

# Supplementary Material for: Learning Sparse Log-Ratios for High-Throughput Sequencing Data

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## A Optimization

### A.1 Continuous Relaxation

We optimized Eq. 10 from the main text using gradient descent with the following specifications:

- **Initialization.** We initialized the weights parameter  $\mathbf{w}$  at zero, which corresponds to assigning no prior “preference” to one covariate over any another. As for the intercept parameter  $\alpha$ , initialization requires some care, particularly in order to account for possibly imbalanced classes and for the stage-wise additive nature of our model. Namely,  $\alpha$  should capture the central tendency of the response so that the gradients propagated to  $\mathbf{w}$  capture the *differential* effect of the covariates on the response (not doing so severely hinders gradient descent). In practice, this amounts to initializing  $\alpha$  at the estimated coefficient of a generalized linear model with nothing but an intercept (which, in the regression case, reduces to the mean of the response). Note that, from the second stage of ensembling onwards, the fitted value of the current ensemble must be incorporated into said generalized linear model as a fixed offset term. Finally, we found the initialization of  $\beta$  to matter less, and simply used the initial value  $\beta = 0.1$  throughout.
- **Epochs.** We trained each continuous relaxation for 100 epochs. While this number of epochs was sufficient for the linear functionals we considered, we expect a higher number would be needed in order to combine our balances (or amalgamations) with nonlinear functionals.

- **Learning rate.** We used an adaptive scheme that exploits the structure of our continuous relaxation. Intuitively, we seek a learning rate that will allow  $\mathbf{w}$  to explore the range of values where our relaxation has non-vanishing gradients, which approximately corresponds to  $w_i \in (-5, 5)$ . This interval corresponds to soft assignments approximately between  $\tilde{w}_i \in (-0.99, 0.99)$ ; outside of this range, the sigmoid starts to saturate and gradients vanish. The question is then: how to choose a learning rate that allows  $\mathbf{w}$  to explore the range  $(-5, 5)$  efficiently (i.e., over a minimal number of epochs). We solve this indirectly; we pick the unique learning rate that would result in an initial gradient step that takes the maximum weight,  $\max(|\mathbf{w}|)$ , to the value 0.5. This learning rate can be found by simply computing one backward pass (and taking the maximum over the gradients w.r.t.  $\mathbf{w}$ ) prior to applying any gradient steps. Note that the value of 0.5 is somewhat arbitrary, and simply represents the size of an initial step that should be “small, but significant relative to the target range of  $(-5, 5)$ ”.
- **Momentum.** We used momentum, with rate 0.9.
- **Minibatching.** We did not use minibatching, as we found it unnecessary on the datasets we considered. Nevertheless, minibatching could be beneficial, particularly for datasets with larger number of observations.

## A.2 Discretization

Given a trained vector of soft assignments  $\tilde{\mathbf{w}}$ , typically only a small number will have converged to values close to  $+1$  or  $-1$ , with most components remaining close to zero. As discussed in Section 3.3, in order to identify a balance it is sufficient to specify a threshold value  $t$ . However, different thresholds  $t \in (0, 1)$  can result in different balances, depending on the values of  $\tilde{\mathbf{w}}$ . Our implementation evaluates a set of 20 “candidate thresholds”,  $t \in \{t_1, \dots, t_{20}\}$ , and settles on the one that yields the best cross-validation score. Any grid of values  $\{t_1, \dots, t_{20}\} \in (0, 1)$  can be used, where we write  $\{t_1, \dots, t_{20}\}$  in decreasing order. A principled choice is to “step through” the weights. Namely, start by rescaling the positive and negative components of  $\tilde{\mathbf{w}}$  so that  $\max \tilde{\mathbf{w}}^+ = \max \tilde{\mathbf{w}}^-$ , and then set  $\{t_1, \dots, t_{20}\}$  to equal the top 20 order statistics of the set  $\{|\tilde{w}_j|\}$ . Thus, the first candidate  $t_1$  will yield a simple log-ratio between two covariates (the rescaling ensure precisely two of our weights are  $\geq t_1$ ), the second candidate  $t_2$  will yield a log-ratio with a total of three covariates, and so forth.

