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SE(3)-UNET

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Visione Artificiale

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Problem statement

- The problem consists in defining a novel architectures resilient to 3D roto-translation
- In others words, we want a network that is equivariant for every transformation in a given abstract group
- Objective: heatmap inference for predicting face landmarks
- Idea: replacing classic convolution block in a U-net architecture by SE(3)-Transformer block

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SE(3)-Transformers

$$\mathbf{f}_{\text{out},i}^{\ell} = \underbrace{\mathbf{W}_V^{\ell\ell}\mathbf{f}_{\text{in},i}^{\ell}}_{\text{③ self-interaction}} + \sum_{k\geq 0}\sum_{j\in\mathcal{N}_i\setminus i} \underbrace{\alpha_{ij}}_{\text{① attention}} \underbrace{\mathbf{W}_V^{\ell k}\left(\mathbf{x}_j - \mathbf{x}_i\right)\mathbf{f}_{\text{in},j}^{k}}_{\text{② value message}} \tag{3}$$

$$\alpha_{ij} = \frac{\exp(\mathbf{q}_i^{\top}\mathbf{k}_{ij})}{\sum_{j'\in\mathcal{N}_i\setminus i}\exp(\mathbf{q}_i^{\top}\mathbf{k}_{ij'})}, \quad \mathbf{q}_i = \bigoplus_{\ell\geq 0}\sum_{k\geq 0}\mathbf{W}_Q^{\ell k}\mathbf{f}_{\text{in},i}^{k}, \quad \mathbf{k}_{ij} = \bigoplus_{\ell\geq 0}\sum_{k\geq 0}\mathbf{W}_K^{\ell k}(\mathbf{x}_j - \mathbf{x}_i)\mathbf{f}_{\text{in},j}^{k} \tag{4}$$

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FaceScape Dataset

1. **Acquisition**:
   - 18,760 high resolution 3D faces with 20 different expressions
   - Acquired by using a multi-view 3D reconstruction system composed by 68 DSLR cameras
   - Resulting in point clouds having 8192 points and 68 corresponding landmark
2. **Pre-processing**:
   - Introducing random 3D roto-translation then realigned by using ICP
   - Simply introducing random 3D roto-translation
3. **Point cloud dimensionality reduction**:
   - Reduced from 8192 to 1024 points by using Farthest Point Sampling (FPS)
   - Heatmap re-computed via a Gaussian function

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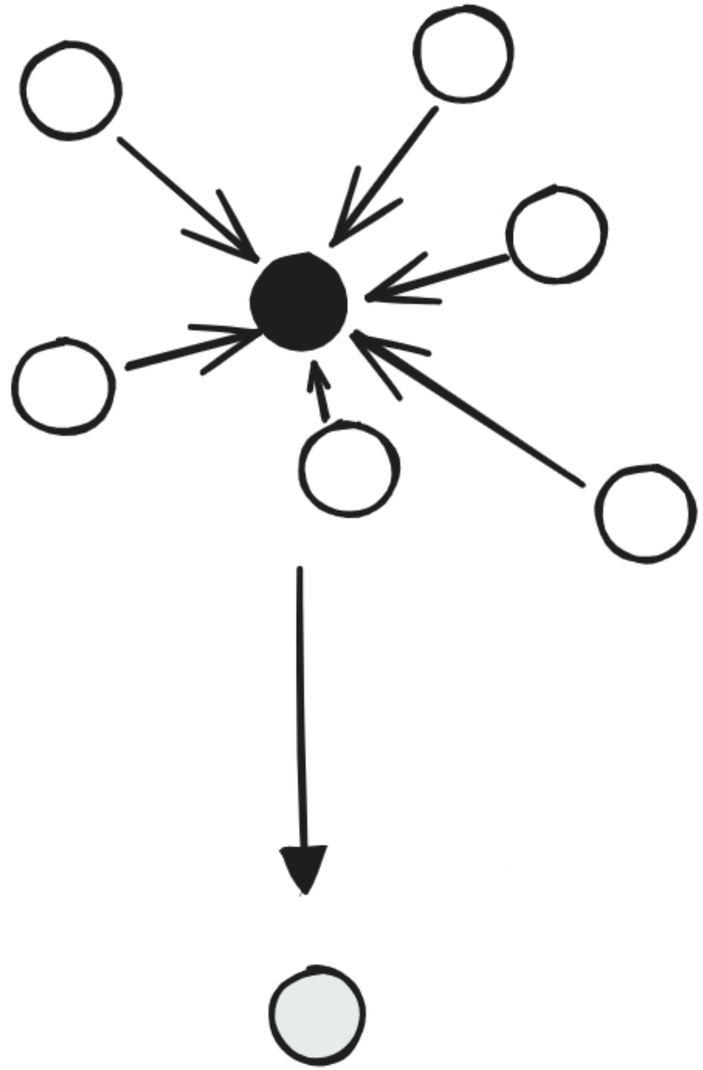
3D - Pooling

