SplineCNN: Fast Geometric Deep Learning with Continuous B-Spline Kernels

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SFB 876 Providing Information by Resource-Constrained Data Analysis

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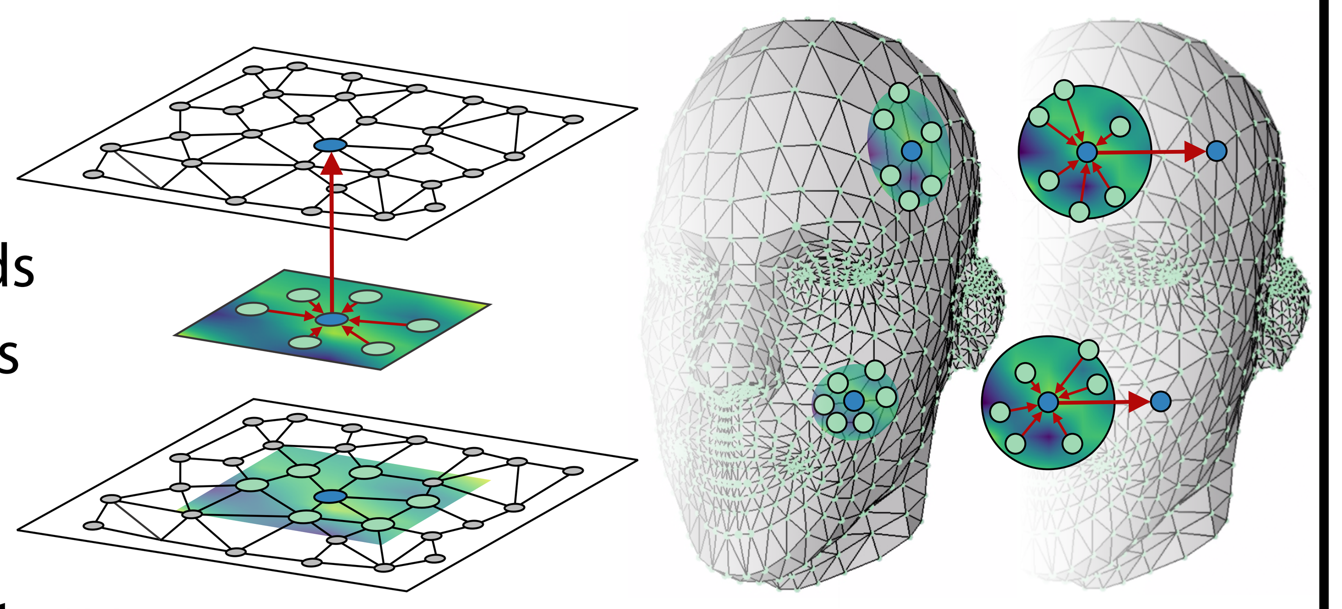
Abstract

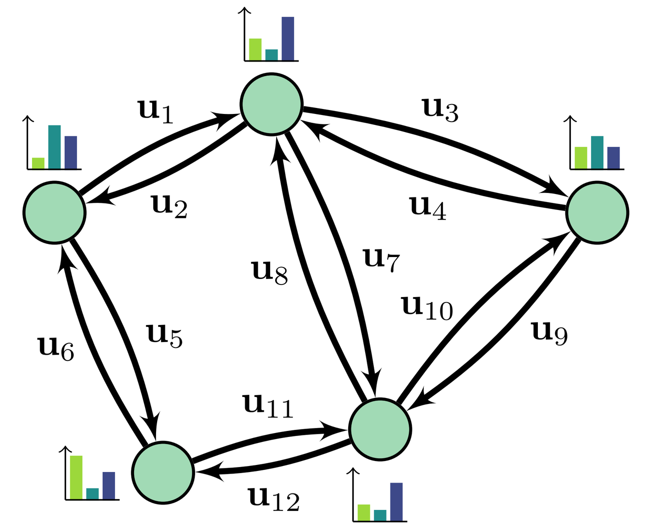
Motivation: convolution on irregular structures instead of on regular grids

Solution: B-spline kernels defined on continuous domains, as building blocks for deep architectures