Given a set of candidate thresholds  $\{t_1, \dots, t_{20}\}$ , we associate a score to each of these via cross-validation. We first split the training data into 5 folds (sampled with stratification by case control (He and Ma, 2013)). Then, for each candidate threshold  $t_i$ , we fit 5 regressors of the form Eq. 3 on the 5 cross-validation training sets, we evaluate on their respective validation folds, and average the results to obtain the overall cross-validation score of  $t_i$ . Finally, we choose the largest threshold (i.e., the sparsest model) whose cross-validation

score is within 1 standard error of the optimum achieved over  $\{t_1, \dots, t_{20}\}$  (with standard errors computed over the 5 cross-validation folds).

Note that we could search in this way over more than 20 candidate thresholds; the choice of the number 20 is by analogy to *selbal* (Rivera-Pinto *et al.*, 2018), where balances of up to (but no more than) 20 covariates are considered. We also found that our results were broadly insensitive to searching over more candidate thresholds; increasing this number can lead to slightly more accurate models that are slightly less sparse, and, evidently, somewhat slower to compute.

## B Datasets

Table 2 provides further details on the 25 datasets used in Section 4 of the the main text. Note also that zero-replacement is necessary prior to applying log-ratio transformations, a standard pre-processing step in the field of CoDa (Martín-Fernández *et al.*, 2000; Aitchison *et al.*, 2003; Martín-Fernández *et al.*, 2012). When necessary, we carried out zero-replacement by simply adding one unit to all counts prior to normalization.

## C Additional Experimental Results

Tables 3, 4, 5, 7 show our evaluation metrics on each individual dataset for a selection of our models. Table 2 from the main text summarizes these four tables by averaging over all datasets.

## References

- Aitchison, J., Kay, J. W., *et al.* (2003). Possible solution of some essential zero problems in compositional data analysis.
- He, H. and Ma, Y. (2013). Imbalanced learning: foundations, algorithms, and applications.
- Martín-Fernández, J., Barceló-Vidal, C., and Pawlowsky-Glahn, V. (2000). Zero replacement in compositional data sets. In *Data analysis, classification, and related methods*, pages 155–160. Springer.
- Martín-Fernández, J. A., Hron, K., Templ, M., Filzmoser, P., and Palarea-Albaladejo, J. (2012). Model-based replacement of rounded zeros in compositional data: classical and robust approaches. *Computational Statistics & Data Analysis*, **56**(9), 2688–2704.
- Rivera-Pinto, J., Egozcue, J. J., Pawlowsky-Glahn, V., Paredes, R., Noguera-Julian, M., and Calle, M. L. (2018). Balances: a new perspective for microbiome analysis. *MSystems*, **3**(4).

Table 1: Data description.  $n$  denotes the number of observations,  $p$  the number of covariates. We also show the number of observations in the case and control groups.

DATASET ID	$n$	$p$	GROUP 1	GROUP 2
1	975	48	CROHN'S DISEASE	WITHOUT
2	128	60	MEN WHO HAVE SEX WITH MEN	WITHOUT
3	220	153	CONTROL	IBD
4	164	158	CROHN'S DISEASE	ULCERATIVE COLITIS
5	220	885	CONTROL	IBD
6	164	885	CROHN'S DISEASE	ULCERATIVE COLITIS
7	182	278	CASE	DIARRHEAL CONTROL
8	247	610	CASE	NON-DIARRHEAL CONTROL
9	292	1133	COLORECTAL CANCER (CRC)	WITHOUT
10	318	1302	COLORECTAL CANCER (CRC)	NON-CRC CONTROL
11	1182	188	PRIMARY SOLID TUMOR	SOLID TISSUE NORMAL
12	1004	188	HER2 CANCER	NOT HER2 CANCER
13	718	188	LUMA CANCER	LUMB CANCER
14	140	992	CROHN'S DISEASE (ILEUM)	WITHOUT (ILEUM)
15	160	992	CROHN'S DISEASE (RECTUM)	WITHOUT (RECTUM)
16	2070	3090	GI TRACT	ORAL
17	180	3090	FEMALE	MALE
18	404	3090	STOOL	TONGUE (DORSUM)
19	408	3090	SUBGINGIVAL PLAQUE	SUPRAGINGIVAL PLAQUE
20	172	980	HEALTHY	COLORECTAL CANCER
21	124	2526	WITHOUT	DIABETES
22	130	2579	CIRRHOSIS	WITHOUT
23	199	660	BLACK	HISPANIC
24	342	660	NUGENT SCORE HIGH	NUGENT SCORE LOW
25	200	660	BLACK	WHITE

Table 2: Data description.

