FACULTY OF APPLIED SCIENCES
UNIVERSITY
OF WEST BOHEMIA

Learning Mesh Geometry Prediction

Filip Hácha, Libor Váša

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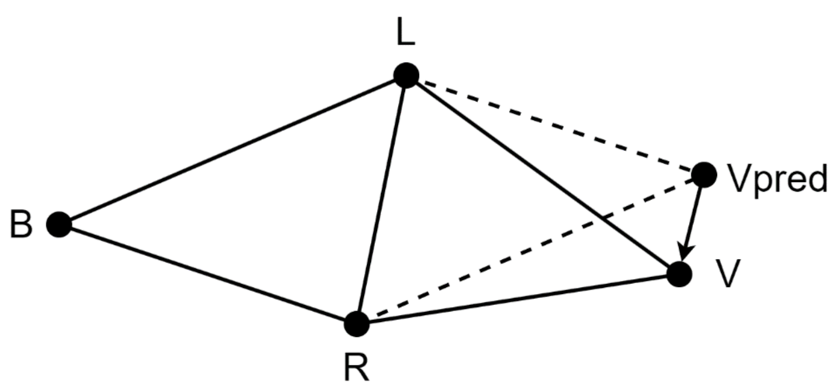
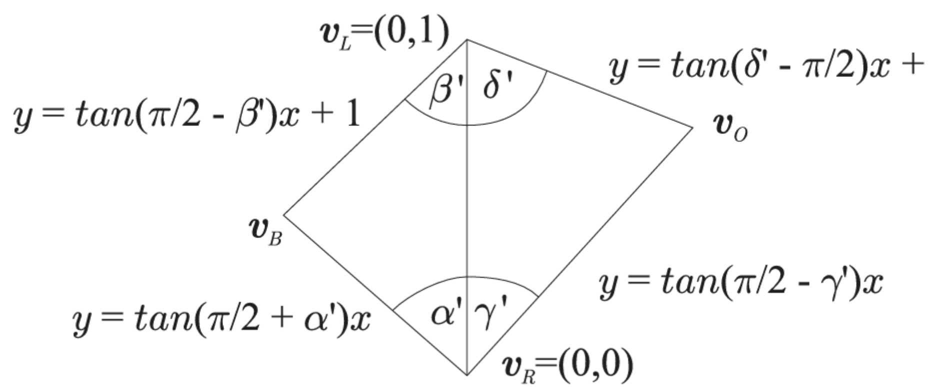
Compression of triangle meshes

- A frequently solved problem - lots of existing methods
  - Single-rate vs. Progressive
  - Geometry – lossy compression
  - Connectivity – lossless compression (otherwise simplification)
  - We compress geometry (and use Edgebreaker [Ross99] for the connectivity)
- Different approaches
  - Traversal based methods (Parallelogram [TG98], Weighted Parallelogram [VB13], Angle-Analyzer [LAD02])
  - Laplacian based (High-Pass Quantization [SCT03], Error Propagation Control [VD18])
  - …

Geometry prediction schemes

- We predict the vertex position based on
  - Previous vertices
  - Connectivity (is encoded first)
- Difference between prediciton and actual position is encoded
- Parallelogram
- Weighted Parallelogram





Neural predictor

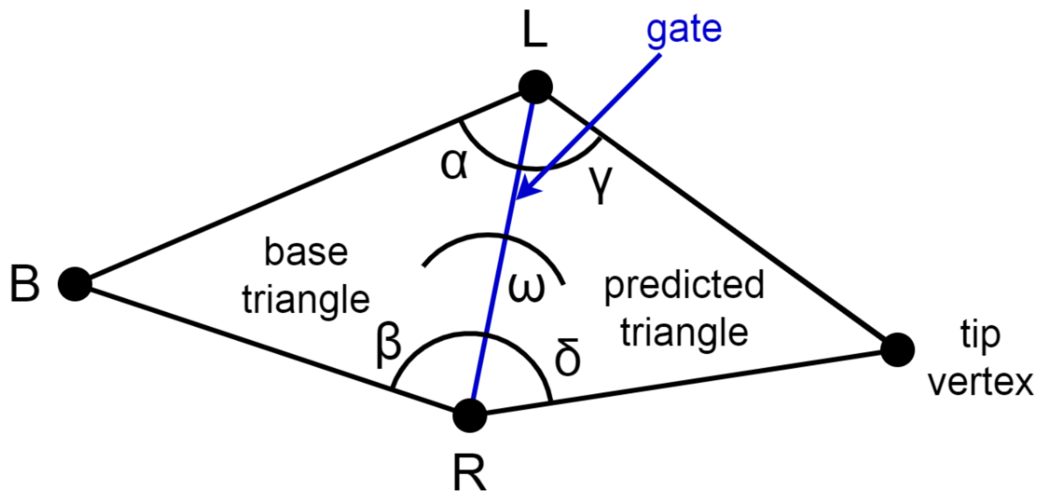
- General prediction scheme
  - Input: Connectivity + Already encoded/decoded part of geometry
  - Output: Next vertex prediction

