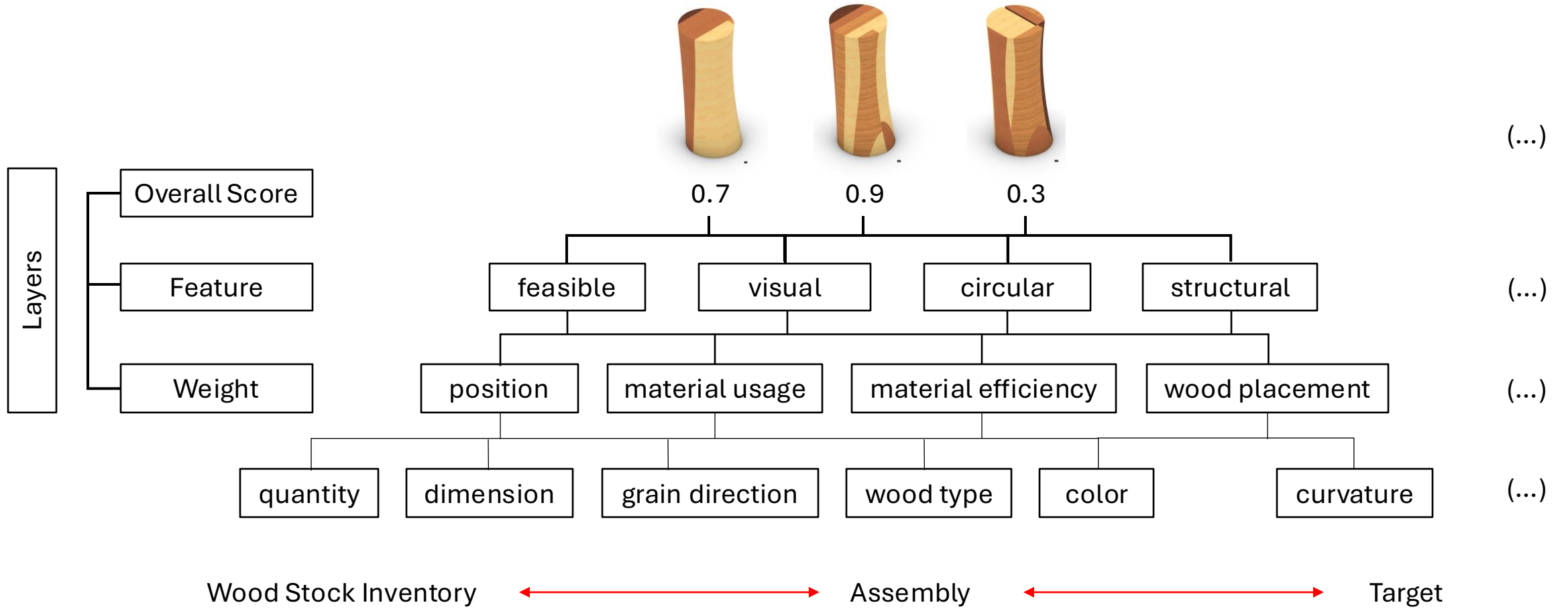
In parallel: visual/spatial and latent environment