3D poling aims to apply classic pooling operation in the 3D filed:

1. A certain number of points are selected, according to a pooling ratio by using FPS
2. On the basis of each point’s neighborhood, features are aggregated (by sum)
3. Points not selected are discarded
4. The result is a point cloud reduced by the pooling ratio defined



05

3D - Upsampling

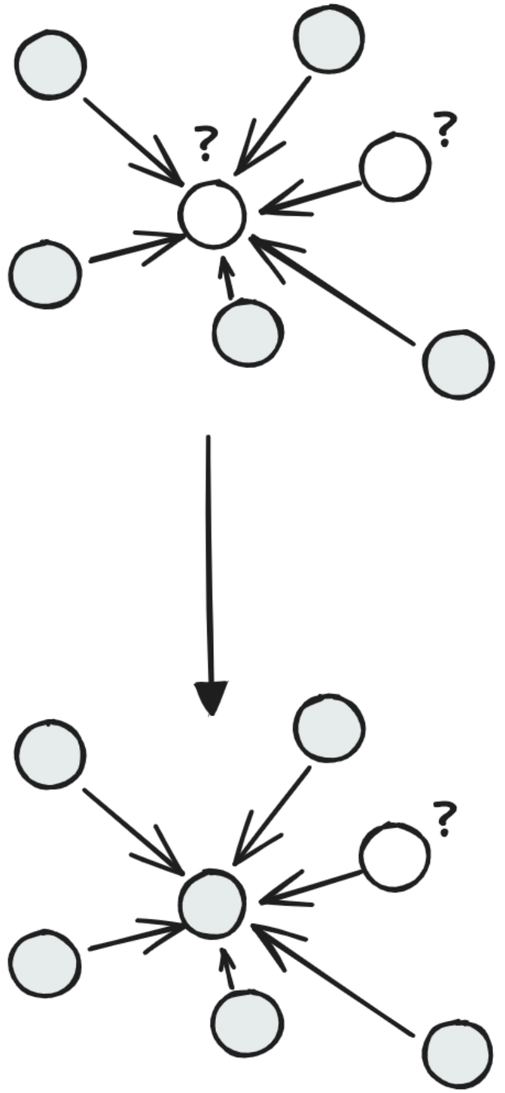
3D upsampling consists in reconstructing the point cloud resolution at the previous step by using IDW:

