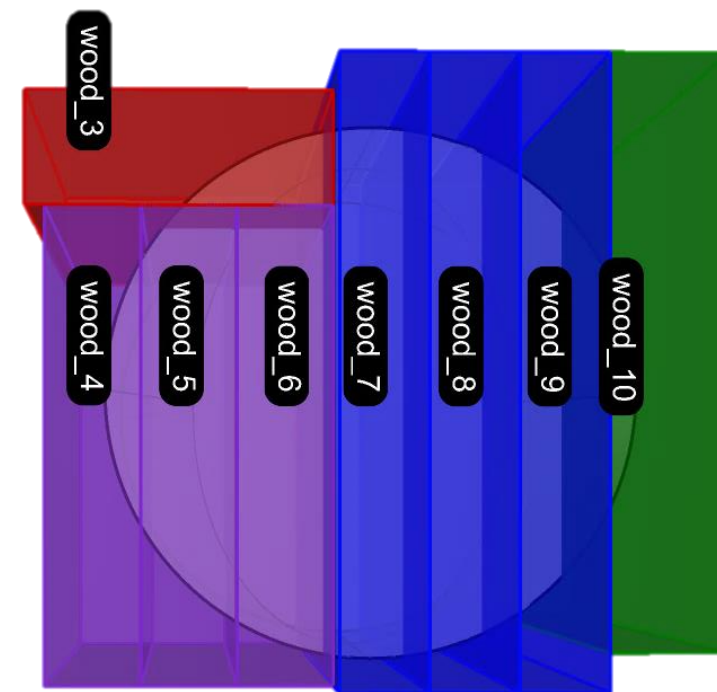


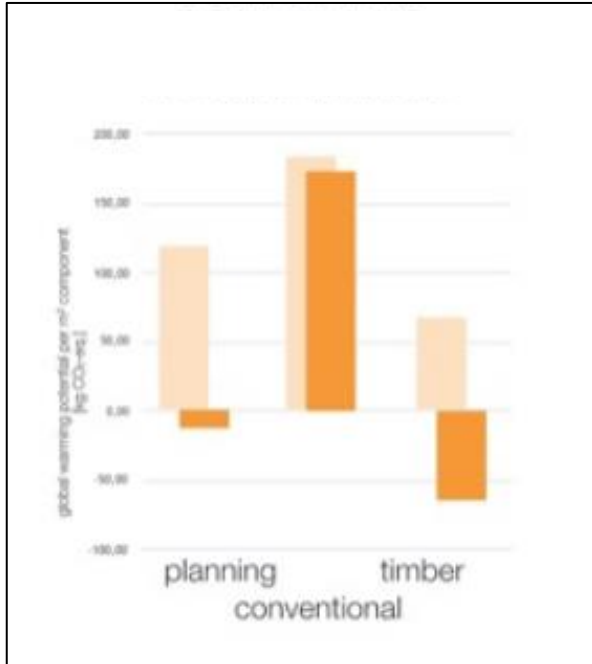
2

Componential Data

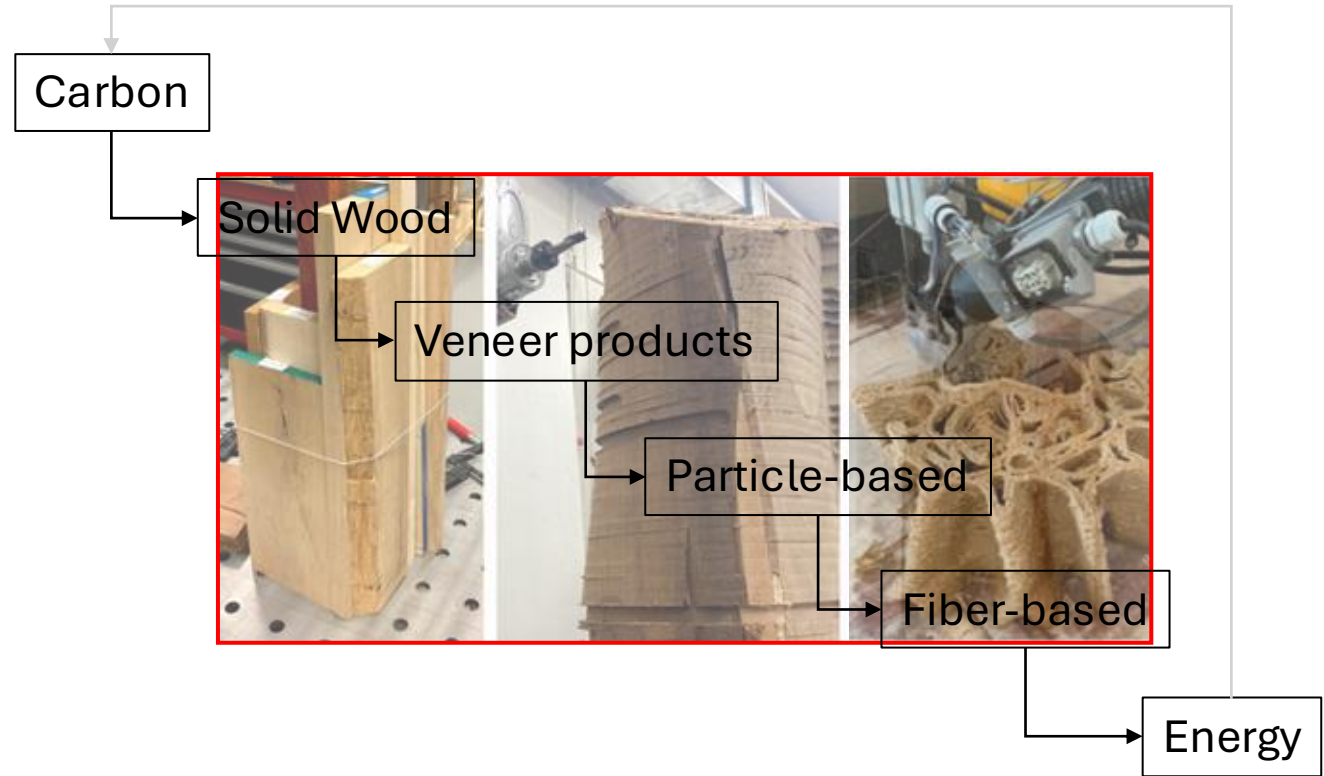
Research/on-going



Digital representation of wood packing



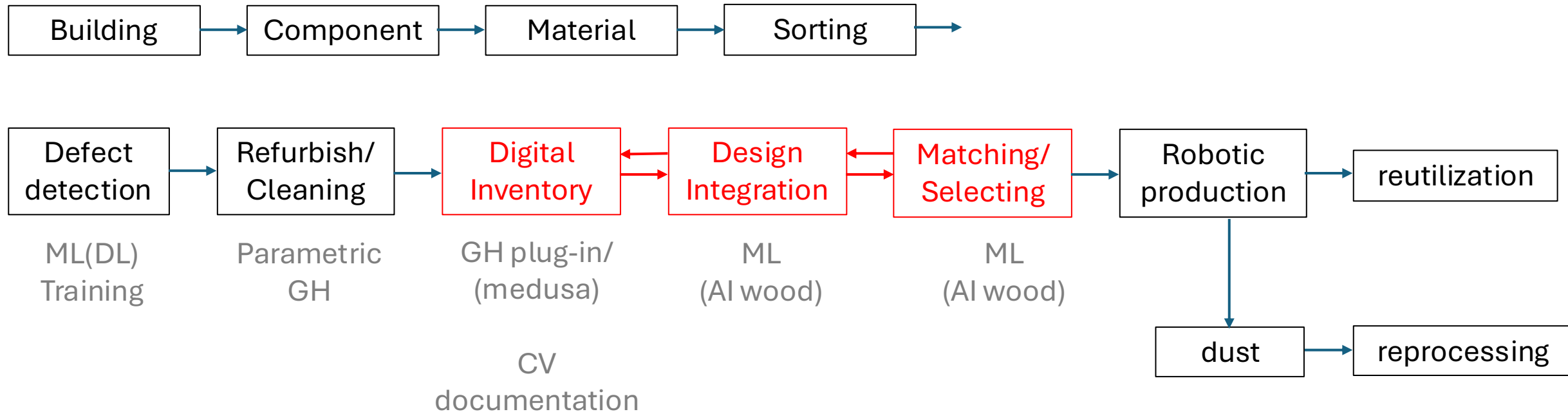
Planning: timber-concrete mix
 Conventional: concrete
 Timber: timber structure
 Light orange: release of carbon in 50 yrs
 Orange: embodied carbon