Methodology



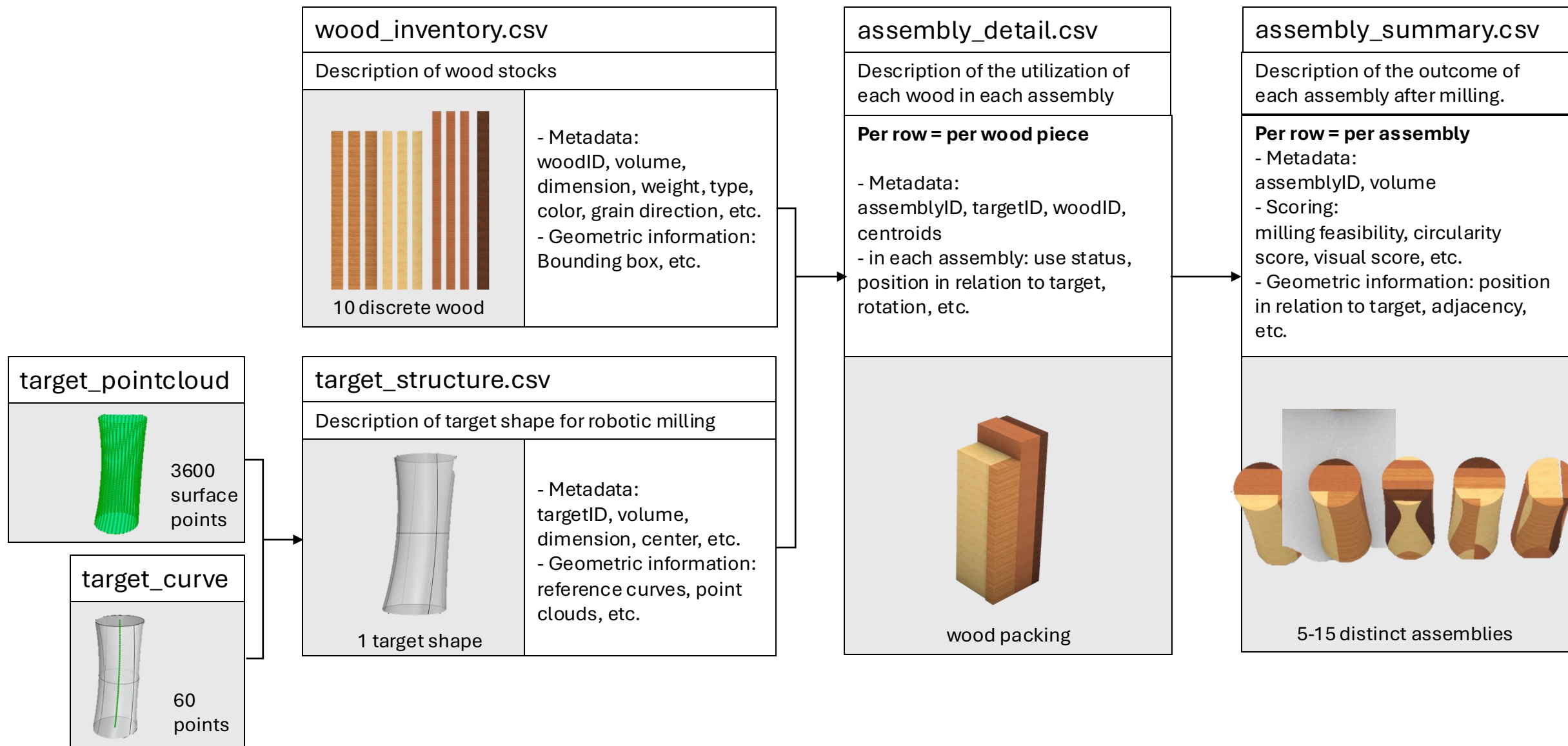
Understand (Non-)Spatial Association within Design Assemblies