1. For each features to estimate weights are computed as:

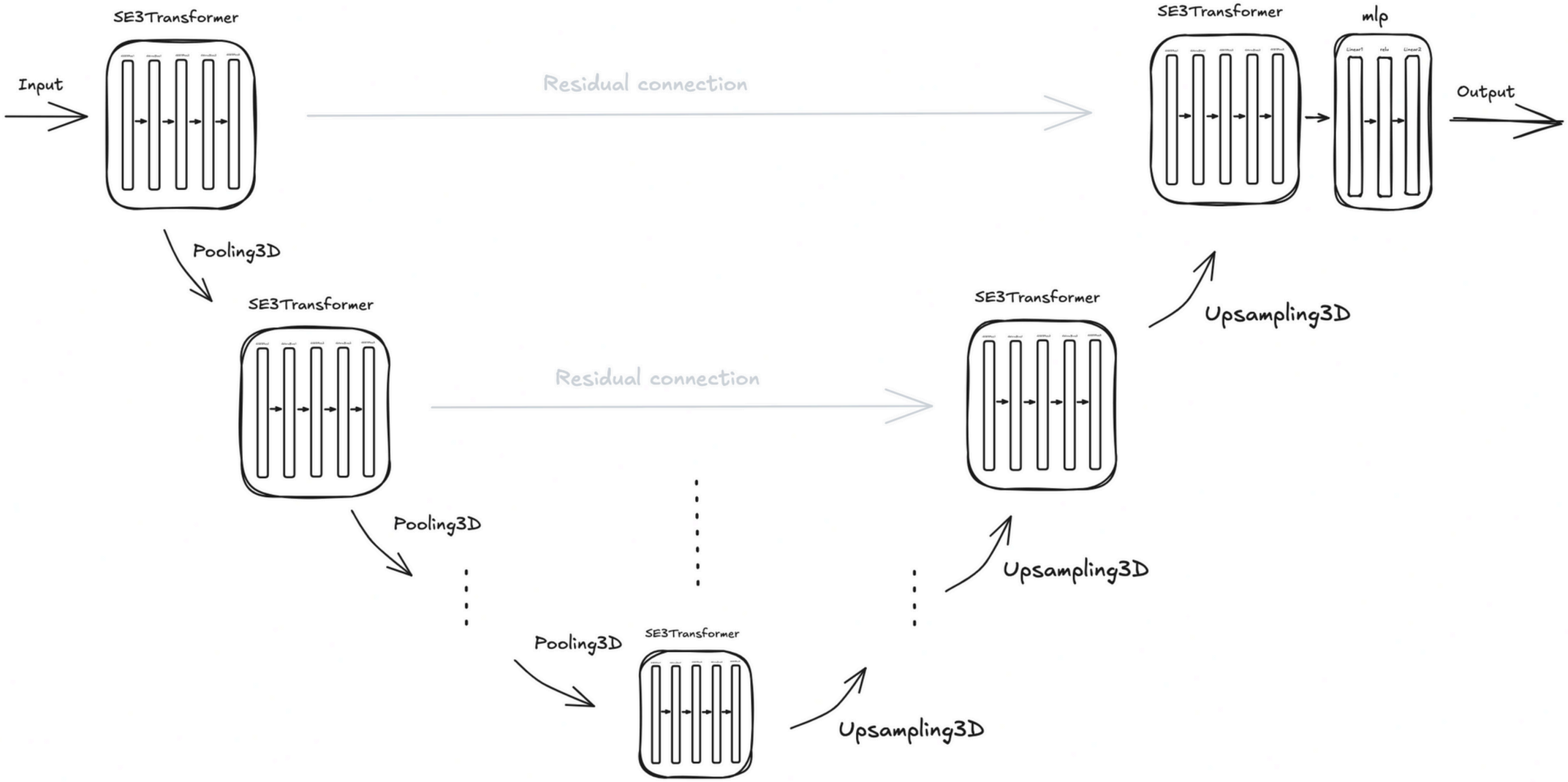
$$w_j = \frac{1}{d(x_i,\, x_j)^p}$$

2. Then features are estimated as the weighted average:

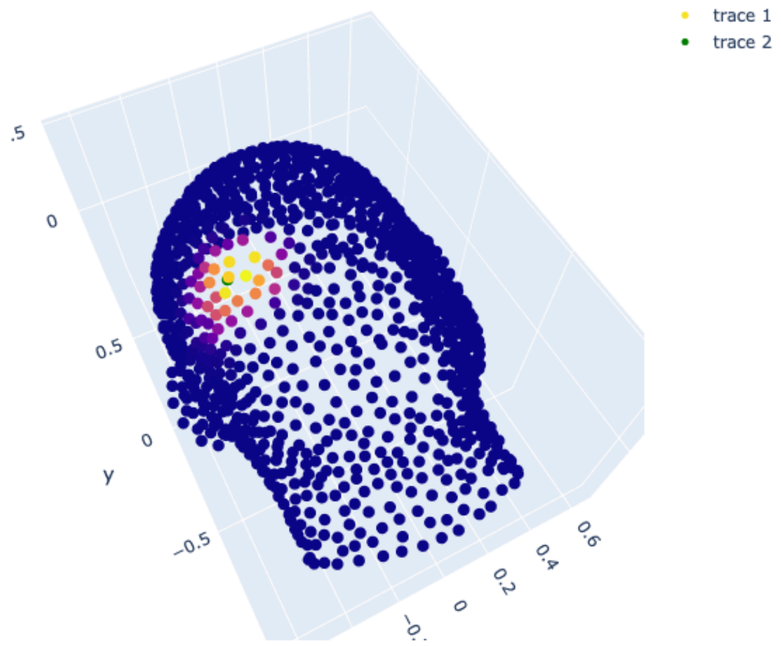
$$f_i = \frac{\sum_{j \in \mathcal{N}_i} w_j f_j}{\sum_{j \in \mathcal{N}_i} w_j}$$