DATASET ID	GROUP 1 SIZE	GROUP 2 SIZE	SOURCE
1	662	313	DOI: 10.1016/J.CHOM.2014.02.005
2	73	55	DOI:10.1016/J.EBIOM.2016.01.032
3	56	164	DOI: 10.1038/s41564-018-0306-4
4	88	76	DOI: 10.1038/s41564-018-0306-4
5	56	164	DOI: 10.1038/s41564-018-0306-4
6	88	76	DOI: 10.1038/s41564-018-0306-4
7	93	89	DOI: 10.1128/MBIO.01021-14
8	93	154	DOI: 10.1128/MBIO.01021-15
9	120	172	DOI: 10.1186/s13073-016-0290-3
10	120	198	DOI: 10.1186/s13073-016-0290-3
11	1078	104	DOI: 10.1038/NG.2764
12	77	927	DOI: 10.1038/NG.2764
13	524	194	DOI: 10.1038/NG.2764
14	78	62	DOI: 10.1016/J.CHOM.2014.02.005
15	68	92	DOI: 10.1016/J.CHOM.2014.02.005
16	227	1843	DOI: 10.1038/NATURE11209
17	82	98	DOI: 10.1038/NATURE11209
18	204	200	DOI: 10.1038/NATURE11209
19	203	205	DOI: 10.1038/NATURE11209
20	86	86	DOI: 10.1101/GR.126573.111
21	59	65	DOI: 10.1038/NATURE11450
22	68	62	DOI: 10.1038/NATURE13568
23	104	95	DOI: 10.1073/PNAS.1002611107
24	97	245	DOI: 10.1073/PNAS.1002611107
25	104	96	DOI: 10.1073/PNAS.1002611107

Table 3: Average runtime over 20 train/test splits, in seconds.

DATASET ID	CoDaCoRe (DEFAULTS)	SELBAL	PAIRWISE LOG-RATIOS	CODA-LASSO	AMALGAM	RANDOM FOREST
1	6	328	17	39	48	2
2	5	354	7	19	40	0
3	5	1307	50	62	145	1
4	4	1291	28	44	212	1
5	4	31407	638	420	2553	5
6	4	26638	387	348	3806	4
7	4	3316	79	39	532	1
8	4	14058	522	157	1965	3
9	4	48394	985	391	4694	11
10	5	60138	1540	505	5300	15
11	5	1954	240	90	315	5
12	6	2290	144	59	277	6
13	5	2014	117	107	307	5
14	4	33619	961	99	2919	2
15	5	35193	1326	116	2957	3
16	6	279072	298672	7776	40949	135
17	5	300431	10449	1628	22777	10
18	3	322726	9997	3131	25130	8
19	6	325642	24691	2890	24908	25
20	4	33150	468	208	2822	3
21	4	196216	1036	2942	15328	6
22	4	208464	769	4668	20612	6
23	4	15818	530	84	1447	2
24	4	16382	969	139	1621	4
25	4	15640	553	113	2349	2
MEAN	5	79034	14207	1043	7361	11

Table 4: Proportion of input variables active (%), averaged over 20 train/test splits