Neural predictor

- Neural predictor
  - Multilayer perceptron
  - Input:
    - Geometry of base triangle
    - Vertex valences
    - Estimates of inner angles (just like Weighted Parallelogram)
  - Output:
    - Geometry of encoded triangle

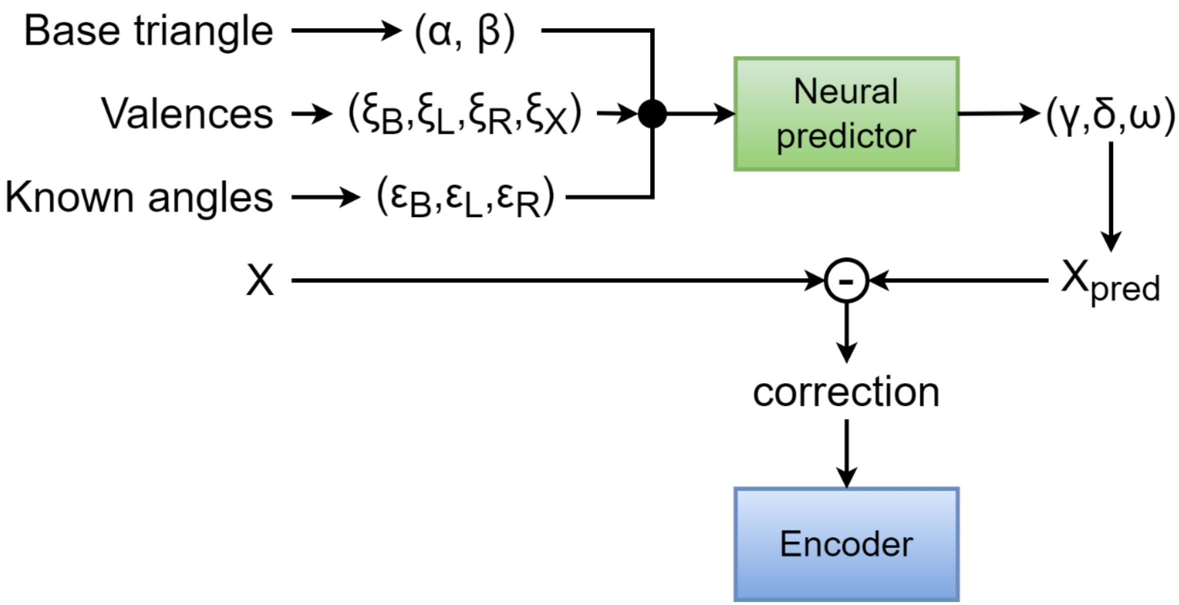
Neural predictor – Data normalization

- Meshes can be of various sizes
  - How to normalize feature space
- Invariance to rigid transformations + uniform scaling
  - Translation, rotation, uniform scale should not change the shape of the predicted triangle.
- Angles
  - Inner angles – α, β, γ, δ
  - Dihedral angle - ω



