## Autoreject: Automated artifact rejection for MEG and EEG data (Supplementary material)

Here, we present additional material that may answer some questions that the reader might have when reading the main text.

 $\ell_2 vs \ell_{\infty} norm.$ : Why not use  $\ell_2$  norm instead of  $\ell_{\infty}$  norm to report the quantitative results in Figure 6 or Figure 7? The reason is that the  $\ell_2$  norm will average across the sensors. If one sensor is badly corrupted, then this would not be obvious with the  $\ell_2$  norm because the average in the  $\ell_2$  norm computation conceals the isolated problematic sensors with large artifacts. However, as the  $\ell_{\infty}$  norm captures the worst sensor, it can be used to visualize pathological cases where even one sensor is corrupted. In Figure S1, we reproduce Figure 6 using the  $\ell_2$  norm instead of  $\ell_{\infty}$ . We can observe that, although the pattern remains the same, it is much less clear where one method outperforms the other. Even where *autoreject* isn't performing as well, it is not visible due to the averaging effect.



Figure S1: Scatter plots for the results with the HCP data. This figure uses the same data as in Figure 6 from the main text, but with  $\|\cdot\|_2$  norm instead of the  $\|\cdot\|_{\infty}$  norm for computing the difference between the HCP ground truth and the method. As before, each circle is a subject. (A) *autoreject (local)* against no rejection, (B) *autoreject (local)* against Sensor Noise Suppression (SNS) (SNS), (C) *autoreject* against FASTER, (D) *autoreject (local)* against RANSAC. Data points below the dotted red line indicate subjects for which *autoreject (local)* outperforms the alternative method.

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