DATASET ID	CoDaCoRe (DEFAULTS)	SELBAL	PAIRWISE LOG-RATIOS	CODA-LASSO	AMALGAM	RANDOM FOREST
1	15.4±2.4	25.6±3.1	21.0±2.4	53.8±5.5	85.2±2.8	100.0±0.0
2	4.5±0.6	5.5±0.4	11.2±1.9	9.4±0.7	86.1±2.2	100.0±0.0
3	2.1±0.3	3.0±0.5	3.5±0.9	6.7±1.6	80.7±2.7	100.0±0.0
4	2.0±0.3	1.8±0.2	4.2±0.8	6.3±1.4	81.6±1.6	100.0±0.0
5	0.6±0.3	0.2±0.0	0.7±0.1	1.9±0.7	84.9±0.9	100.0±0.0
6	0.2±0.0	0.3±0.0	0.8±0.1	0.7±0.1	85.3±0.8	100.0±0.0
7	3.3±0.6	0.8±0.1	0.2±0.1	2.2±0.5	79.6±2.5	100.0±0.0
8	1.3±0.2	1.0±0.1	1.7±0.2	4.2±1.0	81.9±2.2	100.0±0.0
9	0.8±0.1	0.2±0.0	0.2±0.1	1.2±0.4	89.7±1.0	100.0±0.0
10	0.6±0.1	0.2±0.0	0.0±0.0	1.1±0.2	90.0±1.3	100.0±0.0
11	1.8±0.9	4.2±0.5	2.5±0.3	74.2±10.6	91.0±1.7	100.0±0.0
12	5.3±0.9	6.9±0.5	5.0±0.9	62.1±8.8	89.0±1.5	100.0±0.0
13	5.2±0.4	7.1±0.4	5.9±0.8	58.1±12.7	84.5±1.7	100.0±0.0
14	0.8±0.2	0.2±0.0	0.6±0.1	0.4±0.1	92.9±1.4	100.0±0.0
15	0.6±0.2	0.3±0.1	0.6±0.1	0.6±0.2	90.8±1.1	100.0±0.0
16	0.1±0.0	0.4±0.0	0.2±0.0	95.1±9.9	94.8±1.3	100.0±0.0
17	0.1±0.0	0.1±0.0	0.0±0.0	0.0±0.0	94.0±2.6	100.0±0.0
18	0.1±0.0	0.3±0.0	0.3±0.0	100.0±0.0	88.6±4.5	100.0±0.0
19	0.1±0.0	0.1±0.0	0.3±0.0	0.4±0.1	97.8±1.1	100.0±0.0
20	0.5±0.1	0.2±0.0	0.4±0.1	0.4±0.5	89.1±2.5	100.0±0.0
21	0.3±0.1	0.1±0.0	0.0±0.0	1.1±0.9	92.1±3.7	100.0±0.0
22	0.1±0.0	0.1±0.0	0.3±0.1	10.0±10.7	89.9±1.8	100.0±0.0
23	0.5±0.1	0.3±0.0	0.2±0.1	0.5±0.3	86.7±3.3	100.0±0.0
24	1.0±0.1	0.8±0.1	1.9±0.1	1.6±0.1	93.2±1.2	100.0±0.0
25	0.3±0.0	0.3±0.0	0.7±0.1	0.2±0.1	69.8±5.7	100.0±0.0
MEAN	1.9±0.3	2.4±0.2	2.5±0.4	19.7±2.7	87.6±2.1	100.0±0.0

Table 5: Out-of-sample accuracy (%) averaged over 20 train/test splits.

DATASET ID	CODACoRE (DEFAULTS)	SELBAL	PAIRWISE LOG-RATIOS	CODA-LASSO	AMALGAM	RANDOM FOREST
1	71.4±1.1	45.4±2.9	68.5±1.0	72.4±1.7	76.1±1.4	81.5±1.4
2	87.5±2.5	60.6±3.6	88.3±3.1	88.7±2.8	89.4±2.8	90.8±2.3
3	76.7±2.4	73.3±0.0	73.4±0.2	66.0±3.0	73.7±2.4	81.7±1.5
4	61.9±2.6	52.6±1.9	70.0±2.7	64.8±3.0	67.8±3.7	75.0±2.4
5	85.0±2.0	73.4±0.2	82.4±1.5	76.6±3.4	82.7±2.4	87.9±2.0
6	65.3±3.5	55.1±2.0	68.2±3.0	67.3±3.0	63.1±2.9	73.2±3.1
7	69.0±3.8	64.0±2.8	53.0±2.0	66.9±4.0	60.4±2.9	69.7±5.6
8	92.9±1.4	69.2±1.8	88.6±2.3	93.1±1.4	92.1±1.5	96.2±1.0
9	61.4±2.9	64.2±1.4	59.1±0.3	59.1±3.9	65.7±3.2	67.5±2.1
10	63.1±1.6	66.0±0.7	62.5±0.0	65.9±3.3	63.2±2.7	66.4±1.1
11	96.8±0.5	68.1±9.2	98.9±0.3	97.3±0.6	99.1±0.2	99.2±0.2
12	92.9±0.5	92.1±0.0	92.2±0.2	85.8±1.0	92.6±0.6	92.4±0.2
13	79.1±1.0	27.2±0.1	75.5±0.7	80.5±1.2	82.6±1.0	83.7±1.2
14	68.5±3.8	50.3±1.8	68.1±3.8	62.2±4.0	65.0±3.5	63.8±4.3
15	74.5±4.9	57.9±1.8	72.0±3.3	71.5±4.8	65.8±3.2	70.8±5.0
16	99.9±0.1	88.9±0.0	100.0±0.0	99.9±0.1	99.9±0.1	99.9±0.1
17	51.4±3.3	54.8±1.7	53.5±0.7	46.0±0.0	51.9±4.0	61.2±2.9
18	100.0±0.0	49.9±0.5	100.0±0.0	100.0±0.0	99.5±0.5	99.8±0.4
19	64.7±2.5	55.2±1.5	65.2±2.0	70.5±1.8	70.8±1.6	73.2±2.1
20	69.0±4.1	62.4±2.2	66.7±3.6	52.6±2.4	60.6±3.6	68.3±3.0
21	60.8±4.1	54.6±2.6	52.2±0.4	54.8±4.9	57.4±6.1	54.4±5.4
22	77.2±3.2	64.6±4.0	75.9±5.5	72.9±3.9	74.1±3.6	88.0±2.1
23	59.0±3.4	48.9±1.5	52.0±1.8	52.5±1.3	56.2±3.0	54.0±3.0
24	93.3±1.4	76.5±1.6	92.9±1.3	93.8±1.3	93.6±0.8	93.9±1.1
25	59.6±3.1	53.9±1.7	53.7±2.9	51.2±0.0	57.7±3.7	56.5±2.4
MEAN	75.2±2.4	61.2±1.9	73.3±1.7	72.5±2.3	74.4±2.5	78.0±2.2