Decarbonization and circular wood: a cascading approach

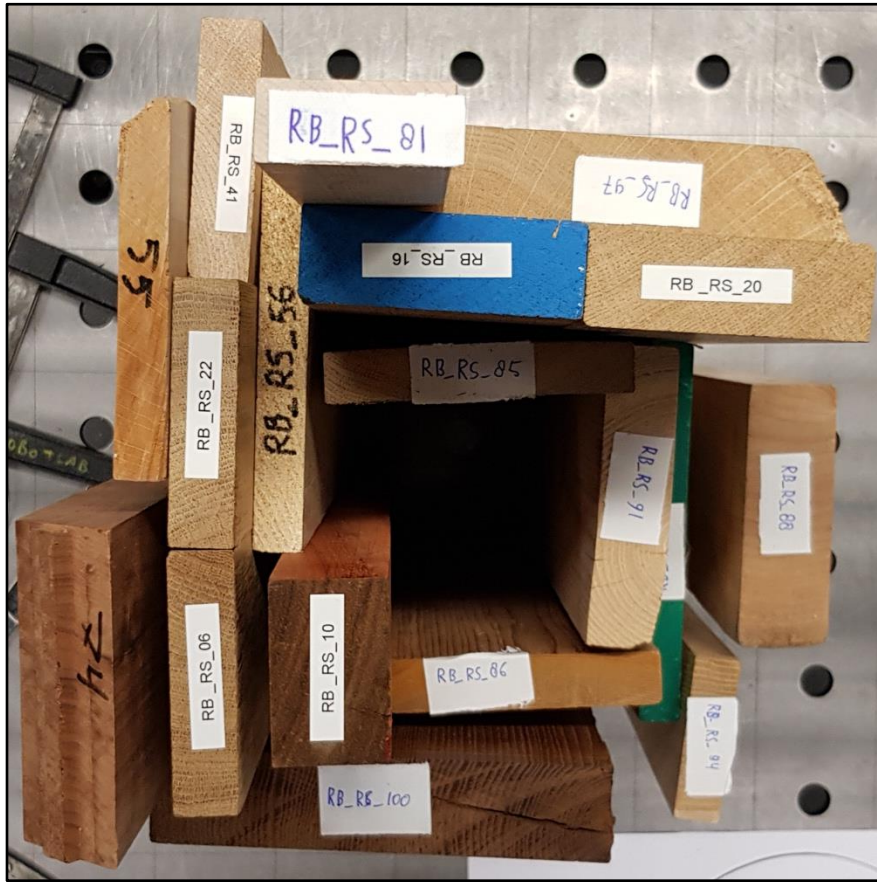
State-of-the-Art

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

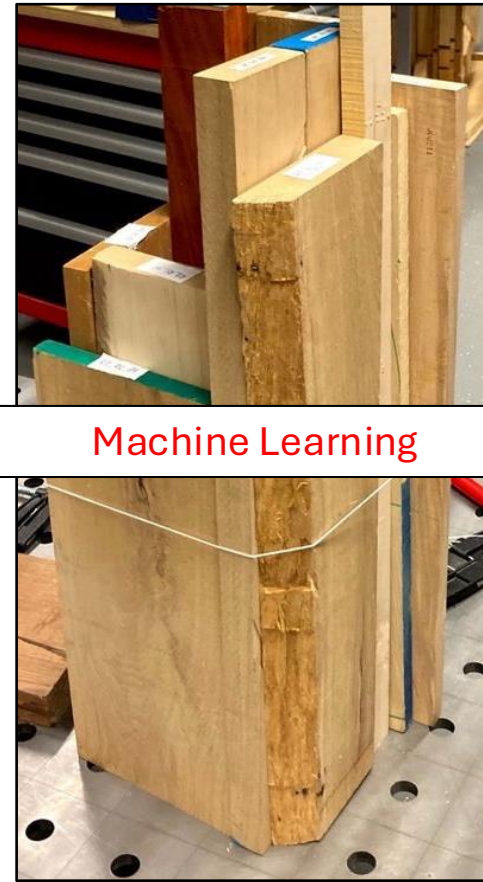


Digital workflow for circular design

State-of-the-Art



Wood Stock Inventory



Assemblies

Machine Learning

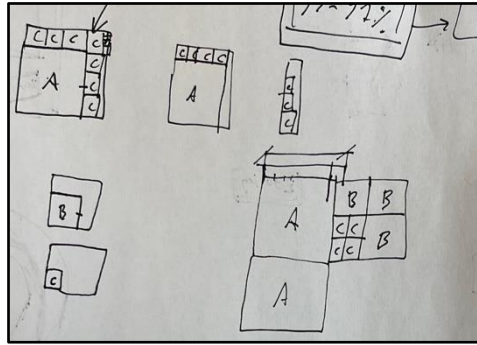


Target

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

Approach

(@Robotic Building, 2022)

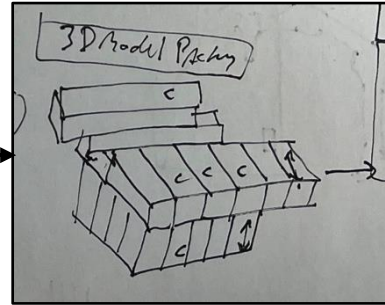


Size: 1, 2, 3

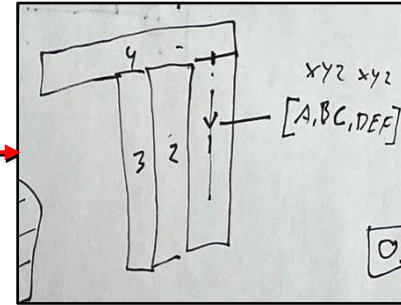


Color/type: 1, 2, 3

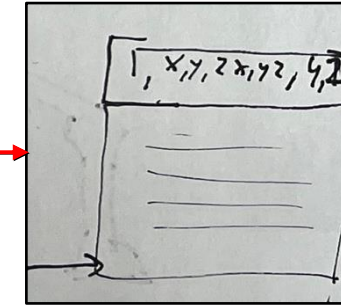
Expected Findings:



Design Variants
3d models



Spatial relation
Sequence/proximity

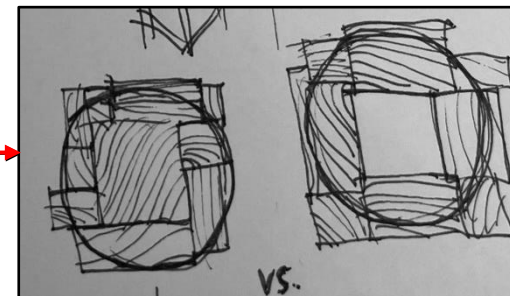


Training input
3D >> 2D

(1)
Output

(2)

Evaluation



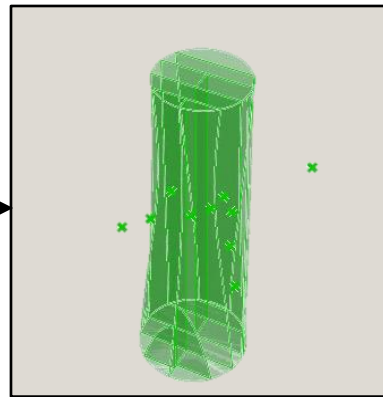
Feedback/rewards



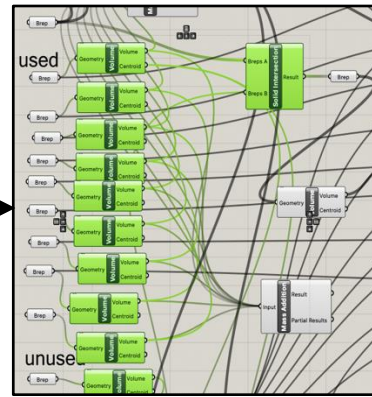
Research Design and Objective



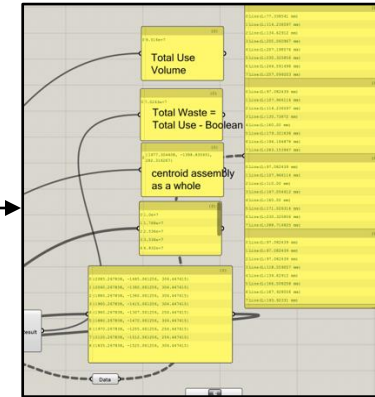
Physical
design outcome



Digital 3D
representation



Transcoding: geo-
metrical relation



Panels: flattened
structured data

assembly_ID	target_ID	visual_score	milling_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

AssemblyID	TargetID	WoodID	Used	CenterX	CenterY	CenterZ	RelX	RelY	RelZ	Width	Depth
0	A2	structure_01	wood_001	1	120	80	0	20	10	0	30
1	A2	structure_01	wood_002	1	130	90	0	50	20	0	25
2	A3	structure_01	wood_003	1	130	70	0	-10	-20	0	20
3	A3	structure_01	wood_004	1	130	100	0	30	10	0	30

WoodID	Width	Depth	Length	Color	WoodType	CenterX	CenterY	CenterZ	WoodVolume
0	W001	160	60	800	brown	-1834.689237	-135.266220	400	7680000.0
1	W002	160	60	800	brown	-1834.689237	-135.266220	400	7680000.0
2	W003	160	60	800	brown	-1834.689237	-135.266220	400	7680000.0
3	W004	250	50	800	red	-1789.689237	6.745304	400	10000000.0
4	W005	250	50	800	red	-1789.689237	50.745304	400	10000000.0
5	W006	250	50	800	red	-1789.689237	150.745304	400	10000000.0
6	W007	320	45	900	yellow	-1754.689237	214.664652	450	12960000.0
7	W008	320	45	900	yellow	-1754.689237	259.664652	450	12960000.0

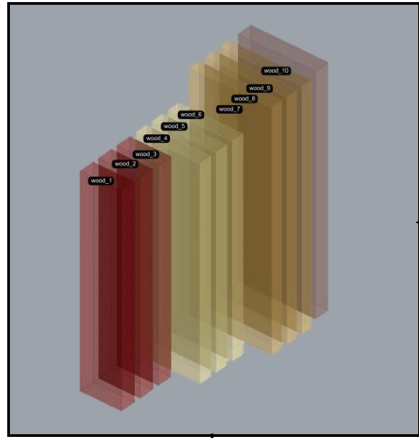
CSVs: input for
python/AI

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

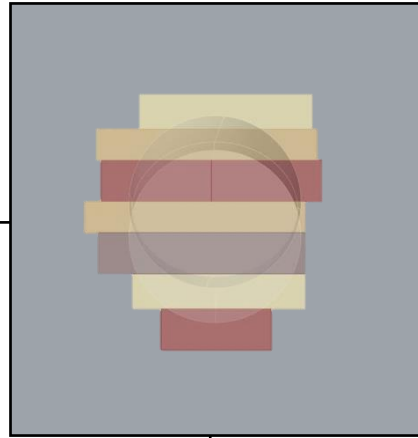
In parallel: visual/spatial and latent environment