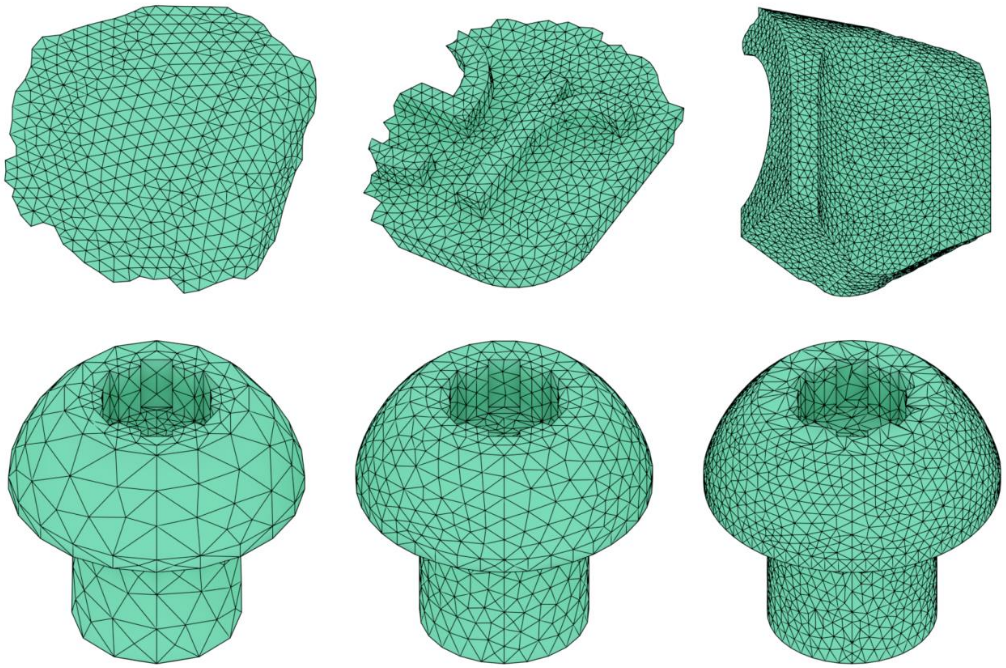
Neural predictor – Data normalization

- More angles
  - Inner angles
  - Dihedral angle
  - 2π / valence
  - Angle estimates
  - Angle between normals of neighboring triangles



Neural predictor – Training

- We sampled ABC dataset [KMJ19]
  - Various shapes and tesselations
- Traversal simulation (different parts of mesh were processed)
  - Different accuracy of estimates of inner angles



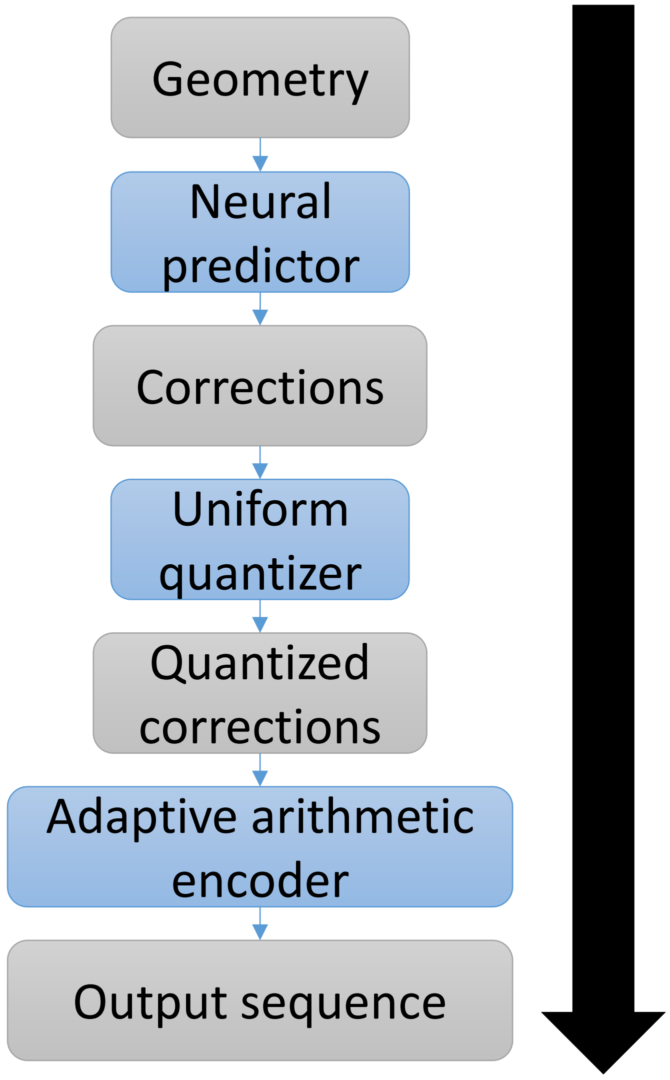
Neural predictor – Training

- L1 loss (inner angles + dihedral angle)
- Different loss for validation (distance between predicted and actual position)

$$\mathcal{L} = \frac{1}{n}\sum_{i=1}^{n}\left(|\gamma_{\text{pred}} - \gamma| + |\delta_{\text{pred}} - \delta| + |\omega_{\text{pred}} - \omega|\right)$$

$$\mathcal{L}_{\text{val}} = \frac{1}{n}\sum_{i=1}^{n}\left\|\mathbf{X}_{\text{pred}}(\gamma_{\text{pred}}, \delta_{\text{pred}}, \omega_{\text{pred}}) - \mathbf{X}\right\|_1$$