Table 6: Out-of-sample AUC (%) averaged over 20 train/test splits.

DATASET ID	CoDaCoRe (DEFAULTS)	SELBAL	PAIRWISE LOG-RATIOS	CODA-LASSO	AMALGAM	RANDOM FOREST
1	75.8±1.7	81.5±1.5	69.9±2.5	81.2±1.8	81.0±1.5	87.8±1.2
2	93.9±1.9	92.3±2.1	94.2±2.0	94.8±1.7	94.7±2.1	96.2±2.0
3	79.2±2.9	76.0±3.2	77.3±3.2	73.9±5.5	76.9±3.9	88.1±1.6
4	69.4±3.3	73.4±4.5	74.3±3.0	74.0±3.3	72.6±3.4	83.2±2.8
5	91.2±1.6	93.1±1.1	90.0±1.8	92.1±1.8	88.8±2.8	93.7±1.3
6	72.0±3.7	74.9±4.1	76.2±3.7	76.0±3.7	68.0±3.5	81.8±3.3
7	73.7±4.0	82.1±3.0	53.0±2.9	75.6±4.9	65.8±3.5	75.3±4.7
8	98.2±0.7	96.5±0.9	94.8±2.0	98.8±0.5	97.6±0.8	99.3±0.3
9	64.6±3.0	61.6±3.5	51.5±1.6	61.9±4.3	67.7±3.5	70.5±2.1
10	66.2±3.7	62.8±2.0	50.0±0.0	68.5±2.7	64.3±3.1	66.0±2.0
11	98.5±0.5	99.6±0.3	99.5±0.4	99.4±0.6	99.4±0.5	99.3±0.7
12	89.2±1.6	91.1±1.5	88.1±1.6	94.4±1.2	90.0±1.6	90.1±1.3
13	82.5±1.4	90.6±1.2	78.0±1.7	88.4±1.2	87.1±1.9	89.7±1.2
14	73.5±4.3	68.8±4.7	70.8±5.1	63.4±5.8	68.8±4.7	71.3±5.1
15	79.9±5.5	79.2±3.7	79.0±3.5	75.4±6.2	69.0±3.6	78.4±4.6
16	100.0±0.0	100.0±0.0	100.0±0.0	100.0±0.0	100.0±0.0	100.0±0.0
17	57.2±2.5	54.2±3.5	50.6±1.7	50.0±0.0	56.1±4.0	65.1±2.8
18	100.0±0.0	100.0±0.0	100.0±0.0	100.0±0.0	99.8±0.3	100.0±0.0
19	71.6±3.6	80.0±1.6	70.2±2.4	79.3±1.6	76.2±1.6	79.8±2.1
20	75.0±4.0	76.9±3.0	70.2±4.8	53.7±3.4	65.1±3.0	72.9±3.0
21	67.7±4.9	62.2±3.8	50.6±1.2	61.2±5.8	67.2±5.4	61.3±4.6
22	85.8±2.6	85.0±2.4	82.0±6.4	89.2±2.1	81.8±3.8	91.8±2.3
23	64.6±3.6	57.3±3.2	52.3±2.8	52.6±2.4	61.7±3.4	57.3±3.1
24	96.2±1.3	97.2±0.8	96.0±1.1	97.5±0.7	96.4±1.5	98.1±0.6
25	62.7±3.8	63.5±3.2	60.8±3.4	49.9±0.1	59.4±3.6	58.2±2.6
MEAN	79.5±2.6	80.0±2.4	75.2±2.4	78.0±2.4	78.2±2.7	82.2±2.2