Methodology

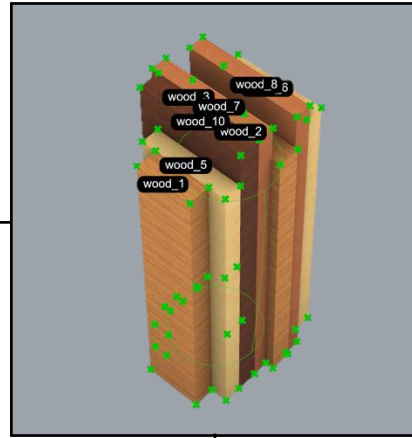
Visual/Spatial



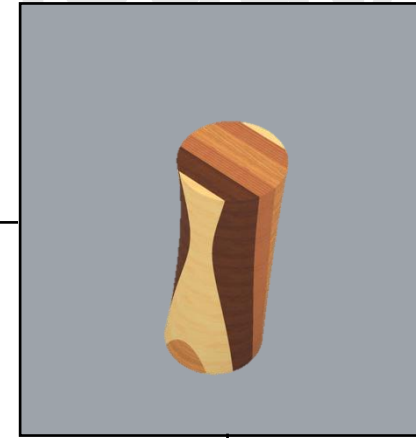
Wood stock



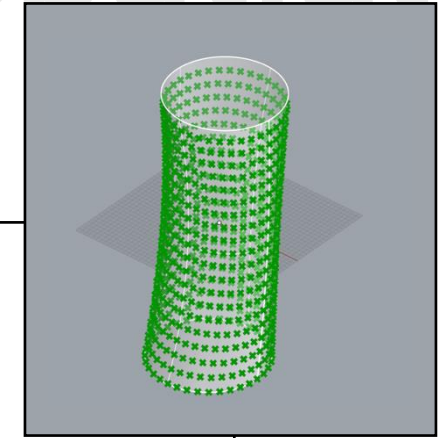
Piece-wise placement to target



Assembly



Quality



Target

Inventory						
	WoodID	Width	Depth	Length	Color	WoodType
0	W001	160	60	800	brown	oak
1	W002	160	60	800	brown	oak
2	W003	160	60	800	brown	oak
3	W004	250	50	800	red	pine
4	W005	250	50	800	red	pine
5	W006	250	50	800	red	pine
6	W007	320	45	900	yellow	birch
7	W008	320	45	900	yellow	birch
8	W009	320	45	900	yellow	birch
9	W010	300	60	900	darkbrown	cedar

Material inventory

	dx	dy	dz
0	-61.489243	80.806816	3.137041
1	56.276402	74.193428	1.135717
2	31.024946	105.680374	1.032206
3	-59.075989	52.907494	4.055572
4	-5.940668	3.229298	-1.050602

width_axis_x	width_axis_y	width_axis_z
0.957094	-0.289542	0.011714
0.903381	-0.428144	0.024398
0.816569	-0.577087	-0.013635
0.989180	-0.146045	-0.013921
0.764114	-0.644990	-0.010812

depth_axis_x	depth_axis_y	depth_axis_z
0.456296	-0.889584	0.020852
0.934880	-0.354935	0.004614
0.952984	0.301886	-0.026193
0.636336	0.771380	0.006951
0.790178	0.612830	-0.007615

Coordinates / pose

	feature	coef
8	compactness_bbox	1.106074
13	min_margin	0.914813
1	used_wood_volume_geom	0.875031
10	target_to_center_dist_p95	-0.746059
14	mean_margin	-0.678492
9	target_to_center_dist_mean	0.643668
3	avg_nn_dist_geom	0.607891
0	used_wood_count_geom	0.440629
6	overlap_count	0.344779
5	overlap_total	-0.221944
2	centroid_spread_mean	0.204700
7	overlap_ratio	-0.190209
11	center_coverage_ratio	0.163934
12	center_undercovered_ratio	0.041919
4	mean_neighbor_count	-0.031361
15	negative_margin_count	0.000000

Pre-computed features

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

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

Score

target_pc				
target_ID	Pc_Index	Pc_X	Pc_Y	Pc_Z
0	T001	0	-915.578734	-1402.611790
1	T001	1	-917.477764	-1380.905772
2	T001	2	-923.117155	-1359.859275
3	T001	3	-932.325558	-1340.111791
4	T001	4	-944.823173	-1322.263345
...	...	...	...	...
2191	T001	2191	-950.372525	-1266.079484
2192	T001	2192	-936.716779	-1283.058254
2193	T001	2193	-926.216831	-1302.150368
2194	T001	2194	-919.191711	-1322.775728
2195	T001	2195	-915.854874	-1344.307640