Framework: deep learning on graphs and manifolds

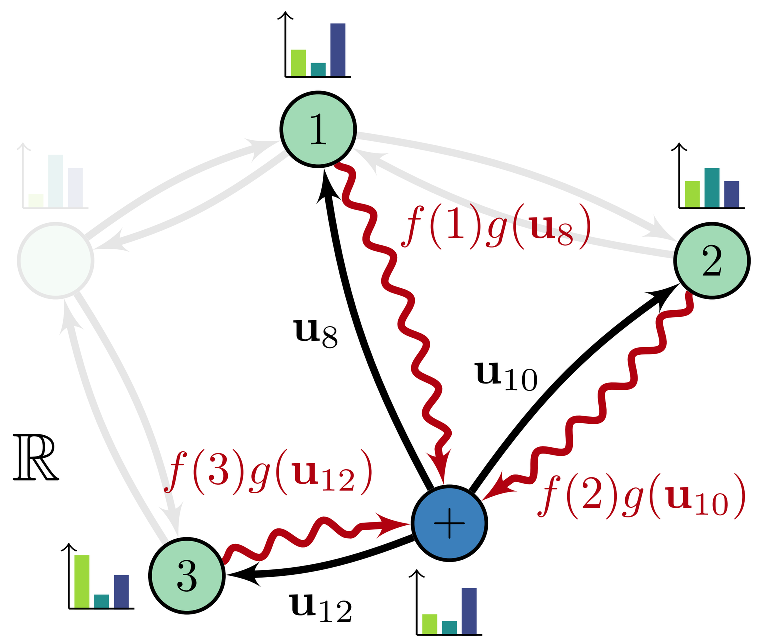
Directed graph $\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathbf{U})$ with pseudo-coordinates $\mathbf{U} \in \mathbb{R}^{|\mathcal{E}| \times D}$ containing a D-dimensional vector for each directed edge, cf. [Monti et al., CVPR 2017], and node features $\mathbf{f}(i)$.



Neighborhood aggregation/convolution:

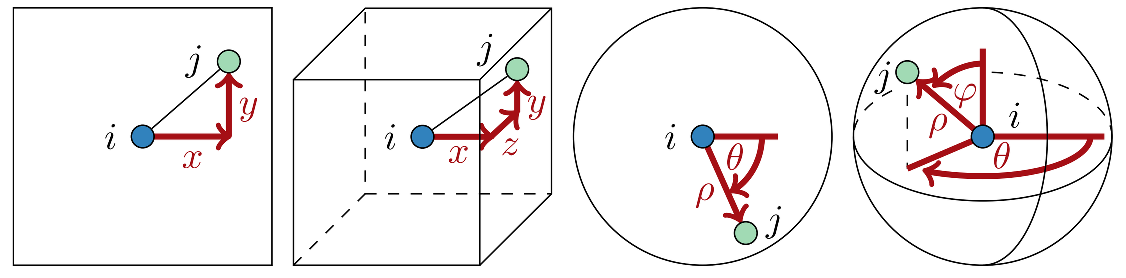
$$(f \star g)(i) = \sum_{j \in \mathcal{N}(i)} f(j) \cdot g(\mathbf{u}(i,j))$$

with trainable continuous kernel $g \colon \mathbb{R}^D \to \mathbb{R}$



Examples for pseudo-coordinates:

- Cartesian coordinates
- polar/spherical coordinates
- arbitrary edge attributes



$\mathbf{u}(i,j) = (x,y)$ $\mathbf{u}(i,j) = (x,y,z)$ $\mathbf{u}(i,j) = (\rho,\theta)$ $\mathbf{u}(i,j) = (\rho,\theta,\varphi)$