Neural predictor - Pipeline



Neural predictor – uncertainty estimation

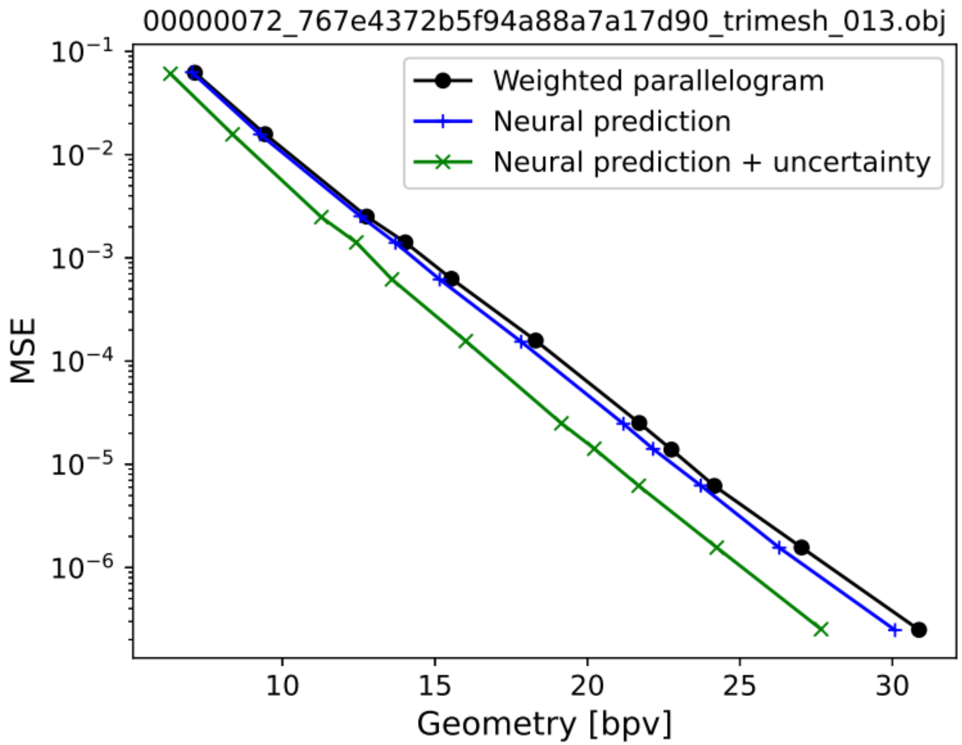
- Maybe we could estimate prediction error
- Corrections with different uncertainty are encoded within different context of arithmetic coder
- Another neural network
- Relative error (with respect to the area of base triangle)
- Concordance Correlation Loss

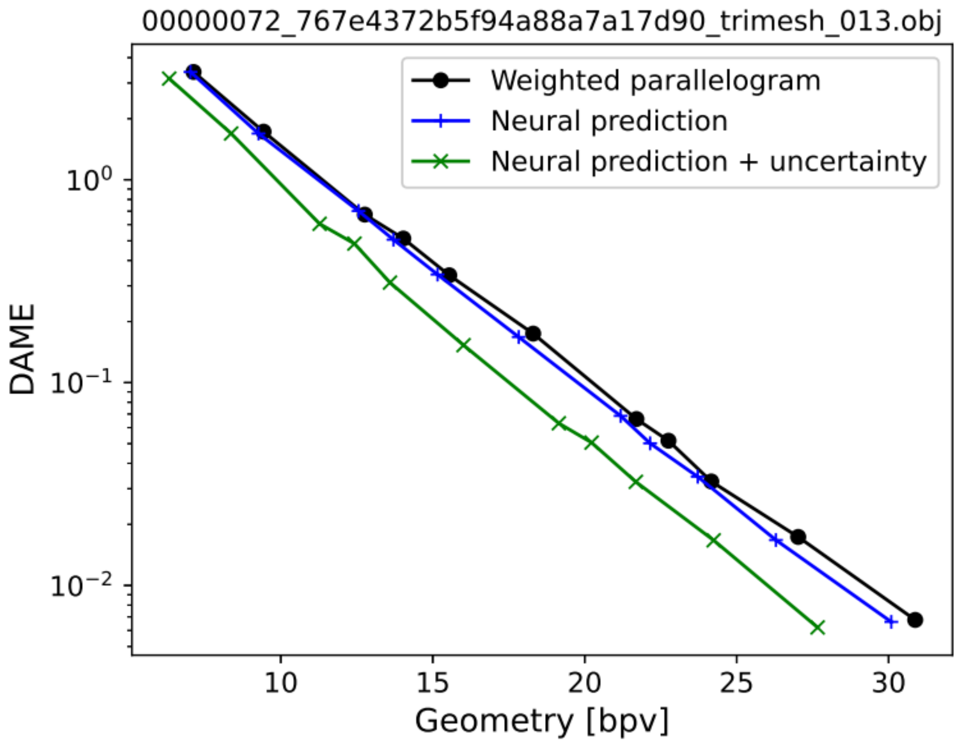
$$e = \frac{||\mathbf{X} - \mathbf{X}_{\text{pred}}||}{\frac{1}{2}||(\mathbf{L} - \mathbf{B}) \times (\mathbf{R} - \mathbf{B})||}$$

$$\mathcal{L}_{\text{unc}} = 1 - \frac{2\rho_{eu}\sigma_e\sigma_u}{\sigma_e^2 + \sigma_u^2 + (\mu_e - \mu_u)^2}$$