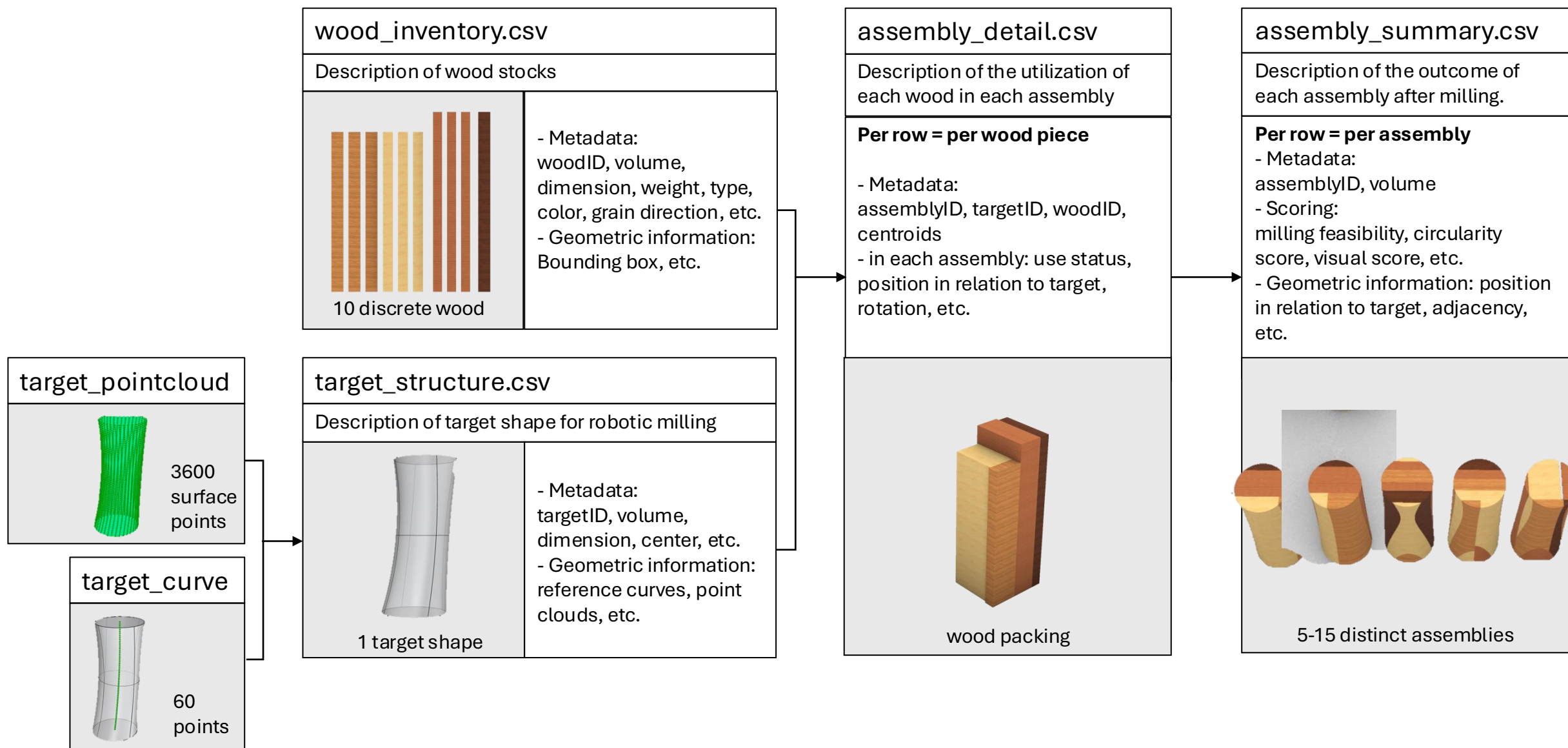
2196 rows x 5 columns

Target shape / requirement

Translation/transcoding tectonic to computational intelligence

Methodology

Text-based



Dataset and Schema



A009T.jpg



A010T.jpg



A011T.jpg



A012T.jpg



A013T.jpg



A014T.jpg



A015T.jpg



A016T.jpg



A017T.jpg



A018T.jpg



A019T.jpg



A020T.jpg



A021T.jpg



A022T.jpg



A023T.jpg



A024T.jpg



A025T.jpg



A026T.jpg



A027T.jpg



A028T.jpg



A029T.jpg



A030T.jpg



A031T.jpg



A032T.jpg



A033T.jpg



A034T.jpg



A035T.jpg



A036T.jpg



A037T.jpg



A038T.jpg



A039T.jpg



A040T.jpg



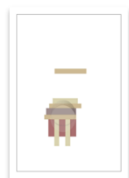
A041T.jpg



A042T.jpg



A043T.jpg



A044T.jpg



A045T.jpg



A046T.jpg



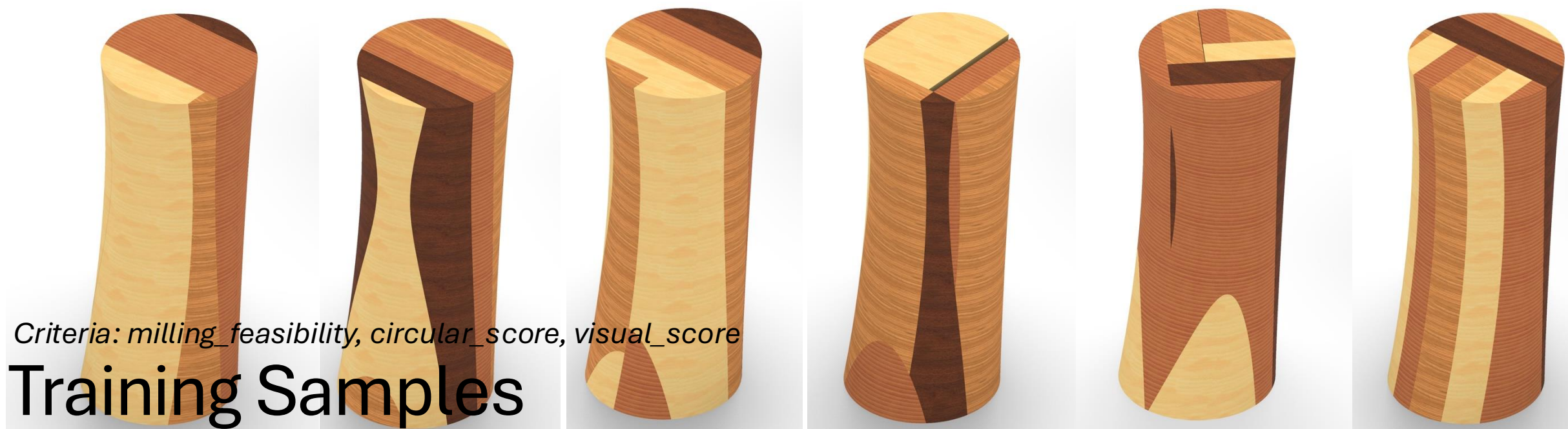
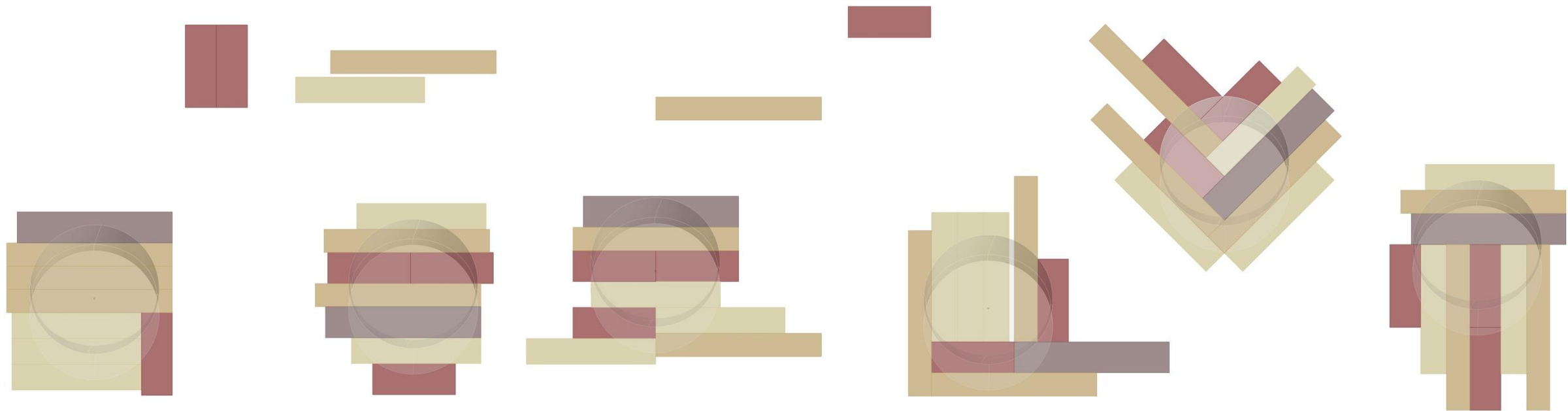
A047T.jpg



