

# Ensemble Feature Extraction for Multi-Container Quality-Diversity Algorithms Supplementary Information

## 1 Projection to the feature descriptors space of the hardcoded-4 case

We want to assess how solutions found for all cases occupy the feature descriptors space of the reference **hardcoded-4** case. To do so, we project these solutions into the feature space of the **hardcoded-4** case. Figures 1 and 2 show representative instances of such projection, over only one experimental run. There are only very few overlaps between the FD spaces of the Feature Extraction cases with the **hardcoded-4**, suggesting that the solutions of the former occupies completely different behavioural niches compared to the solutions of the latter.

## 2 Pairwise KL-Coverage

We consider another way of comparing together the FD spaces, by using the KL-Coverage metric from [2], which was also used in the original AURORA paper [1], to check whether two FD spaces are similar to each other (possibly hinting at their representation capabilities). We extend the original definition to handle multi-containers scenarios:

$$KLC = \sum_c \mathcal{D}_{KL}[E_c||A_c] = \sum_c \sum_{i=1}^{10} E_c(i) \log\left(\frac{E_c(i)}{A_c(i)}\right) \quad (1)$$

where  $C$  is the set of all containers; and for a container  $c$ :  $E_c$  and  $A_c$  are respectively the reference and the compared distributions for container  $c$ . Lower KLC scores indicate more similar FD spaces.

Table 1 contains a pairwise comparison of the distribution of all solutions found by each case, by using the KL coverage metric.