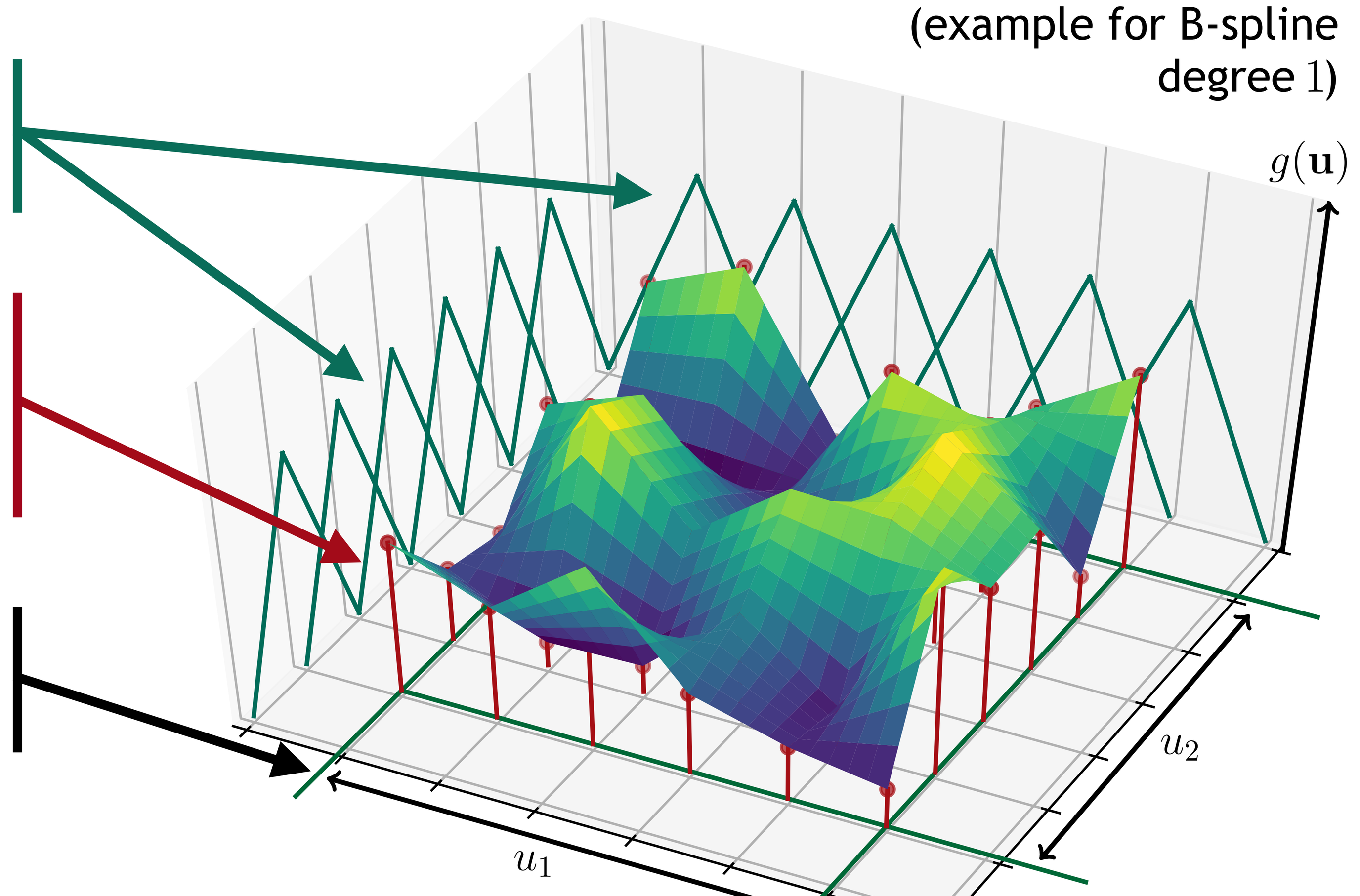
Our method: continuous B-spline kernels

given through B-spline approximation with trainable control points

locally non-zero B-spline bases

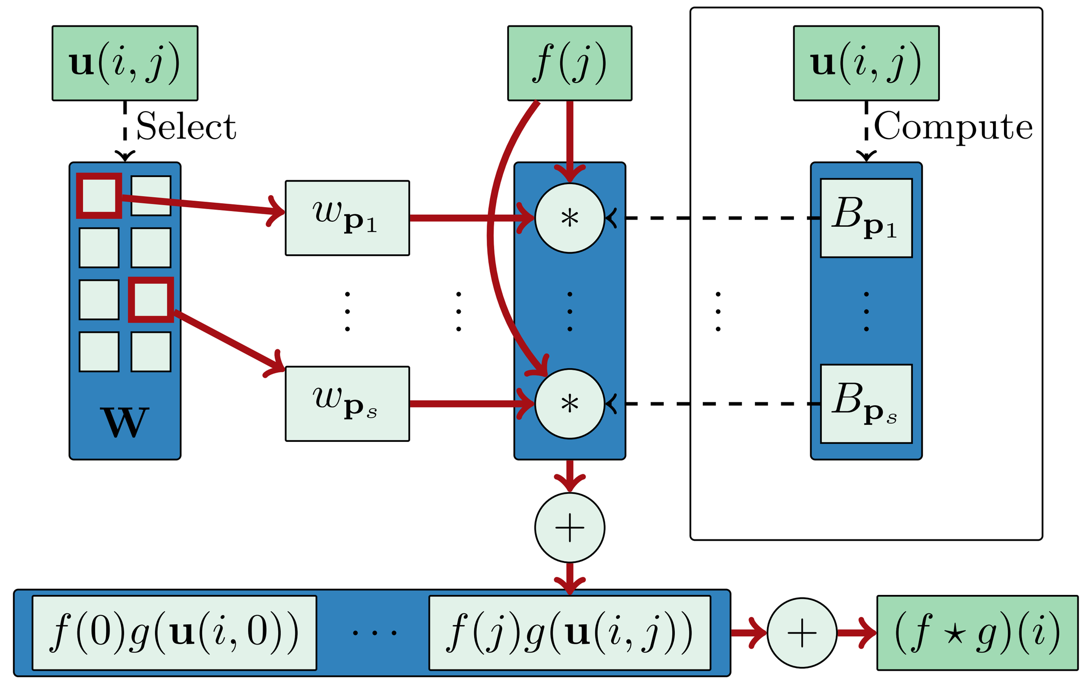
trainable weights $w_{\mathbf{p}}$ at equidistant knot positions $\mathbf{p} \in \mathcal{P}$

fixed pseudo-coordinate interval

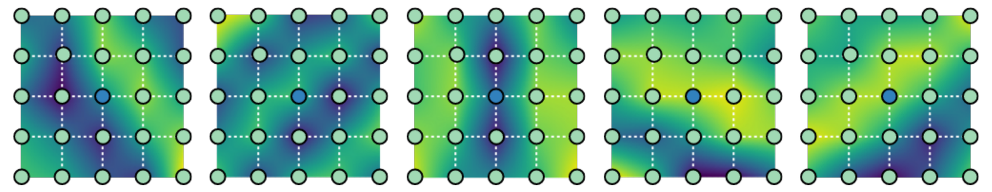


Surface: kernel $g(\mathbf{u})$