A048T.jpg

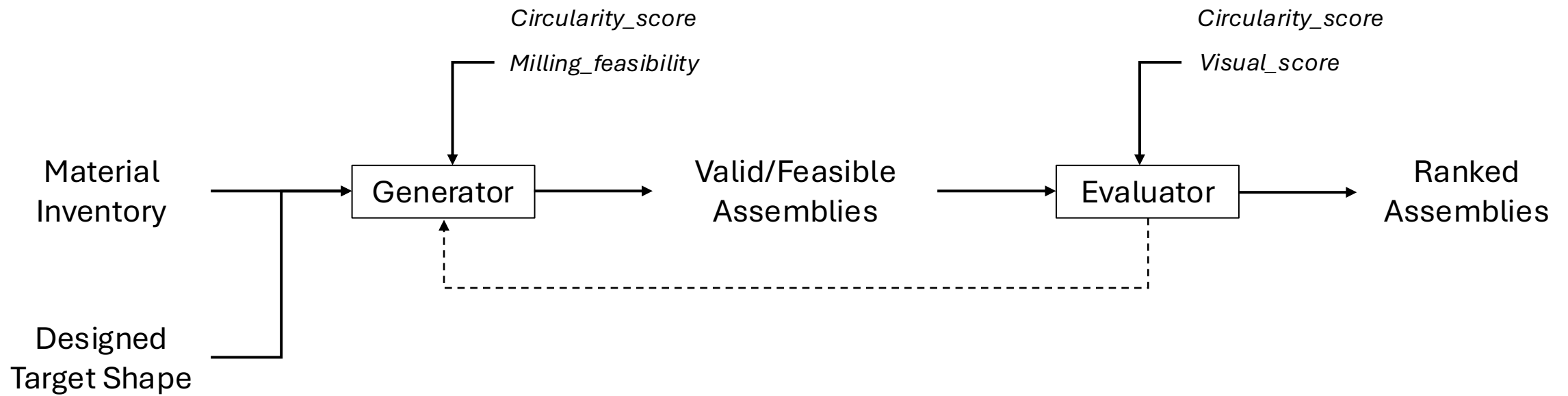
Sample, Generator, and Judge

Training Samples



Criteria: milling_feasibility, circular_score, visual_score

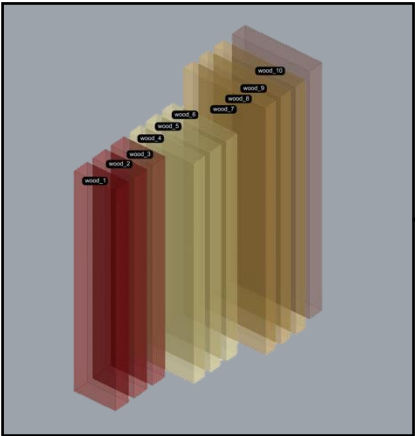
Training Samples



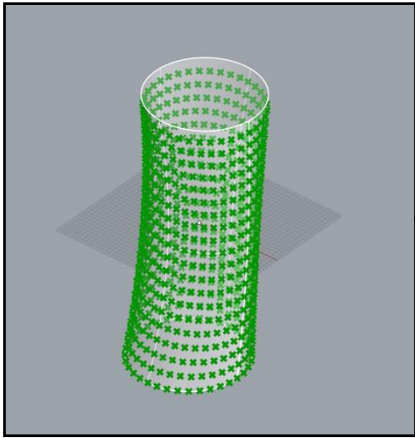
Decision-making: Generator & Evaluator

Model

Input



Wood_inventory



Target_pc

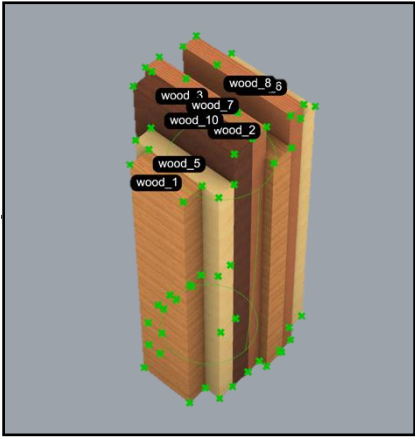
Model & training

Generator

Training Loop

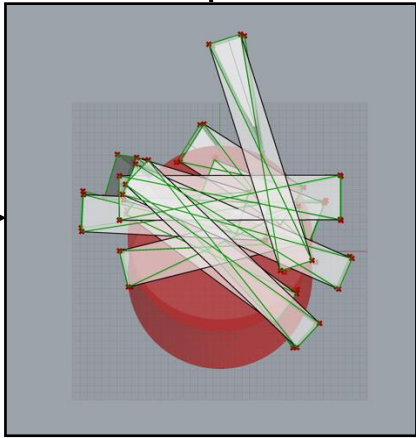


Ground truth / Constraint



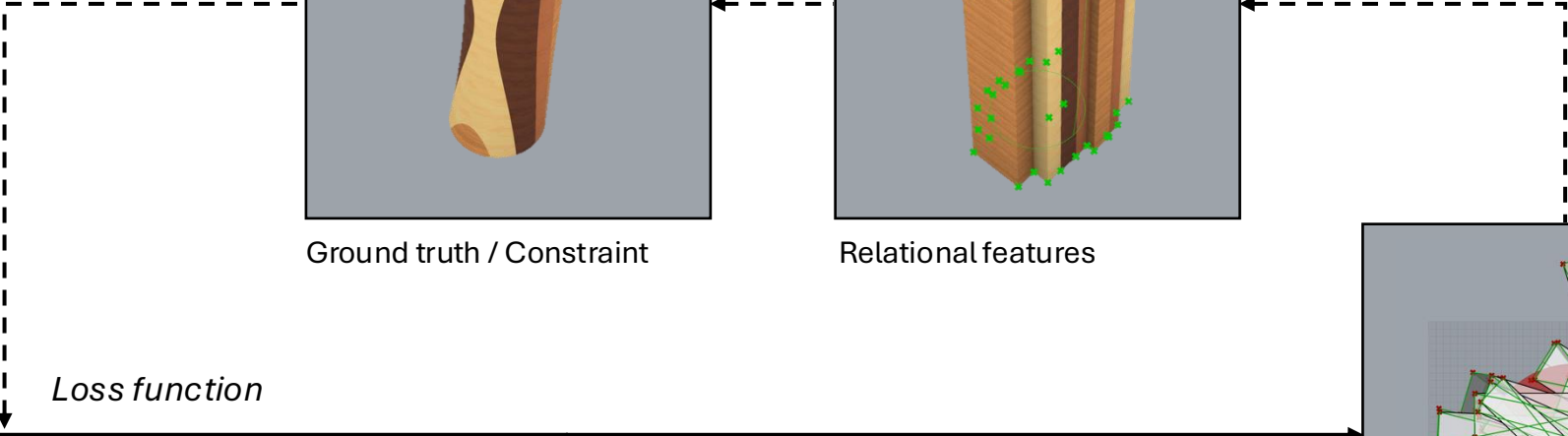
Relational features

Output

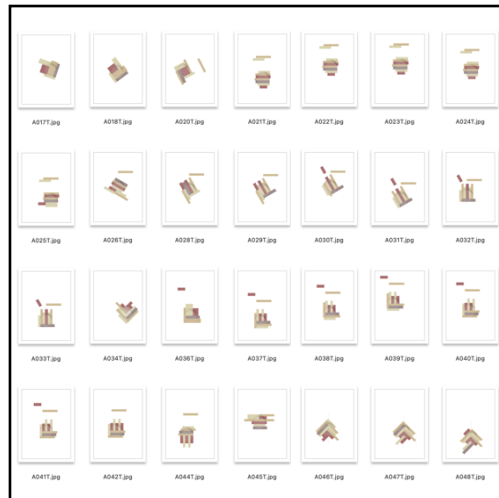


Piece-wise placement / use stage

Use / unused
Dx, Dy, Dz
Rotation matrix / orientation class

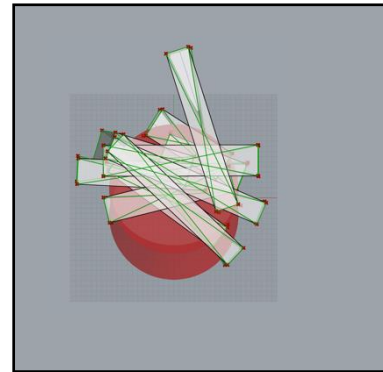


30 >> 50 samples
 Data analysis
 Data processing
 -
 linear models
 Relevant work

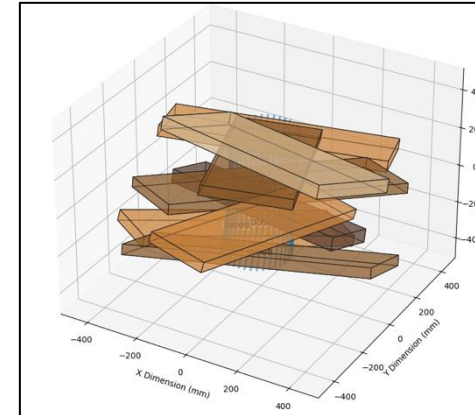


~50 millable samples

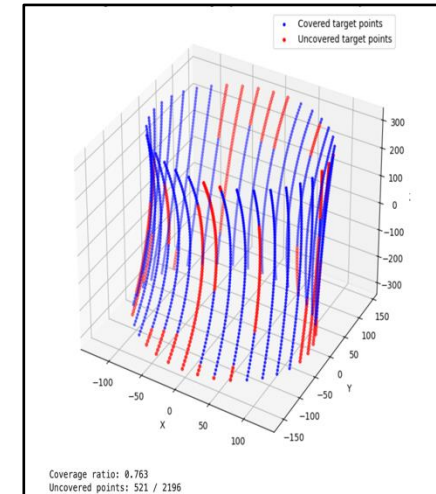
Conditioned Variational Auto Encoder (CVAE) *treating assembly as a distribution of complete solutions*



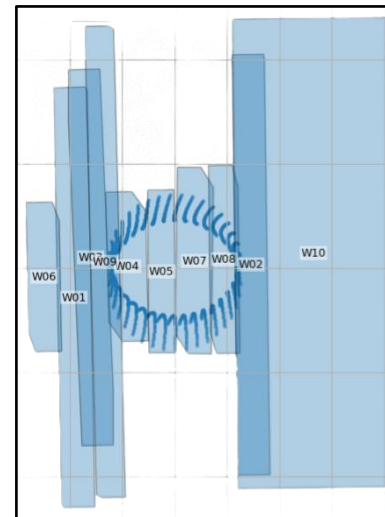
1) Reconstruction



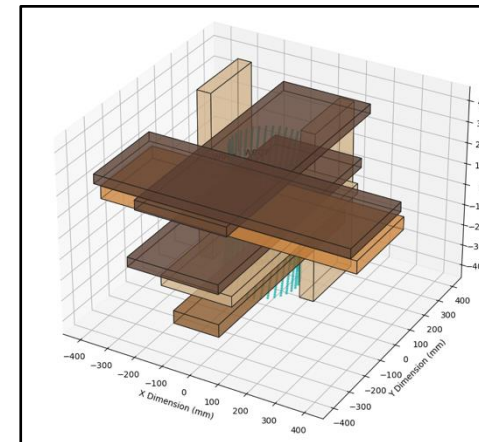
a) Free rotation



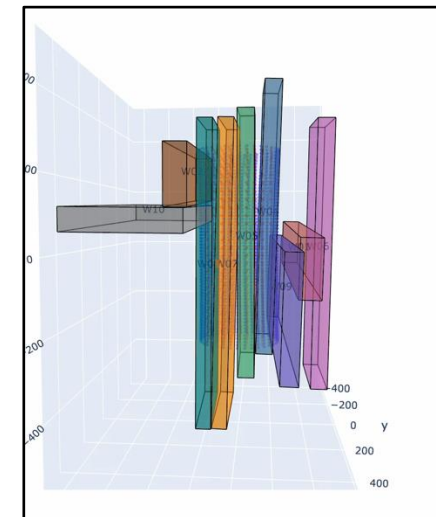
coverage



2) Milling constraints P_s



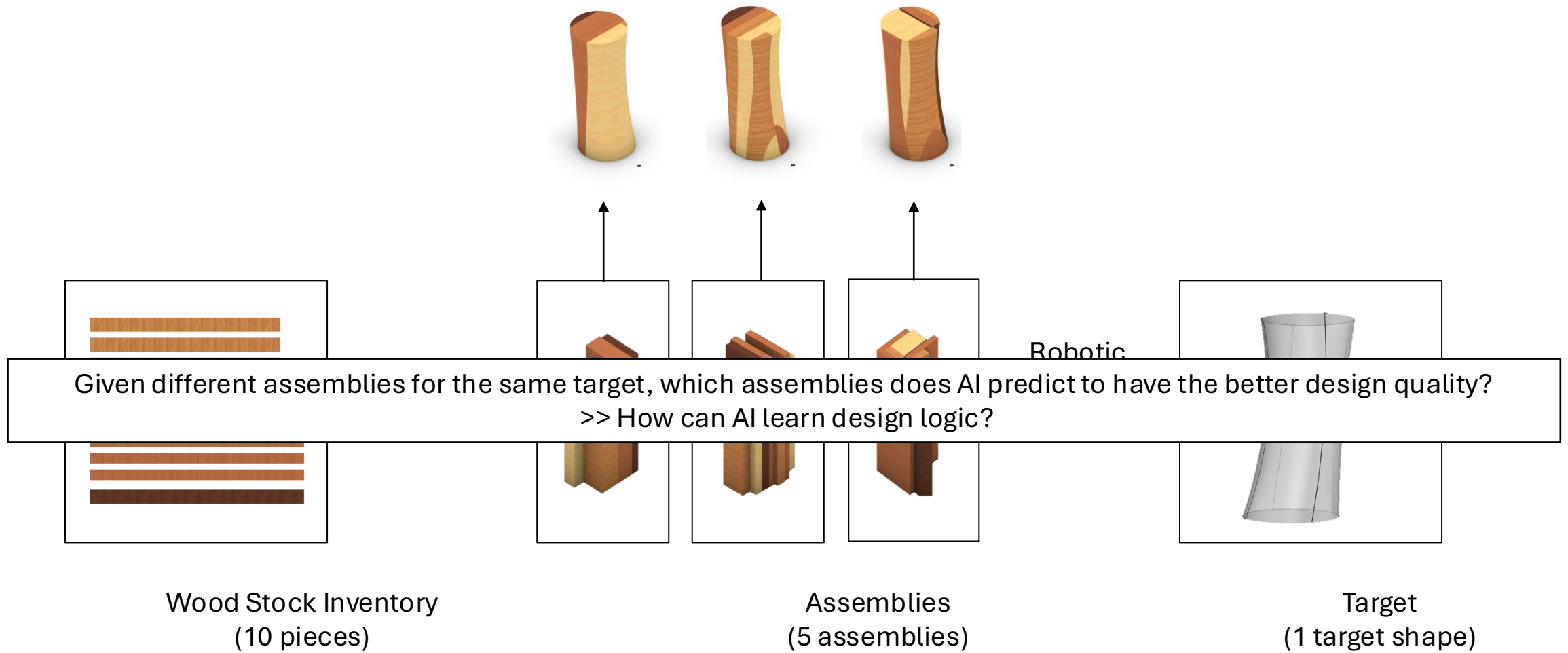
b) Fixed 6 orientation



Plotly.