Results

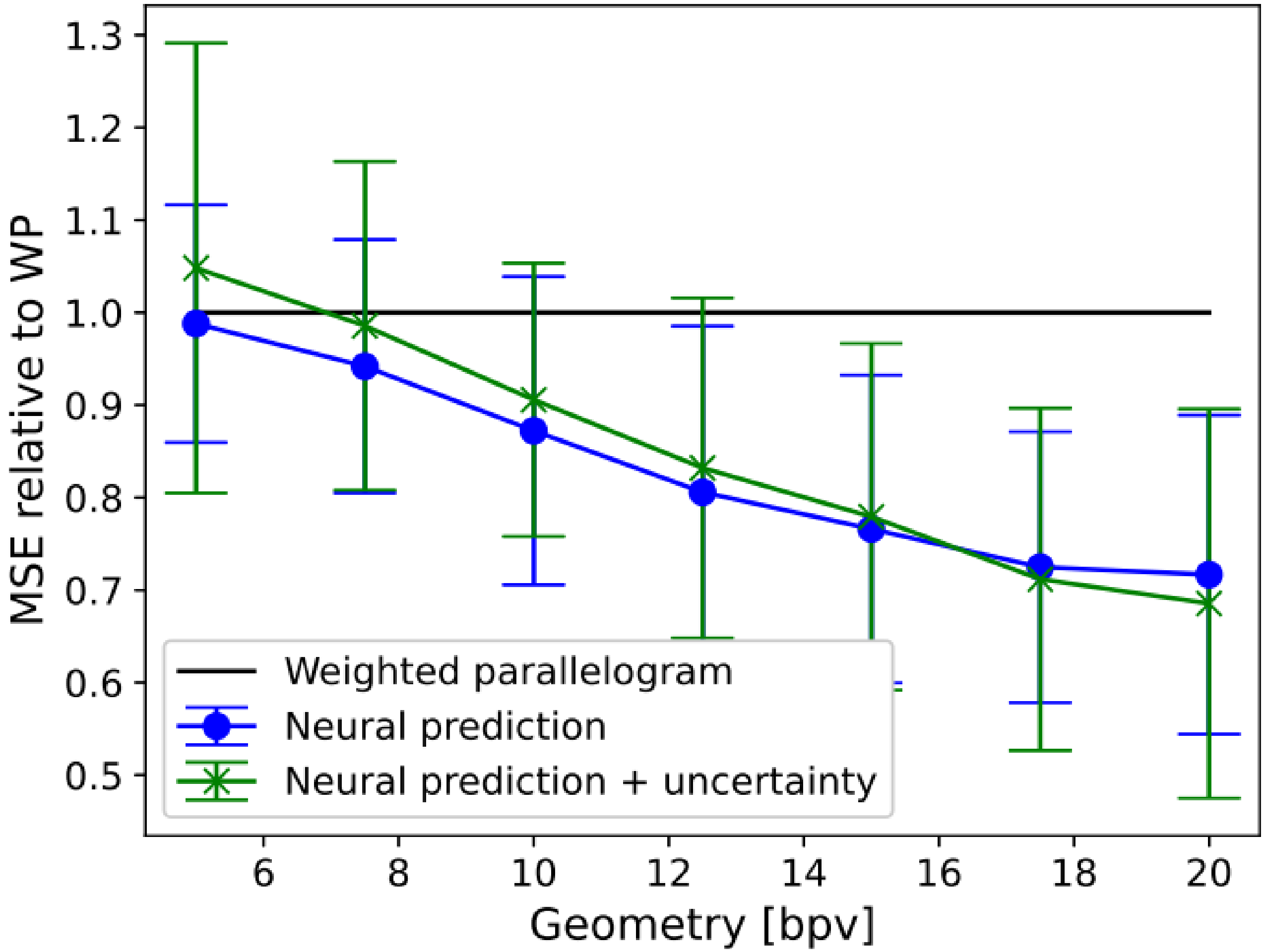
- Comparison with the Weighted Parallelogram (state of the art)
- Rate-Distortion ratio
  - Mechanistic metric - Mean Squared Error (MSE)
  - Perceptual metric - Dihedral Angle Mesh Error (DAME) [VR12]