Fast forward and backward algorithms: execution time does not depend on kernel size (local support of B-spline basis)



Nice analogy to traditional CNNs



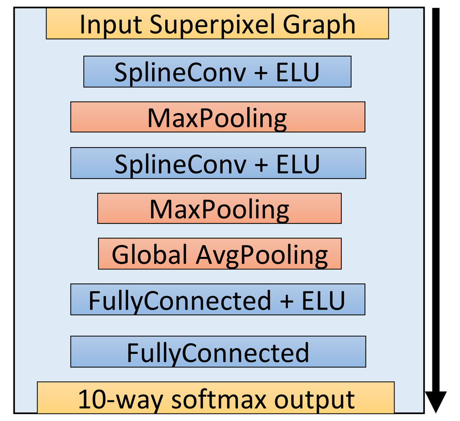
arXiv e-Print:

GPU/CPU implementation and a general framework for geometric deep learning available on GitHub:

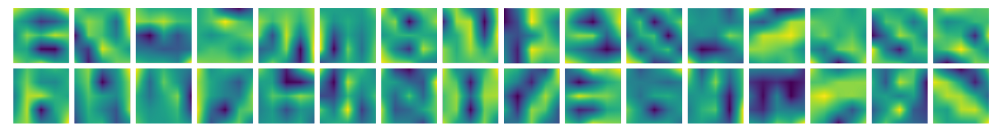
PYTORCH GEOMETRIC

Results

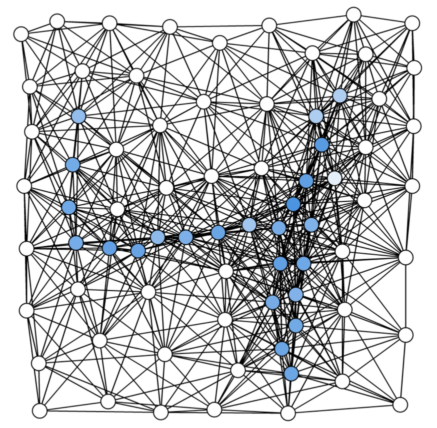
MNIST grid and superpixels classification