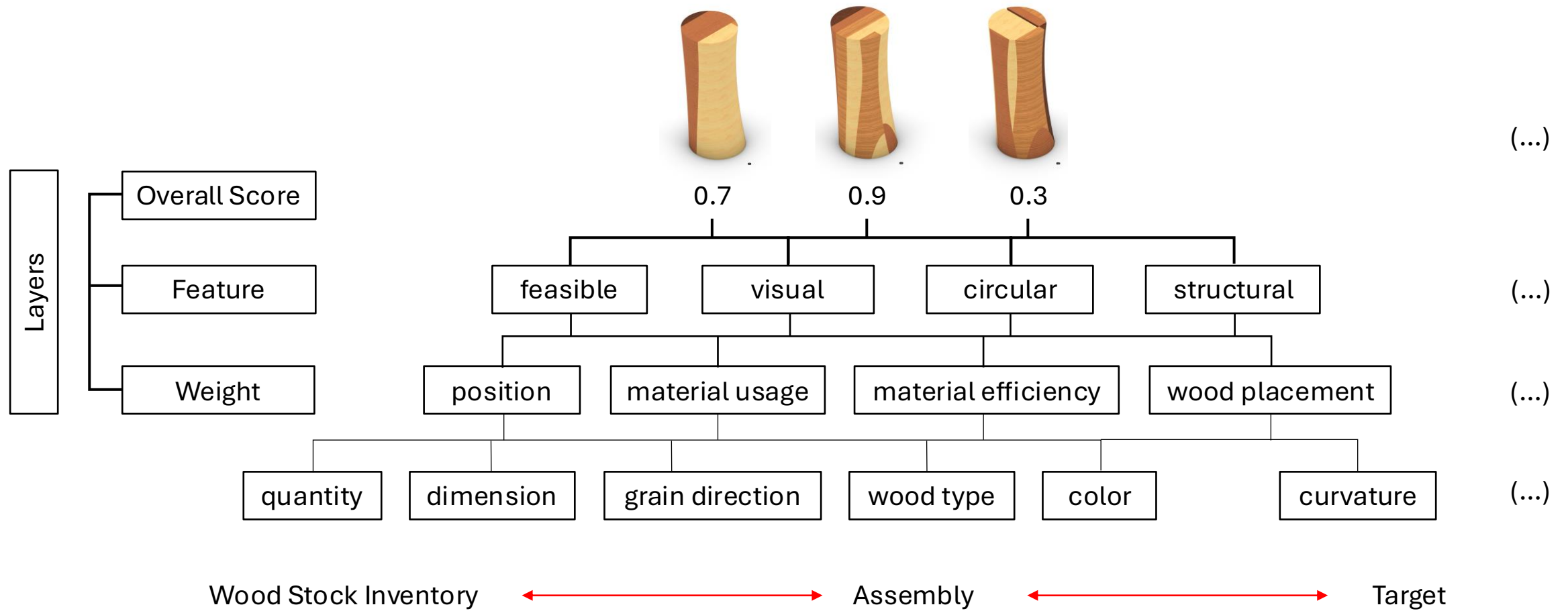
whole-assembly

Generator



Understand (Non-)Spatial Association within Design Assemblies

Evaluator



Machine-learning and neural network

Evaluator

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

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
	1	0.25	1.0	9.0
	2	0.75	1.0	8.0
	3	0.75	1.0	9.0
	4	0.90	0.0	9.0
	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



Which is the most circular assembly?

CS_regressor

2
0.383917 5
0.348795 1
0.393716 3
0.368535 4
0.363053

A001
0.387159



A002
0.365188



A003
0.392595



A004
0.366842



A005
0.361925



Prediction

2

4

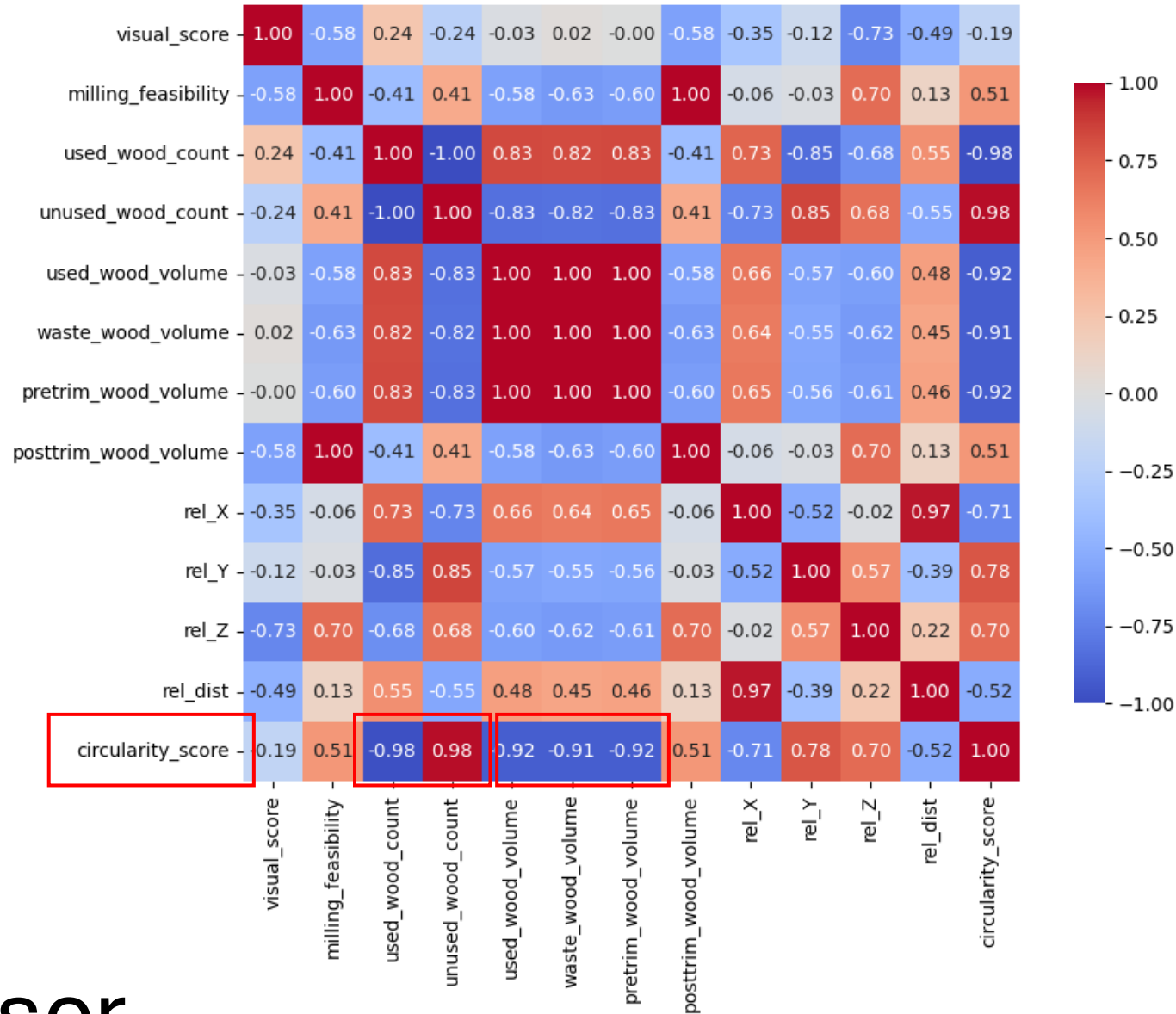
1

3

5

CS_regressor

Feature Correlation Heatmap with Circularity Score



Correlation

CS_regressor

```
[ ]      "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

CS_regressor



	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 = {}
```

All 55 human-rated assemblies plus the stacker's current best candidate, in one place. Each one is attributed the same way — point-in-oriented-box, first used piece wins — against the target's 2,196-point outer shell, then shown either **unrolled flat** (36 positions around the cross-section × 61 height steps) or as the **exposed point cloud** in 3D. Search and sort the list to compare; the strongest single predictor of `visual_score` turned out to be how often the species changes between neighboring surface cells (`species_trans_rate` , $r=0.753$), not how many species are present or how much surface is covered.

Assemblies

Search assembly ID...

Sort: visual_score ↓

56 / 56 shown

A031	0.98
A030	0.95
A035	0.95
A049	0.95
A050	0.95
A052	0.95
A054	0.95
A029	0.90
A034	0.90
A042	0.90
A043	0.90
A048	0.90
A053	0.90
A055	0.90

Assembly view

2196 SURFACE POINTS · A031

Unrolled surface

Exposed point cloud

oak (261)

pine (933)

birch (765)

cedar (237)

gap (0)

0.98

visual_score (human-rated)

Assembly ID

A031

Pieces used

8 / 10

Surface gap

0.0% of surface

Species-transition rate

27.3%

Highest-rated real assembly (0.98). Zero surface gap, zero interior gap, and all four species interleaved in short, frequent runs — the highest species-transition rate among the top scorers.