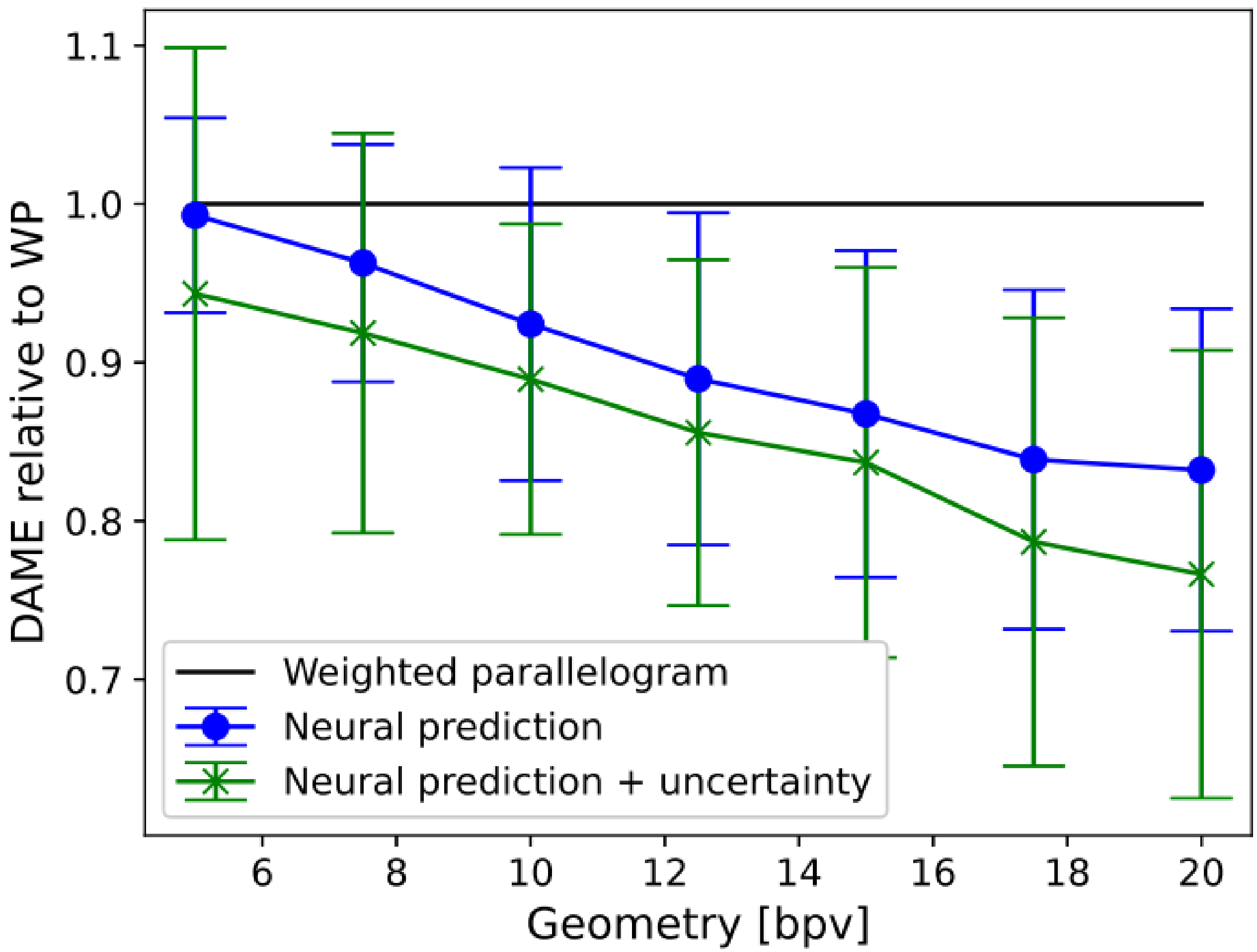
Results (MSE)