Research Aim

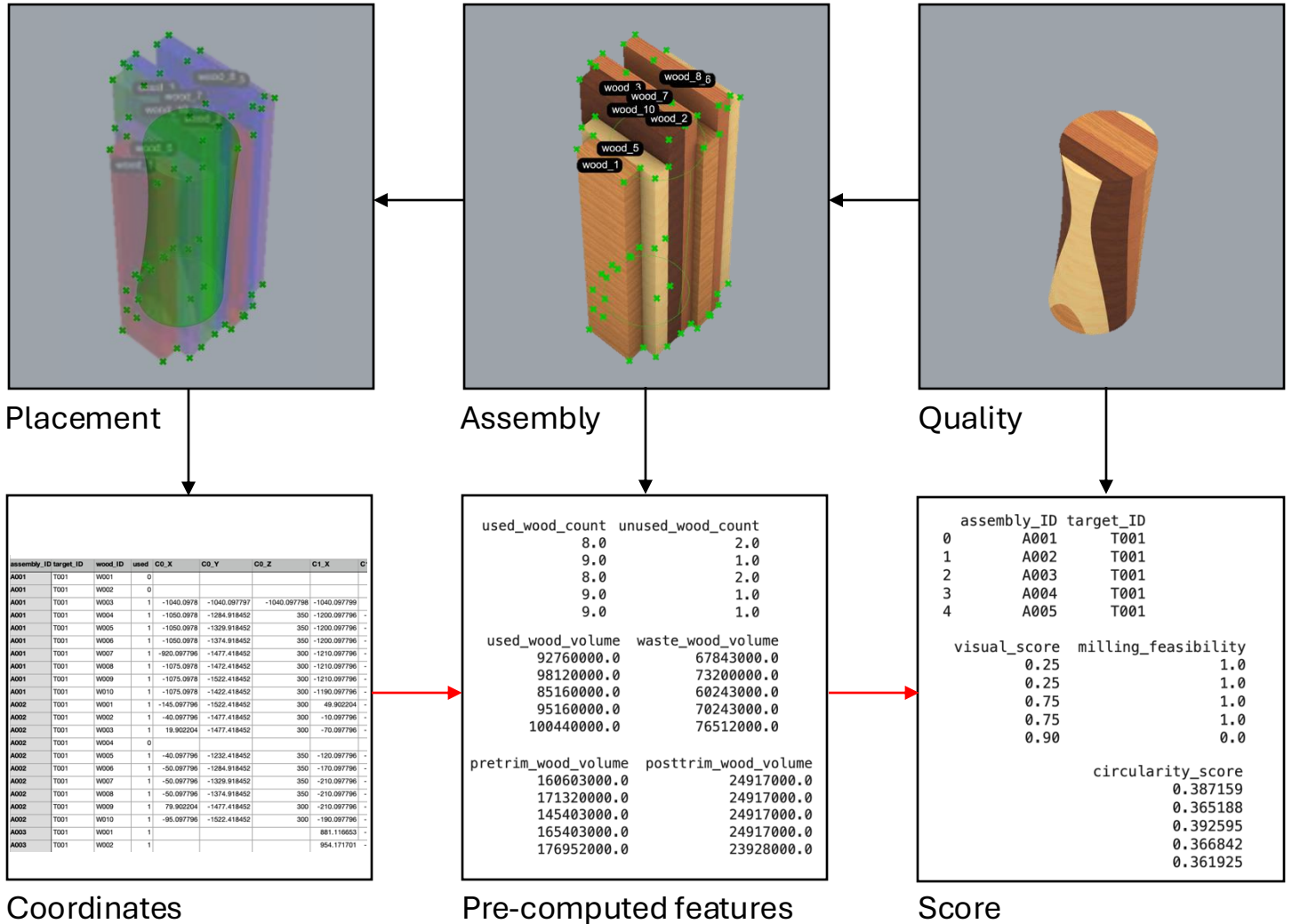


Deep learning and neural network

Method



Dataset and Schema



assembly_ID	target_ID	wood_ID	used	C0_X	C0_Y	C0_Z	C1_X	C1_Y	C1_Z
A001	T001	W001	0						
A001	T001	W002	0						
A001	T001	W003	1	-1040.09779	-1040.09779	-1040.09779	-1040.09779	-1040.09779	-1040.09779
A001	T001	W004	1	-1050.09779	-1284.918452	350	-1200.09779	-1200.09779	-1200.09779
A001	T001	W005	1	-1050.09779	-1329.918452	350	-1200.09779	-1200.09779	-1200.09779
A001	T001	W006	1	-1050.09779	-1374.918452	350	-1200.09779	-1200.09779	-1200.09779
A001	T001	W007	1	-920.09779	-1477.418452	300	-1210.09779	-1210.09779	-1210.09779
A001	T001	W008	1	-1075.09779	-1477.418452	300	-1210.09779	-1210.09779	-1210.09779
A001	T001	W009	1	-1075.09779	-1522.418452	300	-1210.09779	-1210.09779	-1210.09779
A001	T001	W010	1	-1075.09779	-1422.418452	300	-1190.09779	-1190.09779	-1190.09779
A002	T001	W001	1	-145.09779	-1522.418452	300	-49.902204	-49.902204	-49.902204
A002	T001	W002	1	-40.09779	-1477.418452	300	-70.09779	-70.09779	-70.09779
A002	T001	W003	1	19.902204	-1477.418452	300	-70.09779	-70.09779	-70.09779
A002	T001	W004	0						
A002	T001	W005	1	-40.09779	-1232.418452	350	-120.09779	-120.09779	-120.09779
A002	T001	W006	1	-50.09779	-1284.918452	350	-170.09779	-170.09779	-170.09779
A002	T001	W007	1	-50.09779	-1329.918452	350	-210.09779	-210.09779	-210.09779
A002	T001	W008	1	-50.09779	-1374.918452	350	-210.09779	-210.09779	-210.09779
A002	T001	W009	1	79.902204	-1477.418452	300	-210.09779	-210.09779	-210.09779
A002	T001	W010	1	-95.09779	-1522.418452	300	-160.09779	-160.09779	-160.09779
A003	T001	W001	1				881.116653	881.116653	881.116653
A003	T001	W002	1				954.171701	954.171701	954.171701