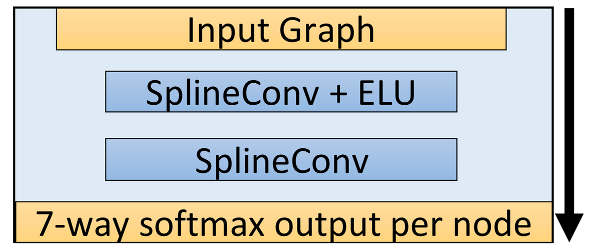
Dataset	LeNet5	MoNet	SplineCNN
Grid	**99.33%**	99.19%	99.22%
Superpixels	–	91.11%	**95.22%**



learned kernels of first layer



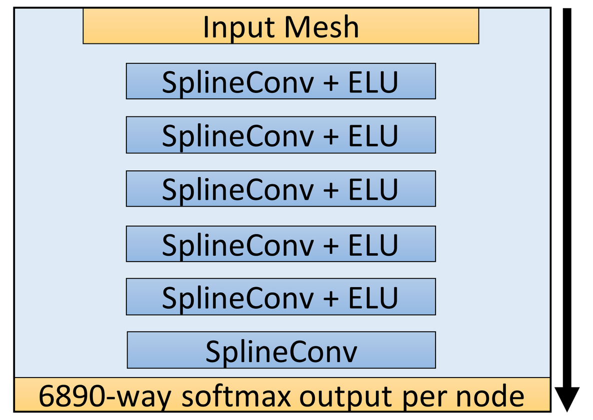
Cora graph node classification (1708 train/500 val/500 test split)

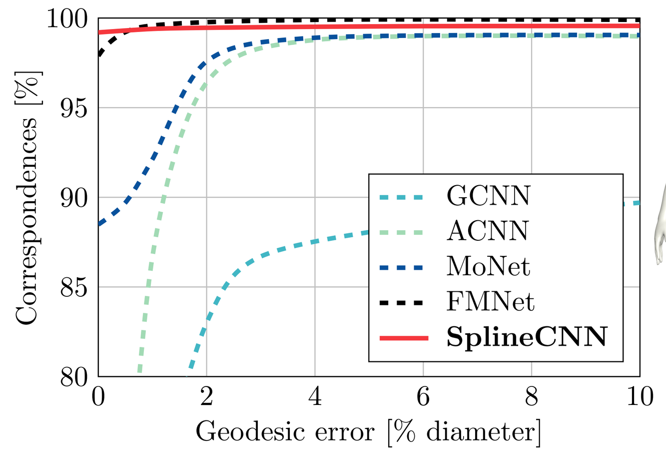


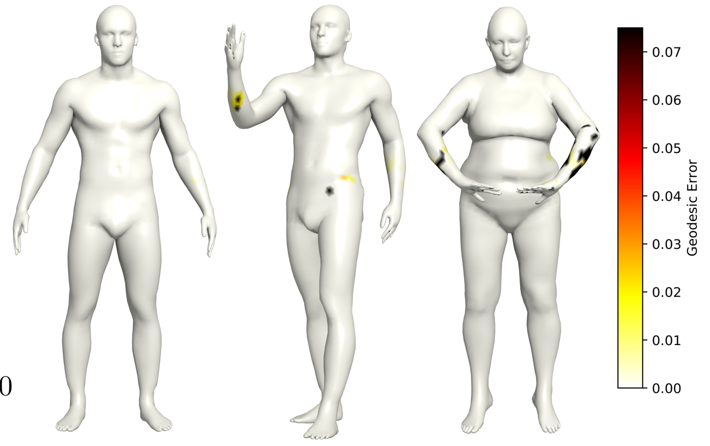
Pseudo-coordinates: $\mathbf{u}(i,j) = \deg(j) / \max_{v \in \mathcal{V}} \deg(v)$

ChebNet	GCN	CayleyNet	SplineCNN
87.12 ± 0.60	87.17 ± 0.58	87.90 ± 0.66	$\mathbf{89.48 \pm 0.31}$

FAUST shape correspondence (end-to-end, no pre-processing)







Takeaway

SplineCNN provides a generalized convolution operator for irregular domains and fast GPU implementations for forward and backward steps. It allows to perform deep end-to-end learning on geometry and graphs without the need of pre-processed input features. It achieves state-of-the-art results on several benchmark tasks.

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