AutoSew: A Geometric Approach to Stitching Prediction with Graph Neural Networks
Supplementary Material

In this Supplementary Material, we provide additional details to support the main contributions of the paper. These materials are intended to enhance reproducibility and offer a deeper understanding of key design choices:

A. Details of Geometric Edge Features
B. Details of Curated Dataset Extension
C. Sinkhorn Algorithm

A. Details of Geometric Edge Features

Each garment is represented by a set of disconnected 2D panels. A panel is a closed polygon defined by N edges, $E = \{e_j\}_{j=1}^{N}$, where each edge may be a straight segment, circular arc, quadratic Bézier spline, or a cubic Bézier spline. Additionally, we introduce B-splines to represent edges created during panel merge (e.g., in sleeve reconstruction). These are formed by concatenating two Bézier splines using their control points and midpoint, allowing the modeling of more complex edge shapes.

To capture the geometric and structural variability of these edges, we extract 22 raw features per edge. These include both local shape descriptors and topological properties. A complete list of these features, along with their definitions, is provided in Table 1. Finally, these features are preprocessed into a 24-dimensional edge vector.

B. Detailed M-E.GarmentCodeData

We start by selecting every pattern in GarmentCodeData.v2 that contains at least one sleeve. The extension pipeline then proceeds in three short stages:

1. **Panel mirroring:** The back-sleeve panel is reflected on its horizontal axis.
2. **Geometric merging:** The mirrored back sleeve is compared with the front sleeve; if the length of the edge and curvature match, both halves are merged into a single sleeve panel.
3. **Edge collapsing:** Adjacent edges are merged, and their stitch labels are mapped to multi-edge annotations. Straight and coplanar edges are collapsed into one longer segment. Quadratic or cubic Bézier edges are concatenated by joining control points to form a B-spline, preserving curvature continuity. After merging, all original one-to-one annotations along the collapsed or concatenated edges are reassigned to the new unified edge. This ensures that every multi-edge relationship is mapped.

We apply the mirroring on its vertical axis, fusion, and stitch-update steps to each sleeve cuff and then merge the front and back upper body panels into unified pieces, keeping all original stitch annotations.

This pipeline produces 18 003 patterns with merged sleeves and sleeve cuffs, and unified torsos. This increases realism and structural complexity. The resulting dataset provides a stronger benchmark for training and evaluating multi-edge stitch-prediction models.

C. Sinkhorn Algorithm

We adopt the entropic optimal transport (OT) framework [2], solved efficiently via the Sinkhorn algorithm [1, 3]. This approach introduces an entropy term to the standard OT cost, resulting in a smooth and differentiable objective. This regularization is crucial for stable and efficient computation of transport plans, which we utilize for AutoSew. Formally, the objective is:

$$OT_{\varepsilon}(a, b) = \min_{\mathbf{P} \in U(a,b)} \langle C, \mathbf{P} \rangle - \varepsilon H(\mathbf{P}). \quad (1)$$

where $H(\mathbf{P})$ represents the entropy of the assignment matrix $\mathbf{P}$, and $\epsilon > 0$ regulates the strength of the entropy-based smoothing, and $U(a, b)$ is the set of feasible transport plans with given marginals a and b. In our case, $a = b \in \mathbb{R}^M$ are uniform distributions over the M panel edges.

The Sinkhorn algorithm efficiently computes a doubly stochastic approximation to the optimal transport plan via iterative row and column normalization. The entropic regularization introduced by this method provides crucial differentiability, ensuring that small perturbations in the cost matrix or marginals result in predictable gradient updates. This property is essential for end-to-end training of our network. By utilizing a Sinkhorn-based layer, we leverage gradient-

Geometric Features	Feature	Description
Local Shape	Start vertex (x_0, y_0)	Coordinates of the edge's starting point
	End vertex (x_1, y_1)	Coordinates of the edge's ending point
	Length l	Euclidean distance between start and end
	Orientation (o_x, o_y)	Unit vector between the initial and end edge point
	Curvature type k_t	$\{0 \dots 5\}$: straight segment, circular arcs quadratic Bézier, cubic Bézier and B-Splines
	Curvature params $k = (k_1, \dots, k_{10})$	All zeros for straight segment $(r, d, \theta, 0, \dots, 0)$ for circular arc $(q_x^1, q_y^1, 0, \dots, 0)$ for quadratic Bézier $(q_x^1, q_y^1, q_x^2, q_y^2, 0, \dots, 0)$ for cubic Bézier $(q_x^1, q_y^1, q_x^2, q_y^2, c_x, c_y, q_x^3, q_y^3, q_x^4, q_y^4)$ for B-splines
Topological Properties	Interior angle left α_l	Interior angle with left neighbor edge (radians)
	Interior angle right α_r	Interior angle with right neighbor edge (radians)
	Edge count N	Total number of edges in panel
	Panel ID u	Unique identifier for this panel

Table 1. Geometric edge features composed of Local Shape descriptor and Topological properties.

based optimization for partial matching, effectively bypassing the challenges posed by non-differentiable combinatorial solvers.

References

[1] Marvin Eisenberger, Aysim Toker, Laura Leal-Taixé, Florian Bernard, and Daniel Cremers. A unified framework for implicit sinkhorn differentiation. In *2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 499–508, 2022. 1

[2] Gabriel Peyré and Marco Cuturi. Computational optimal transport, 2020. 1

[3] Richard Sinkhorn and Paul Knopp. Concerning nonnegative matrices and doubly stochastic matrices. *Pacific Journal of Mathematics*, 21(2):343–348, 1967. 1