	hardcoded-4	hardcoded-4-ns	pt-reco-4	qt-reco-4-ns	hardcoded-1	qt-reco-1	qt-reco-9-ns	qt-reco-25-ns	qt-outputs-4-ns	qt-covmin-4-ns	qt-covmax-4-ns	qt-cmd-4-ns
hardcoded-4	3.532 ± 2.279	37.529 ± 5.204	237.401 ± 138.267	67.478 ± 58.851	45.213 ± 9.204	15.145 ± 26.647	110.498 ± 60.944	381.826 ± 103.125	33.672 ± 24.755	41.156 ± 53.640	88.725 ± 90.881	64.773 ± 68.020
hardcoded-4-ns	2.161 ± 0.703	6.556 ± 4.013	217.568 ± 30.985	60.626 ± 55.809	28.818 ± 6.043	13.950 ± 24.685	110.802 ± 51.521	372.828 ± 83.181	29.310 ± 24.720	41.447 ± 49.777	81.032 ± 70.991	60.412 ± 64.112
pt-reco-4	3.758 ± 0.134	4.028 ± 1.109	261.816 ± 96.423	47.333 ± 52.903	23.149 ± 6.437	15.965 ± 28.100	123.597 ± 65.578	394.563 ± 107.843	34.616 ± 22.830	32.684 ± 48.329	69.403 ± 79.034	51.481 ± 50.419
reco-4	3.637 ± 0.375	3.313 ± 0.643	223.318 ± 88.989	41.457 ± 41.054	17.760 ± 5.380	18.787 ± 40.915	128.605 ± 74.571	372.045 ± 100.057	31.613 ± 21.247	31.097 ± 42.560	55.783 ± 52.321	53.082 ± 52.378
qt-reco-4	3.271 ± 0.406	3.099 ± 0.923	267.139 ± 89.560	51.507 ± 49.455	18.478 ± 5.756	17.875 ± 34.182	135.863 ± 71.914	407.154 ± 86.430	31.978 ± 21.130	26.666 ± 37.319	60.443 ± 58.063	50.702 ± 38.753
qt-reco-4-ns	2.084 ± 0.267	1.156 ± 0.391	220.504 ± 49.952	61.870 ± 66.211	21.708 ± 5.960	13.462 ± 24.528	125.668 ± 50.074	402.748 ± 63.233	29.157 ± 19.563	29.572 ± 35.750	67.997 ± 61.700	44.575 ± 27.637
hardcoded-1	6.486 ± 1.832	26.617 ± 7.624	200.256 ± 65.087	61.268 ± 52.100	11.683 ± 7.774	15.867 ± 27.894	113.038 ± 63.244	394.578 ± 95.579	32.772 ± 26.580	41.489 ± 56.487	81.368 ± 69.214	64.164 ± 72.541
qt-reco-1	2.901 ± 0.609	3.005 ± 1.020	244.099 ± 100.073	49.318 ± 45.511	19.863 ± 8.580	15.005 ± 28.277	127.464 ± 67.042	405.576 ± 66.359	29.161 ± 19.047	27.656 ± 37.383	69.335 ± 70.539	53.770 ± 46.366
qt-reco-6-ns	2.099 ± 0.327	0.893 ± 0.150	224.688 ± 46.879	61.226 ± 61.438	21.702 ± 5.647	14.487 ± 26.782	127.950 ± 54.268	396.338 ± 59.380	29.915 ± 20.218	28.606 ± 35.372	64.242 ± 60.267	50.063 ± 34.534
qt-reco-9-ns	2.199 ± 0.218	2.716 ± 1.116	238.029 ± 86.652	56.751 ± 51.980	21.300 ± 5.790	15.079 ± 27.784	130.979 ± 70.728	407.644 ± 68.638	31.054 ± 20.840	32.416 ± 43.633	76.785 ± 80.134	53.509 ± 44.164
qt-reco-25-ns	1.976 ± 0.173	0.863 ± 0.123	230.240 ± 52.536	58.067 ± 53.512	23.484 ± 5.822	13.652 ± 24.422	123.643 ± 51.230	395.059 ± 64.495	30.882 ± 20.510	29.721 ± 39.078	72.903 ± 74.861	51.196 ± 36.077
qt-outputs-4-ns	2.143 ± 0.417	1.384 ± 0.469	232.550 ± 54.277	60.858 ± 63.674	22.180 ± 6.173	13.206 ± 24.088	127.940 ± 48.767	413.868 ± 70.623	29.645 ± 19.025	29.538 ± 36.087	66.162 ± 59.543	48.303 ± 33.298
qt-covmin-4-ns	2.199 ± 0.220	1.054 ± 0.509	224.056 ± 48.199	61.159 ± 63.017	25.768 ± 5.595	13.498 ± 24.646	126.980 ± 49.664	407.084 ± 70.724	31.167 ± 19.692	32.825 ± 36.941	68.111 ± 63.922	47.500 ± 30.976
qt-covmax-4-ns	2.175 ± 0.214	0.928 ± 0.254	213.556 ± 49.202	59.329 ± 60.668	21.273 ± 5.913	13.184 ± 24.116	125.341 ± 52.401	407.264 ± 66.606	30.564 ± 19.857	30.020 ± 35.265	67.472 ± 63.610	48.234 ± 32.006
qt-cmd-4-ns	2.001 ± 0.233	0.879 ± 0.264	227.694 ± 55.555	63.944 ± 64.977	24.530 ± 7.232	13.675 ± 24.866	130.660 ± 50.915	415.388 ± 67.833	29.847 ± 19.153	30.252 ± 36.339	68.877 ± 64.653	47.890 ± 30.716

Table 1: Mean pairwise KL-coverage of all studied cases over 20 runs and using 10 bins per dimension: reference distributions are computed over the column cases and tested distributions over the row cases (so each pairwise score is averaged over  $20 * 20 = 400$  KL-coverage scores). Lower scores mean distributions that are more similar. The numbers following the symbol  $\pm$  represent the standard deviation.

The results in Table 1 show that the distributions of solutions of pre-trained and online cases are larger than the ones of the human-designed cases (with low pairwise KL-coverage scores when human-designed cases are used to compute reference distributions).