- Relative improvement wrt. WP



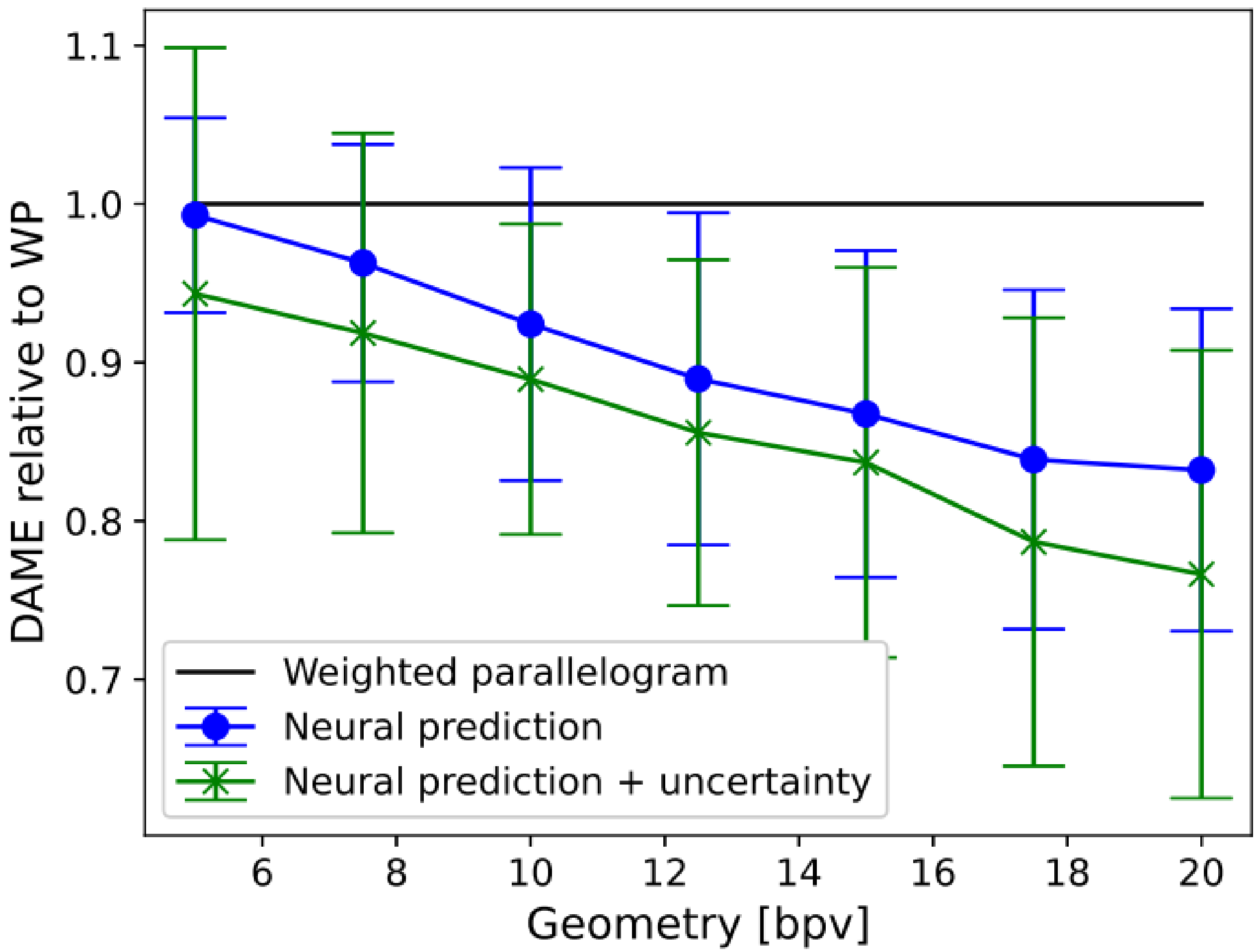
Results (DAME)

- Relative improvement wrt. WP



Results (DAME)

- Relative improvement wrt. WP



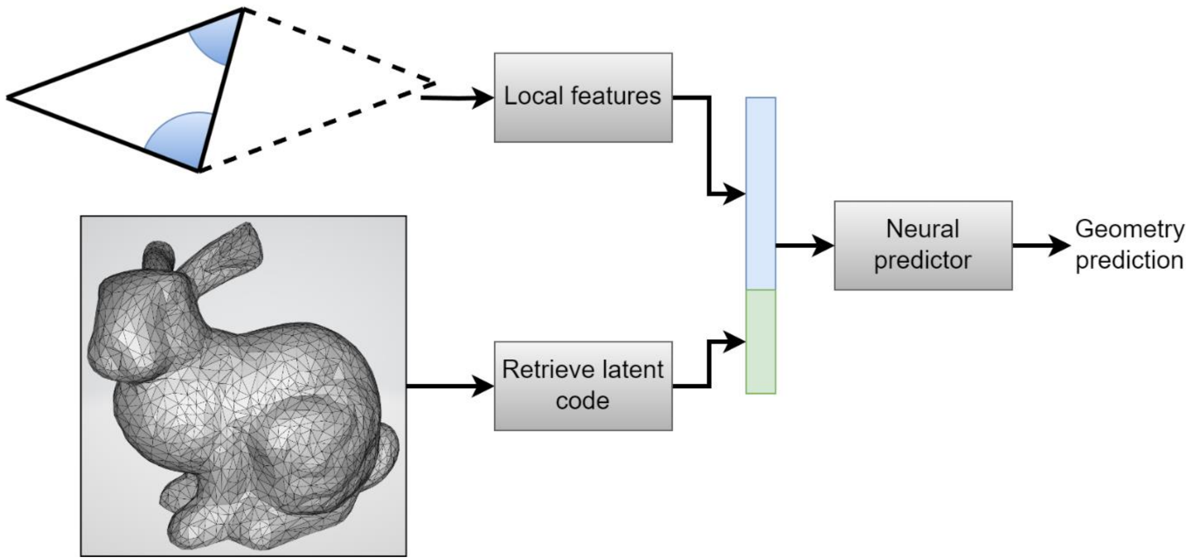
Reference

- Published at ICCS2024
  - Hácha F., Váša L.: Learning Mesh Geometry Prediction, Learning Mesh Geometry Prediction. In: Franco, L., de Mulatier, C., Paszynski, M., Krzhizhanovskaya, V.V., Dongarra, J.J., Sloot, P.M.A. (eds) Computational Science – ICCS 2024. ICCS 2024. Lecture Notes in Computer Science, vol 14832. Springer, Cham. https://doi.org/10.1007/978-3-031-63749-0_12