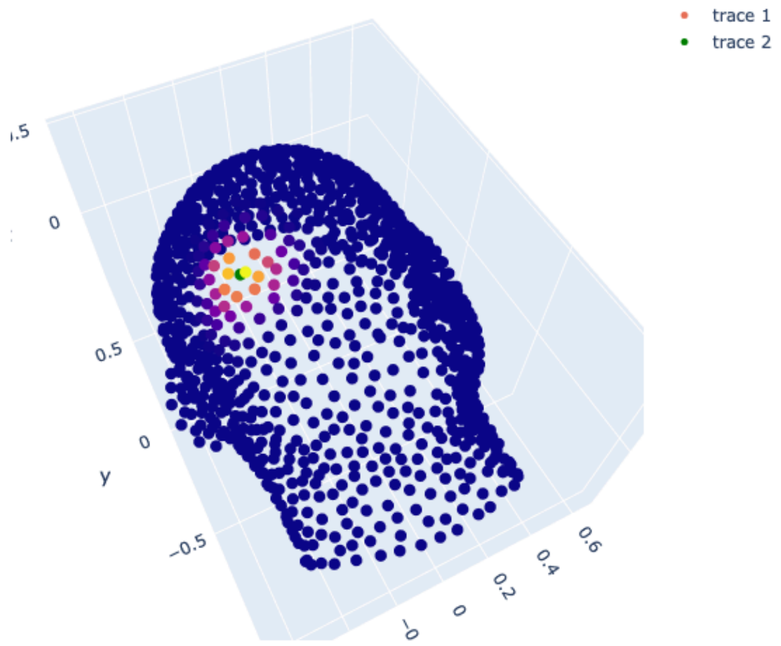
Model architecture



Results: no pre-processing

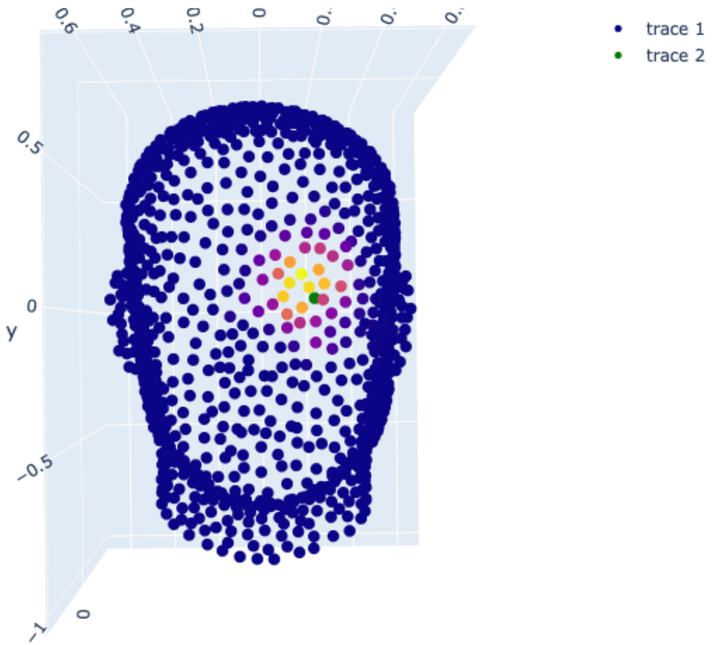


Model prediction

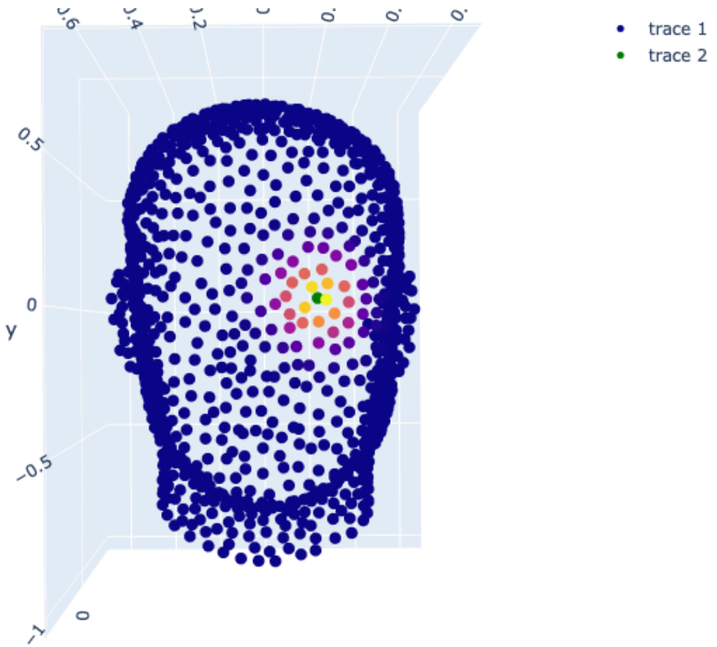


Groundtruth

Results: ICP - rt

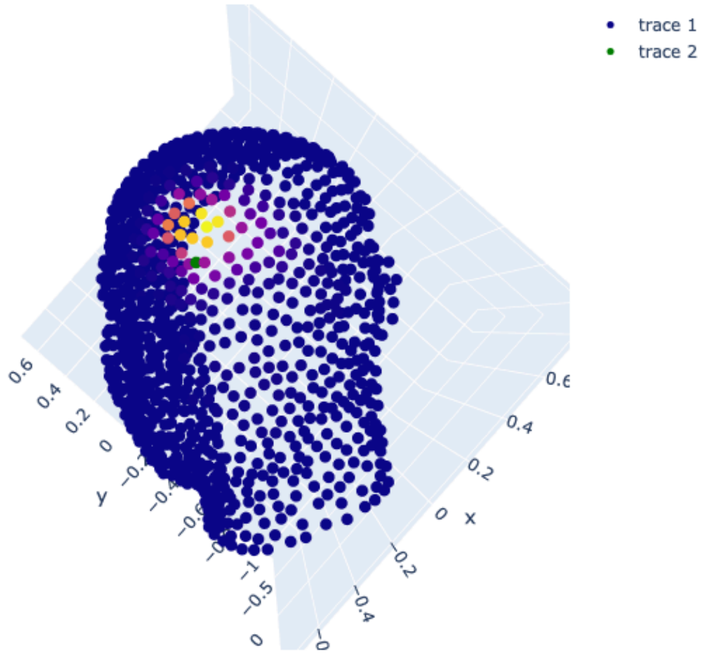


Model prediction

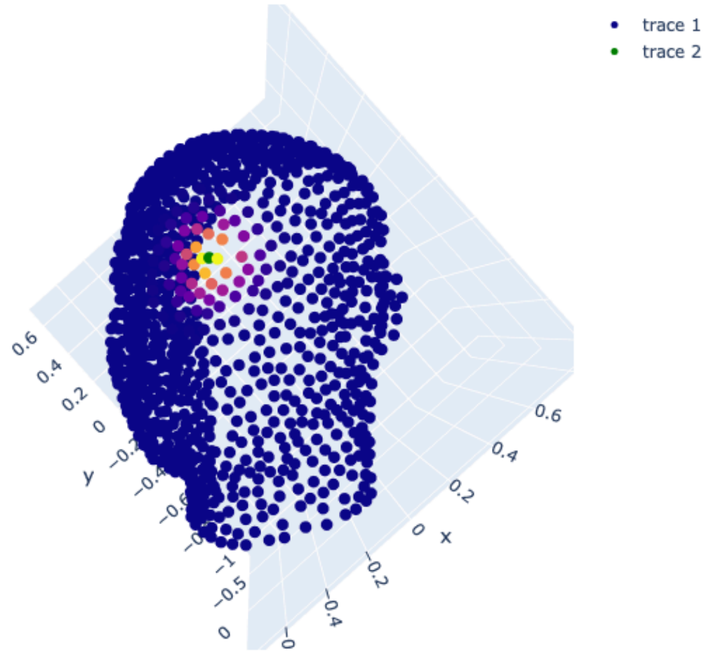