used_wood_count	unused_wood_count
8.0	2.0
9.0	1.0
8.0	2.0
9.0	1.0
9.0	1.0

used_wood_volume	waste_wood_volume
92760000.0	67843000.0
98120000.0	73200000.0
85160000.0	60243000.0
95160000.0	70243000.0
100440000.0	76512000.0

pretrim_wood_volume	posttrim_wood_volume
160603000.0	24917000.0
171320000.0	24917000.0
145403000.0	24917000.0
165403000.0	24917000.0
176952000.0	23928000.0

assembly_ID	target_ID
0	A001 T001
1	A002 T001
2	A003 T001
3	A004 T001
4	A005 T001

visual_score	milling_feasibility
0.25	1.0
0.25	1.0
0.75	1.0
0.75	1.0
0.90	0.0

circularity_score
0.387159
0.365188
0.392595
0.366842
0.361925

Translation/transcoding of componential information

Training Input and Output

$$\text{circularity_score} = \text{material_efficiency} \times e^{-\alpha \cdot N_{\text{used}}}$$

assembly_summary.csv					
Y (output) circularity_score					
X (input)	visual_score	milling_feasibility	used_wood_count	unused_wood_count	
	0	0.25	1.0	8.0	2.0
	1	0.25	1.0	9.0	1.0
	2	0.75	1.0	8.0	2.0
	3	0.75	1.0	9.0	1.0
4	0.90	0.0	9.0	1.0	
	used_wood_volume	waste_wood_volume	pretrim_wood_volume	posttrim_wood_volume	
	92760000.0	67843000.0	160603000.0	24917000.0	
	98120000.0	73200000.0	171320000.0	24917000.0	
	85160000.0	60243000.0	145403000.0	24917000.0	
	95160000.0	70243000.0	165403000.0	24917000.0	
	100440000.0	76512000.0	176952000.0	23928000.0	
	rel_X	rel_Y	rel_Z	rel_dist	
	-5.094741	-1.232805	29.870649	30.327081	
	86.856718	-17.736956	28.248800	93.041301	
	-8.207530	1.353125	30.782349	31.886478	
	17.883142	-28.879282	-17.502605	38.212051	
	28.258722	-10.763132	-27.238227	40.697929	

A001
0.387159



A002
0.365188



A003
0.392595



A004
0.366842



A005
0.361925



Which is the most circular assembly?

