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Lilienkamp, H., von Specht, S., Weatherill, G., Caire, G., Cotton, F. (2022): Ground-Motion Modeling as an Image Processing Task: Introducing a Neural Network Based, Fully Data-Driven, and Nonergodic Approach. - Bulletin of the Seismological Society of America, 112, 3, 1565-1582.

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to

Ground-Motion Modeling as an Image Processing Task: Introducing a Neural Network Based, Fully Data-Driven, and Nonergodic Approach

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We found a typo in our python codes that affects the training of U-Net neural networks presented in Lilienkamp et al. (2022) but leaves the results and conclusions unaffected. As described in the article, we split our dataset according to both seismic stations (into five chunks) and events (training and validation events). We originally intended to use four out of five station chunks and the training events to train a U-Net and to use the remaining station chunk and validation events for validation during the training procedure (to detect and avoid overfitting) and for the evaluation of results after completed training. In the actual implementation, validation during the training procedure is performed on the same four station chunks that are used for training (but using validation events). For the evaluation of the interpolation capabilities, we used the retained station chunk as shown in Figure 13 c,d and Table 1 of the original article. All results and conclusions presented in the article are unaffected by the typo and hold true for the models that we actually trained. With the originally intended strategy, we aimed to avoid overfitting to training station locations that might potentially result in a reduced ability to generalize to new locations. However, the presented results indicate that this ability is also given using the actually implemented training procedure, within the error-bounds that we provide. We conclude that this ability is predominantly achieved via the ensemble averaging introduced on p. 1568, right side, line 1 in the original article Lilienkamp et al. (2022).

The python code developed within the scope of this study is now available at <u>https://git.gfz-potsdam.de/lilienka/unetgmm</u>.

In the following, we provide revised formulations concerning affected explanations in the article:

Page 1568, left side, pp. 43–45: "3. One U-Net is trained per station chunk, using the respective station chunk and validation events for validation and all other station chunks and training events for training."

Revision: 3. One U-Net is trained per station chunk, in which the respective station chunk is excluded from the training procedure and the remaining four chunks are used for both training and validation on the training and validation events, respectively. The fifth chunk is then used to evaluate the capability to generalize to new locations after training.

Page 1571, right side, ll.16–19: "Therefore, we also derive partial ensemble estimators \hat{Y}^i , which only average over those respective 10 U-Nets that share the same *i*th station chunk for validation."

Revision: Therefore, we also derive partial ensemble estimators \hat{Y}^i , which only average over

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those respective 10 U-Nets for which the same *i*th station chunk was excluded from the training procedure and is used to evaluate the ability to interpolate spatially after training.

Page 1572, right side, ll.15–18: "For this purpose, we use the partial ensemble estimators \hat{Y}^i , for which the *i*th station chunk was used for validation only and can thus be used to evaluate interpolated predictions."

Revision: For this purpose, we use the partial ensemble estimators \hat{Y}^i , for which the *i*th station chunk was excluded from training and can thus be used to evaluate interpolated predictions.

Figure 9 caption: "Partial ensemble estimators \hat{Y}^i are derived via averaging over those subsets of U-Nets that share the same station validation chunk."

Revision: Partial ensemble estimators \hat{Y}^i are derived via averaging over those subsets of U-Nets for which the same *i*th station chunk was excluded from training and can thus be used to

evaluate interpolated predictions.

In addition to these coding related issues, we want to take the opportunity and revise one of our statements that notably causes some confusion among readers:

Page 1573, l.1: "Each of the five \hat{Y}^i can be evaluated in four different categories:"

Revision: Each of the five $\widehat{\Upsilon}^i$ can be compared with the observed data in four different categories.

DECLARATION OF COMPETING INTERESTS

The authors acknowledge that there are no conflicts of interest recorded.

REFERENCE

Lilienkamp, H., S. von Specht, G. Weatherill, G. Caire, and F. Cotton (2022). Ground-motion modeling as an image processing task: Introducing a neural network based, fully data-driven, and nonergodic approach, Bull. Seismol. Soc. Am. 112, no. 3, 1565–1582, doi: 10.1785/0120220008.