Groundtruth

Results: ST - r

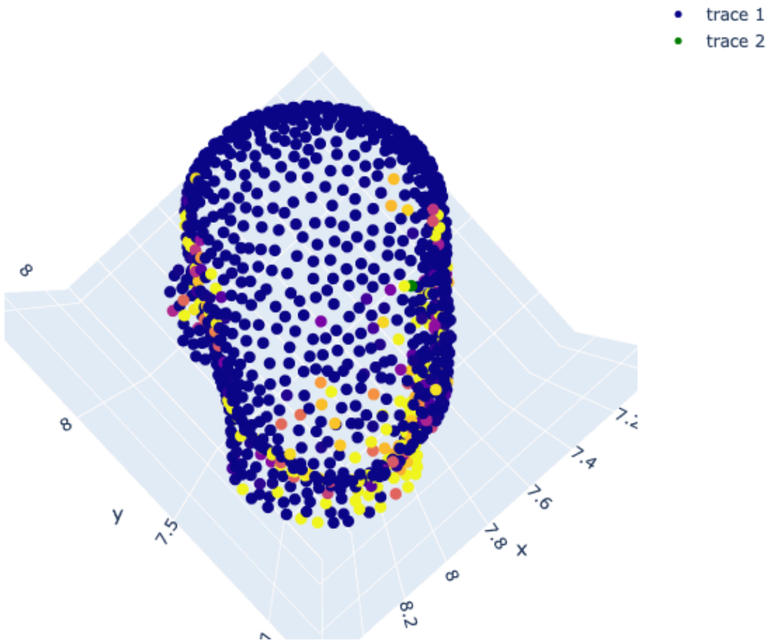


Model prediction

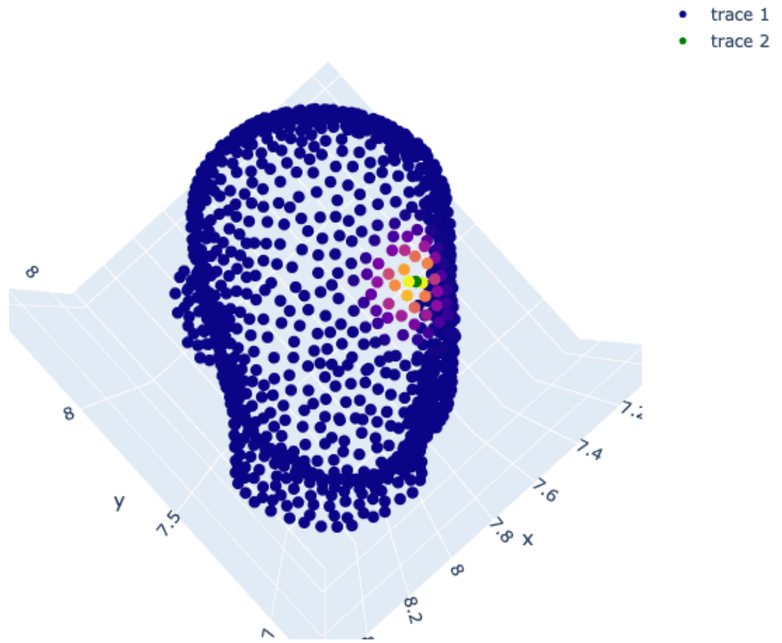


Groundtruth

Results: ST - rt



Model prediction



Groundtruth

Conclusion

- When no-preprocessing is applied the model works well
- When little noise is introduced the model is still able to handle the data
- When stronger noise is introduce the model has some difficulties with a well defined heatmap but not very well centered in the landmark location
- When a roto-translation is applied to the input the model is completely broken

In conclusion, there is still room for improvement!