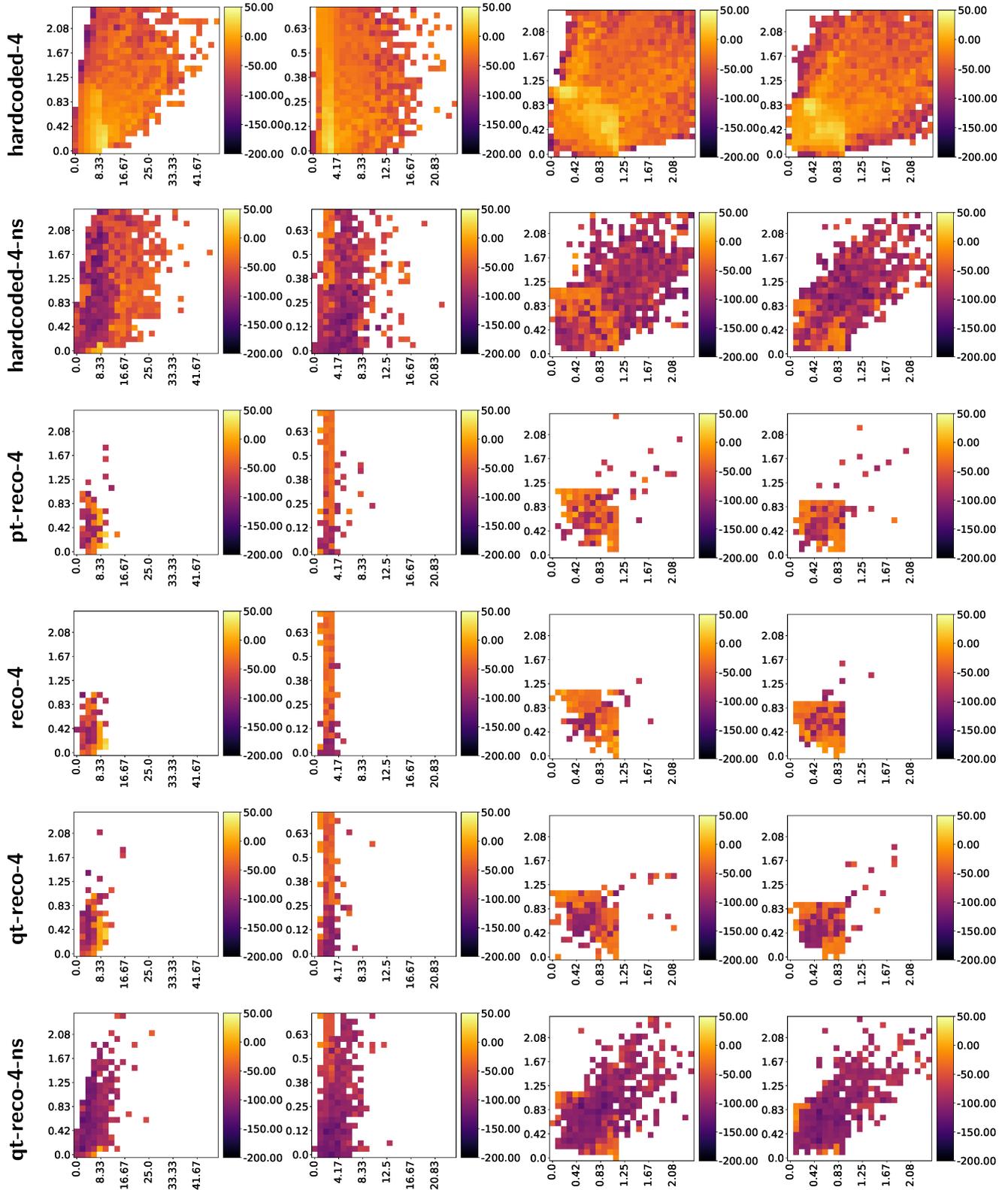


Figure 1: Representation instances (over one experimental run) of the projection of experimental cases into the feature descriptors space of case **hardcoded-4**.