In progress

Global mesh features

- Local features
  - Characterize the shape of the base triangle and its surroundings
- Global features
  - Global mesh properties (curvature, tesselation, …)
  - Encoded at the beginning of the stream

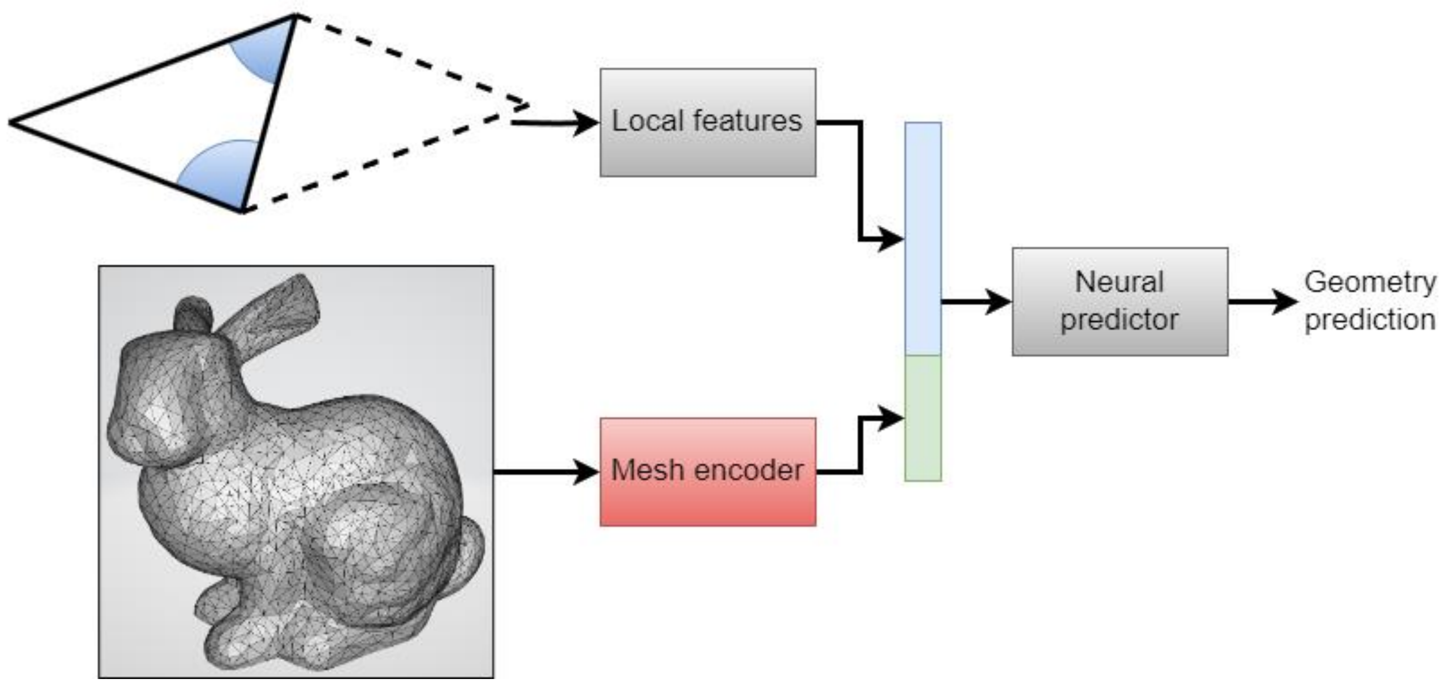


Global mesh features

- Currently 7 handcrafted features
  - Variance of inner angles
  - Average dihedral angle
  - Variance of dihedral angles
  - Deviation from isoscelesness $|\alpha-\beta|$ (avg. + var.)
  - Deviation from parallelogram $|\alpha-\delta|+|\beta-\gamma|$ (avg. + var.)

Global mesh features

- End-to-end learning
  - Still should be invariant to rigid transformations
    - Also to permutation of vertices and faces
  - Requires proper neural network architecture (MeshNet, PointNet?)



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Thank You For Your Attention

Filip Hácha / hachaf@kiv.zcu.cz