Extracting 2D features

VS regressor

Assemblies

Sort: visual_score ↓

56 / 56 shown

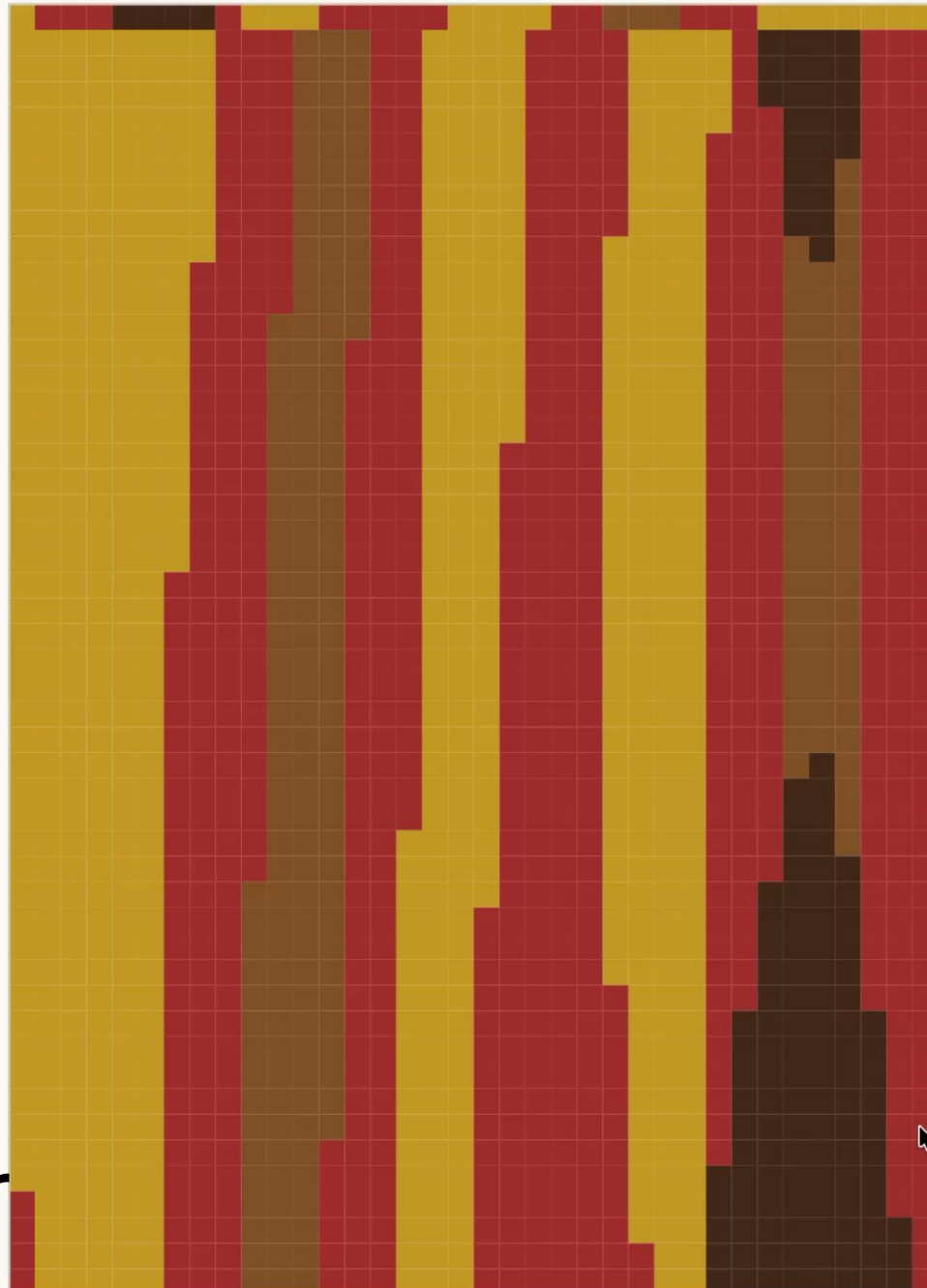
A031	0.98
A030	0.95
A035	0.95
A049	0.95
A050	0.95
A052	0.95
A054	0.95
A029	0.90
A034	0.90
A042	0.90
A043	0.90
A048	0.90
A053	0.90
A055	0.90
A005	0.85
A022	0.85
A028	0.85
A041	0.85
A007	0.80
A027	0.80

Assembly view

36 × 61 · A031

Unrolled surface

Exposed point cloud



0.98

visual_score (human-rated)

Assembly ID

A031

Pieces used

8 / 10

Surface gap

0.0% of surface

Species-transition rate

27.3%

oak (261) pine (933) birch (765)
cedar (237) gap (0)

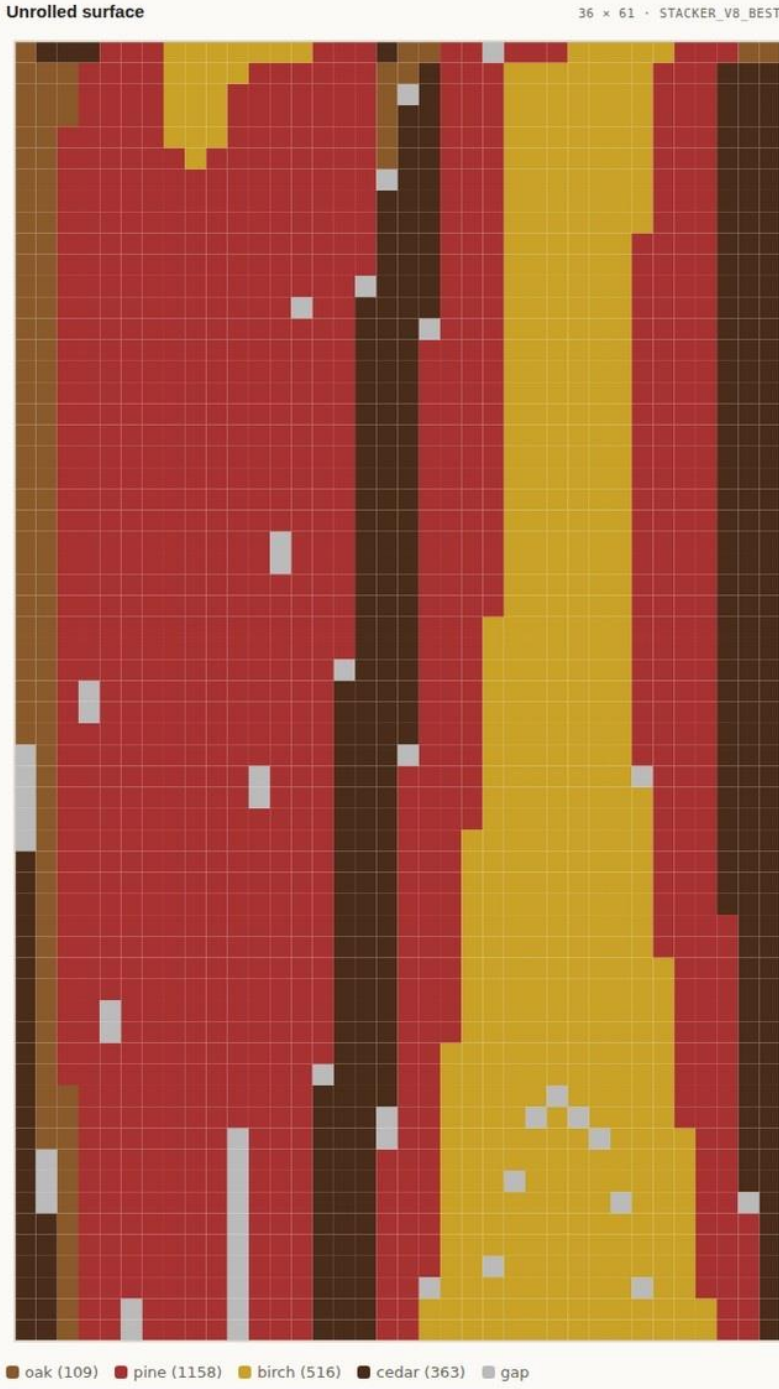
Highest-rated real assembly (0.98). Zero surface gap, zero interior gap, and all four species interleaved in short, frequent runs — the highest species-transition rate among the top scorers.

Extracting 2D features

VS_regressor

Prediction w Ridge (RSME 0.160)

VS_regressor



0.71*

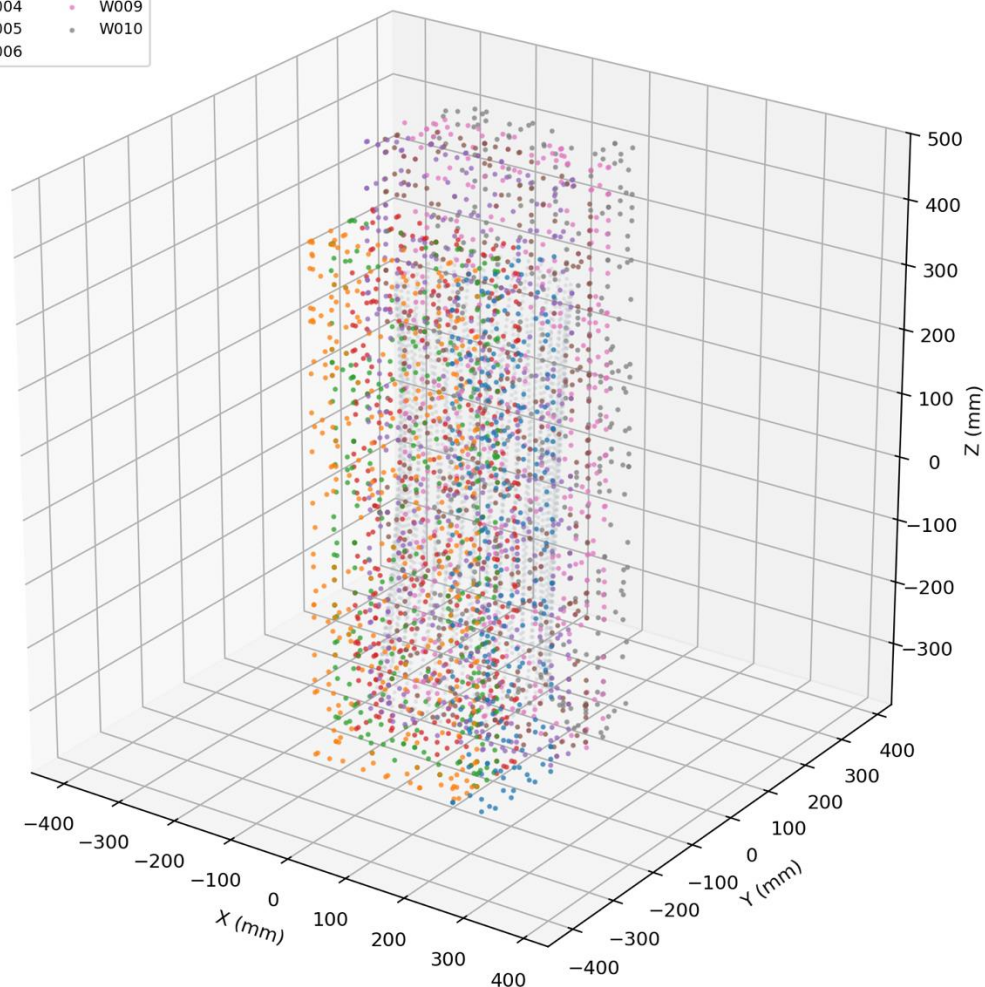
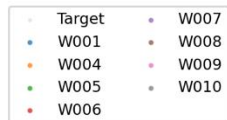
visual_score — model prediction, ±0.16 RMSE