Table 7: Out-of-sample F1 score (%) averaged over 20 train/test splits.

DATASET ID	CoDAcORE (DEFAULTS)	SELBAL	PAIRWISE LOG-RATIOS	CODA-LASSO	AMALGAM	RANDOM FOREST
1	46.9±2.8	53.8±1.2	10.9±6.5	65.3±1.8	58.6±2.6	65.7±2.8
2	85.6±2.6	68.0±2.1	86.0±3.6	86.4±3.8	87.1±3.6	89.1±2.8
3	84.1±1.8	84.6±0.0	84.6±0.1	73.3±2.9	82.2±1.6	88.4±0.9
4	56.8±3.6	65.7±1.1	65.0±3.1	65.0±3.6	66.4±4.0	71.7±3.0
5	89.6±1.4	84.7±0.1	88.7±0.9	81.0±3.5	87.9±1.7	91.8±1.4
6	60.9±4.5	66.2±1.6	63.6±4.6	66.2±3.5	56.9±4.5	70.4±3.9
7	69.0±3.9	72.9±1.7	10.6±9.5	70.0±7.8	60.3±3.6	69.3±5.2
8	94.3±1.2	80.2±0.9	91.2±1.7	94.6±1.0	93.7±1.2	97.0±0.8
9	68.3±2.5	76.8±0.7	74.2±0.3	62.2±10.2	70.9±2.9	76.6±1.6
10	72.1±1.3	78.6±0.4	76.9±0.0	73.6±4.0	70.6±2.4	77.9±0.7
11	80.8±2.8	38.9±3.9	93.5±1.8	87.0±2.5	94.9±1.3	95.2±1.4
12	96.2±0.3	95.9±0.0	95.9±0.1	91.8±0.7	96.1±0.3	96.0±0.1
13	54.7±2.1	42.7±0.1	31.6±3.9	68.2±1.9	64.5±2.8	62.7±3.5
14	63.2±3.9	64.1±1.1	52.9±9.8	38.1±13.7	60.5±4.3	53.0±6.9
15	77.5±4.4	72.5±1.2	75.9±3.0	75.0±4.7	69.8±3.5	75.9±4.0
16	100.0±0.0	94.1±0.0	100.0±0.0	100.0±0.0	100.0±0.0	99.9±0.1
17	58.4±3.6	69.8±1.2	69.4±1.1	0.0±0.0	57.0±4.2	65.8±2.9
18	100.0±0.0	66.3±0.2	100.0±0.0	100.0±0.0	99.5±0.5	99.8±0.4
19	64.5±2.5	69.0±0.7	65.7±2.1	73.0±1.8	71.3±1.7	73.4±2.3
20	69.5±3.6	71.9±1.2	68.9±2.6	14.8±11.9	60.5±3.6	66.9±3.1
21	62.1±4.5	67.1±2.5	68.2±0.4	34.1±14.8	59.3±5.9	55.8±6.1
22	76.8±3.1	72.7±2.2	74.4±6.4	77.4±2.6	73.2±4.1	88.1±1.9
23	60.8±5.0	64.1±1.0	7.3±4.8	10.2±7.8	51.6±3.6	50.4±3.3
24	95.4±0.9	85.8±0.8	95.2±0.9	95.8±0.8	95.6±0.6	95.7±0.8
25	54.7±3.8	66.8±1.0	43.0±8.0	2.5±5.0	59.7±4.2	55.5±2.9
MEAN	73.7±2.6	70.9±1.1	67.8±3.0	64.2±4.4	73.9±2.8	77.3±2.5