Ground Truth

Training_V1

2
0.383917

A001
0.387159



2

5
0.348795

A002
0.365188



4

1
0.393716

A003
0.392595



1

3
0.368535

A004
0.366842



3

4
0.363053

A005
0.361925

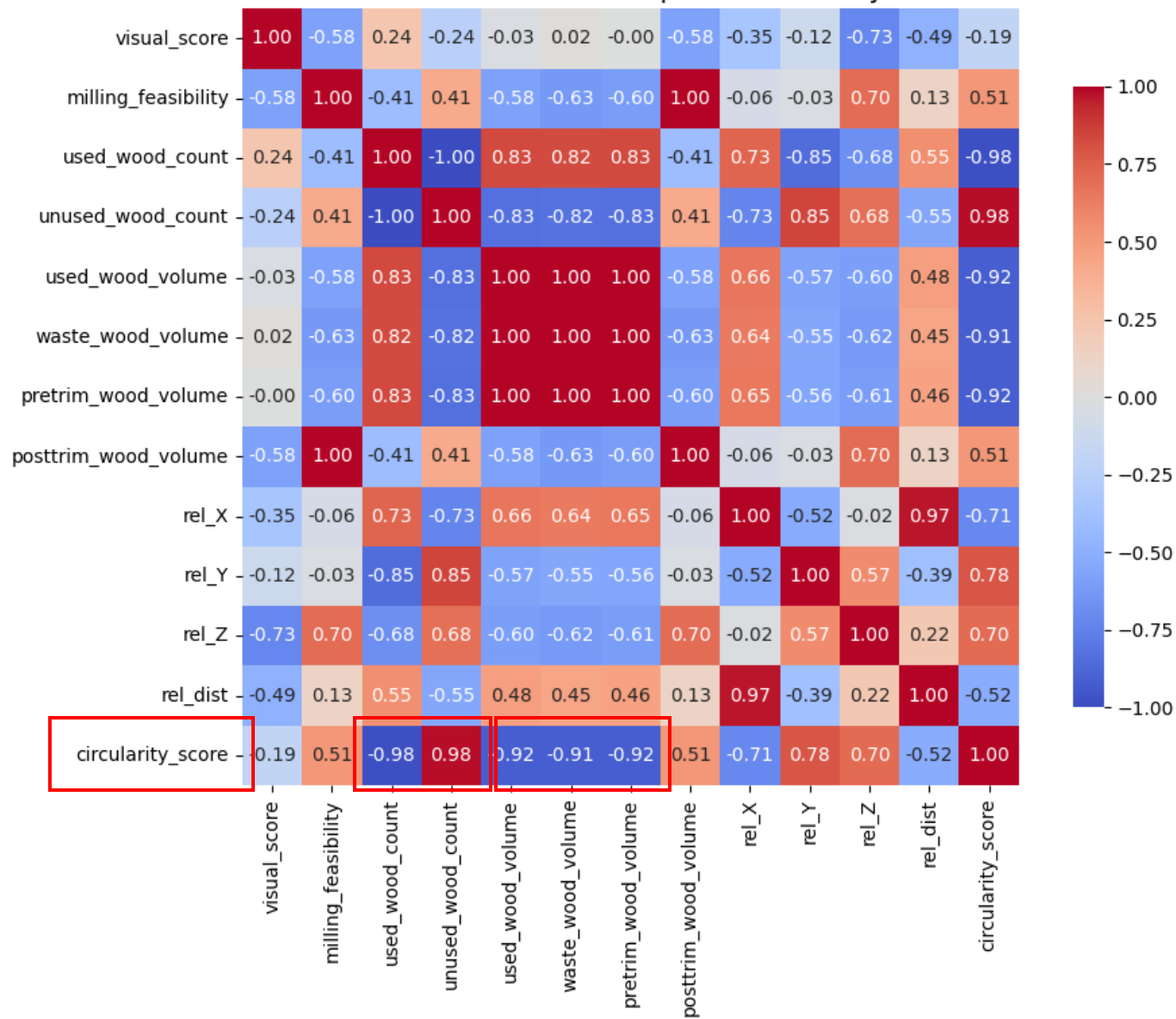


5

Prediction

Result_V1

Feature Correlation Heatmap with Circularity Score



Correlation

Result_V1

```
[ ]
    "circ": float(row["circularity_score"]),
    "vis": float(row["visual_score"])
}

print("Example labels:")
for k in list(labels.keys())[:3]:
    print(k, labels[k])
```

```
Example labels:
A001 {'feas': 1.0, 'circ': nan, 'vis': 0.25}
A002 {'feas': 1.0, 'circ': nan, 'vis': 0.25}
A003 {'feas': 1.0, 'circ': nan, 'vis': 0.75}
```

```
[ ]
# STEP 4 – Combine into DeepSets dataset format
# -----
assemblies = [] # List of (wood_piece_matrix, label_dict)

for a_id in assembly_groups:
    assemblies.append((assembly_groups[a_id], labels[a_id]))

print("DeepSets dataset assembled.")
print("Total assemblies =", len(assemblies))
```

```
DeepSets dataset assembled.
Total assemblies = 5
```

```
[ ]
X = df[coord_cols].values

y_feas = df["milling_feasibility"].values # classification
y_circ = df["circularity_score"].values # regression
y_vis = df["visual_score"].values # regression
```

Coordinates as input

Training_V2



	assembly_ID	target_ID	wood_ID	used	C0_X	C0_Y	C0_Z	C1_X	C1_Y	C1_Z
0	A001	T001	W001	0	NaN	NaN	NaN	NaN	NaN	NaN
1	A001	T001	W002	0	NaN	NaN	NaN	NaN	NaN	NaN
2	A001	T001	W003	1	0.480938	329.858872	-1339.916670	0.480935	329.858869	-1339.916673
3	A001	T001	W004	1	-9.519062	85.038217	50.181128	-159.519062	-177.461783	-399.818872
4	A001	T001	W005	1	-9.519062	40.038217	50.181128	-159.519062	-127.461783	-399.818872

5 rows x 41 columns

```
# STEP 1 – Detect coordinate feature columns
# -----

coord_cols = [
    c for c in detail.columns
    if (c.startswith("C") and c[1].isdigit() and c[2] == "_")
]

print(len(coord_cols), "feature columns:", coord_cols)
```

27 feature columns: ['C0_X', 'C0_Y', 'C0_Z', 'C1_X', 'C1_Y', 'C1_Z', 'C2_X', 'C2_Y', 'C2_Z', 'C3_X', 'C3_Y']

```
# STEP 2 – Group wood pieces by assembly
# -----
```

assembly_groups = {}