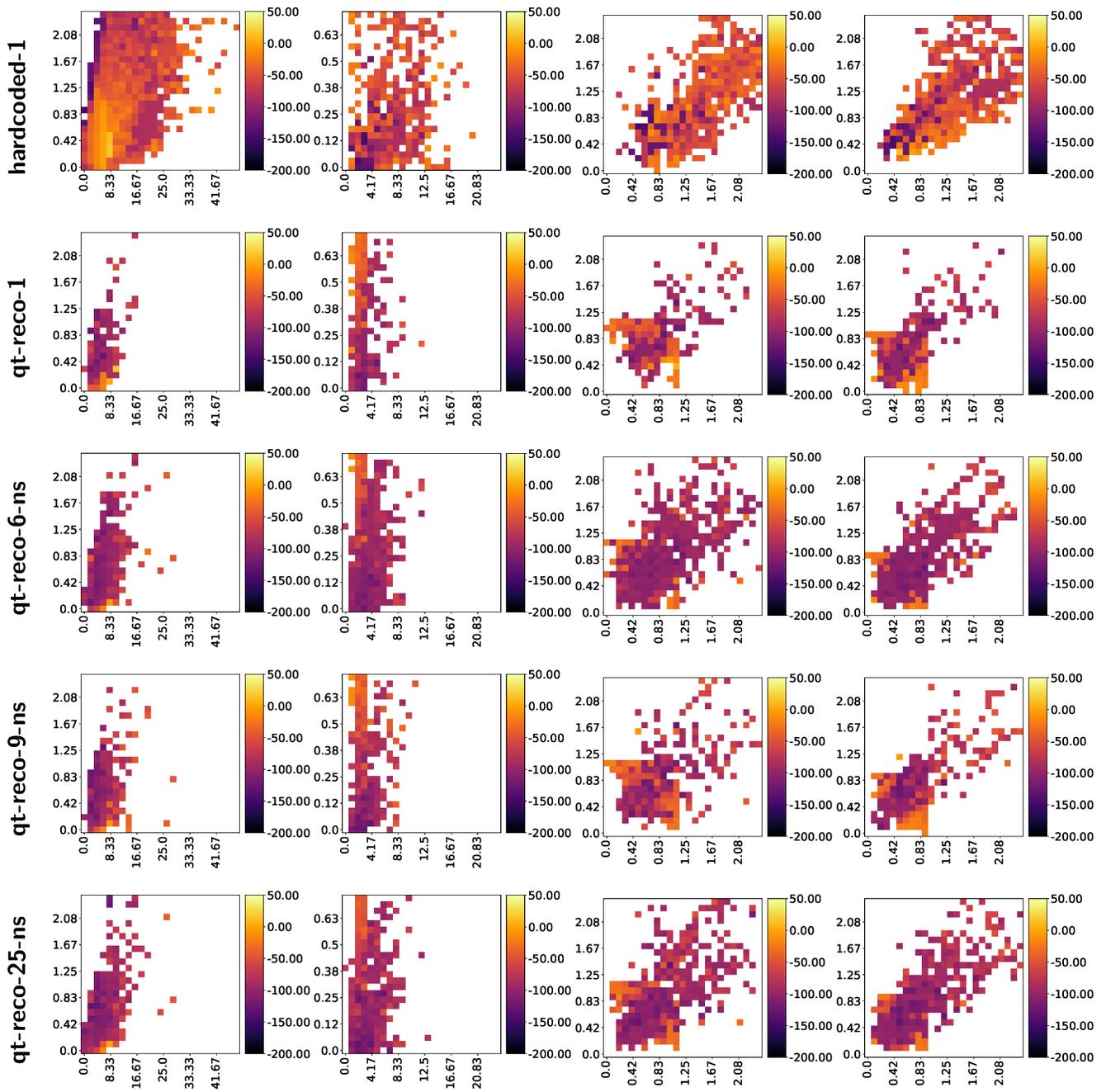


Figure 2: Representation instances (over one experimental run) of the projection of experimental cases into the feature descriptors space of case **hardcoded-4**.

## References

- [1] A Cully. Autonomous skill discovery with quality-diversity and unsupervised descriptors. In *Proceedings of the Genetic and Evolutionary Computation Conference*, pages 81–89, 2019.
- [2] A Péré, S Forestier, O Sigaud, and PY Oudeyer. Unsupervised learning of goal spaces for intrinsically motivated goal exploration. *arXiv preprint arXiv:1803.00781*, 2018.