Assembly ID	stacker_v8_best9
Pieces used	9 / 10
Surface gap	2.3% of surface

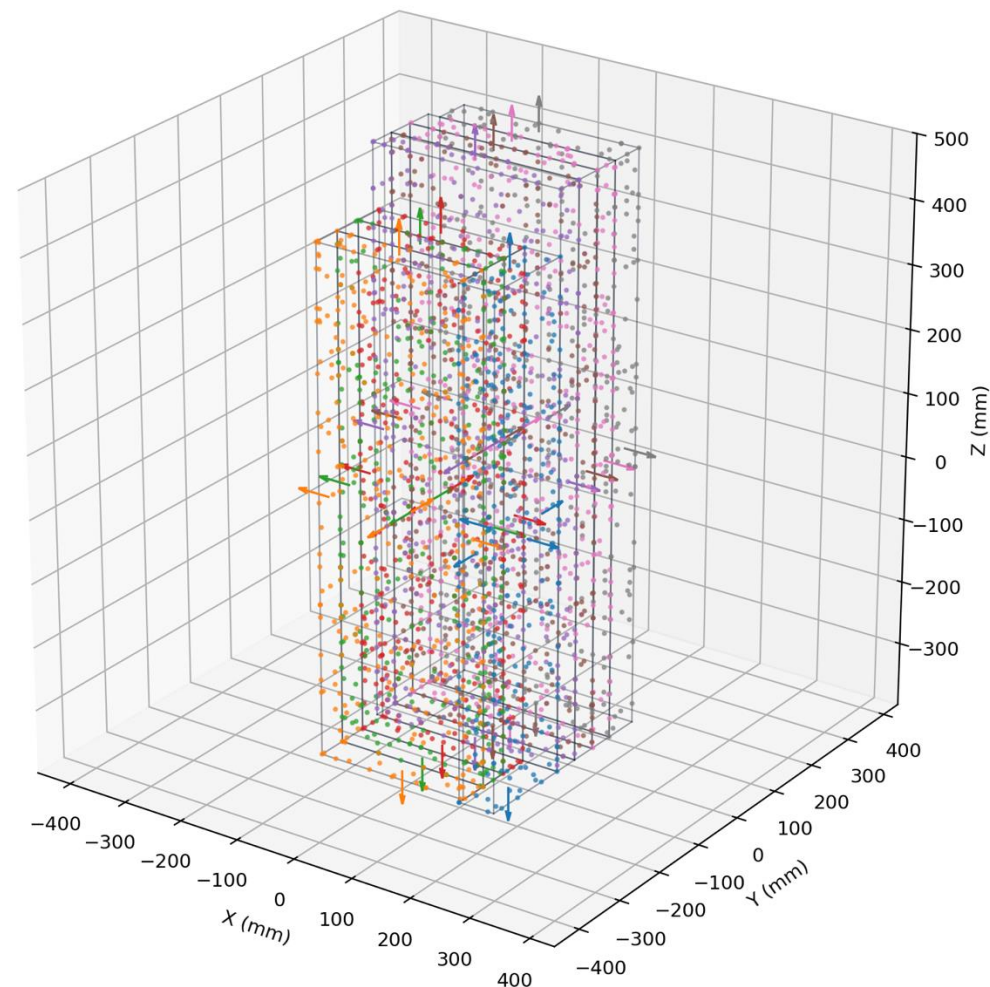
Not a real sample — the stacker's current best output (97.9% volumetric / 97.7% surface coverage by its own greedy voxel metric), scored by the engineered-feature model. Predicted 0.71: good species-transition rate, but pine alone covers 54% of the visible surface while oak “present, just poorly placed” covers only 5% (visible as the thin brown sliver on the right). The stacker's coverage objective doesn't know that, the judge does.

rawV5 deterministic centre-out surface-grid validation

A001: sampled wood surfaces relative to target
(displaying 18% of wood points)



Sampled surfaces, recorded OBB edges, and face-centre normals



Input w 3D coordinates (PointNet++)

VS_regressor

assembly_ID	ng_feasibility	circularity_score	material_efficiency	total_stock_volume	used_wood_count	unused_wood_count	target_inside_ratio	target_outside_ratio	target_multi_inside_ratio	outside_point_count	outside_point_ratio
A001	1.0	0.1800632123160020	0.2686227472696350	108120.0	8.0	2.0	1.0	0.0	0.0	0	0.0000000000000000
A002	1.0	0.1619248373917670	0.253948695615023	108120.0	9.0	1.0	1.0	0.0	0.0	0	0.0000000000000000
A003	1.0	0.1961327274424020	0.292595646814319	108120.0	8.0	2.0	1.0	0.0	0.0	0	0.0000000000000000
A004	1.0	0.1669602787568980	0.2618458396672780	108120.0	9.0	1.0	0.9981785063752280	0.0018214936247723500	0.0	4	0.0000000000000000
A005	0.0	0.1519035714346110	0.238232222100376	108120.0	9.0	1.0	0.9904371584699450	0.0095628415300546	0.0	21	0.0000000000000000
A006	1.0	0.1397816837905340	0.2304610353197330	108120.0	10.0	0.0	1.0	0.0	0.0	0	0.0000000000000000
A007	0.0	0.1390722668615550	0.2292914045391300	108120.0	10.0	0.0	0.9963570127504550	0.0036429872495445900	0.0	8	0.0000000000000000
A008	1.0	0.1800632764140920	0.2686228428927490	108120.0	8.0	2.0	1.0	0.0	0.0	0	0.0000000000000000
A009	1.0	0.1800631782941520	0.2686226965150000	108120.0	8.0	2.0	1.0	0.0	0.0	0	0.0000000000000000
A010	1.0	0.1800632488165040	0.2686228017219860	108120.0	8.0	2.0	1.0	0.0	0.0	0	0.0000000000000000
A011	1.0	0.1800631665657190	0.2686226790182340	108120.0	8.0	2.0	1.0	0.0	0.0	0	0.0000000000000000
A012	0.0	0.1800194843679070	0.2685575128366910	108120.0	8.0	2.0	0.994535519125683	0.005464480874316950	0.0	12	0.0000000000000000
A013	1.0	0.1800631980366530	0.2686227259673500	108120.0	8.0	2.0	1.0	0.0	0.0	0	0.0000000000000000
A014	0.0	0.1605110161146860	0.2517313824780700	108120.0	9.0	1.0	0.9385245901639340	0.061475409836065600	0.0	135	0.0000000000000000
A015	1.0	0.1619248317771050	0.2539486868094790	108120.0	9.0	1.0	1.0	0.0	0.0	0	0.0000000000000000
A016	0.5	0.1397816950942640	0.2304610539564330	108120.0	10.0	0.0	1.0	0.0	0.0	0	0.0000000000000000
A017	1.0	0.1397816639150430	0.2304610025505880	108120.0	10.0	0.0	1.0	0.0	0.0	0	0.0000000000000000
A018	1.0	0.1397816626808890	0.2304610005158120	108120.0	10.0	0.0	1.0	0.0	0.0	0	0.0000000000000000
A019	1.0	0.1619248534689390	0.2539487208290470	108120.0	9.0	1.0	1.0	0.0	0.0	0	0.0000000000000000
A020	1.0	0.1669616322559910	0.2618479623763990	108120.0	9.0	1.0	1.0	0.0	0.0	0	0.0000000000000000
A021	1.0	0.2266265416857020	0.321598370956097	108120.0	7.0	3.0	1.0	0.0	0.0	0	0.0000000000000000
A022	1.0	0.1961327182093650	0.2925956330402470	108120.0	8.0	2.0	1.0	0.0	0.0	0	0.0000000000000000
A023	1.0	0.1961327223417990	0.2925956392051130	108120.0	8.0	2.0	1.0	0.0	0.0	0	0.0000000000000000
A024	0.0	0.2335701714384150	0.3314518506076180	108120.0	7.0	3.0	0.9977231329690350	0.0022768670309654100	0.0	5	0.0000000000000000
A025	1.0	0.196132702679287	0.2925956098720930	108120.0	8.0	2.0	1.0	0.0	0.0	0	0.0000000000000000
A026	0.0	0.1667816987108560	0.2615657704049860	108120.0	9.0	1.0	0.988615664845173	0.011384335154827000	0.0	25	0.0000000000000000
A027	1.0	0.1669616165967120	0.2618479378177610	108120.0	9.0	1.0	1.0	0.0	0.0	0	0.0000000000000000
A028	0.5	0.1669616583815920	0.2618480033494970	108120.0	9.0	1.0	1.0	0.0	0.0	0	0.0000000000000000
A029	1.0	0.1669616871405240	0.2618480484524820	108120.0	9.0	1.0	1.0	0.0	0.0	0	0.0000000000000000
A030	1.0	0.1909312635659220	0.2848359745394970	108120.0	8.0	2.0	1.0	0.0	0.0	0	0.0000000000000000
A031	1.0	0.1909312761401690	0.28483599329807	108120.0	8.0	2.0	1.0	0.0	0.0	0	0.0000000000000000
A032	0.0	0.190827091072324	0.2846805674407330	108120.0	8.0	2.0	0.9927140255009110	0.007285974499089300	0.0	16	0.0000000000000000
A033	1.0	0.1909312803392480	0.284835999562359	108120.0	8.0	2.0	1.0	0.0	0.0	0	0.0000000000000000
A034	0.5	0.1397816191769550	0.2304609287899510	108120.0	10.0	0.0	1.0	0.0	0.0	0	0.0000000000000000
A035	1.0	0.1581837410391920	0.230089956735520	108120.0	9.0	1.0	1.0	0.0	0.0	0	0.0000000000000000
A036	1.0	0.15184866637250	0.223092936673300	108120.0	9.0	1.0	1.0	0.0	0.0	0	0.0000000000000000
A037	1.0	0.1909312667305560	0.2848359792605760	108120.0	8.0	2.0	1.0	0.0	0.0	0	0.0000000000000000

Why Computational?

