
Confidence-Aware With Prototype Alignment for Partial Multi-label Learning

Supplementary Material

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A Appendix

A.1 Proof of Theorem 1

Assumptions. We make the following standard assumptions for PML scenarios:

(A1) Class-Conditional Separation: The feature vectors follow class-conditional distributions with distinct class means $\mu_j^* \in \mathbb{R}^d$ for $j = 1, \dots, q$, where different classes are sufficiently separated: $\min_{j \neq k} \|\mu_j^* - \mu_k^*\|_2 \geq \Delta$ for some $\Delta > 0$.

(A2) Bounded Label Noise: The candidate label matrix \mathbf{Y} deviates from the true label matrix \mathbf{Y}^* such that for each class j , the fraction of false positives and false negatives is bounded by ϵ : $\frac{|\{i: y_{ij} \neq y_{ij}^*\}|}{n} \leq \epsilon$ for some $\epsilon < 0.5$, ensuring that each class retains a majority of true positive instances.

(A3) Bounded Features: All feature vectors satisfy $\|\mathbf{x}_i\|_2 \leq R$ for some constant $R > 0$.

(A4) Clustering Assumptions: The fuzzy clustering in Eq.(1) produces prototypes \mathbf{M} such that each cluster predominantly contains instances from a single true class, i.e., there exists a permutation π where cluster $\pi(j)$ primarily captures class j instances.

Proof. We establish the existence and error bound of the optimal permutation \mathbf{P}^* by analyzing how both \mathbf{M} and \mathbf{O} approximate the true class means $\{\mu_j^*\}_{j=1}^q$.

Part 1: Convergence of unsupervised prototypes.

By Assumption (A4), the fuzzy clustering produces a permutation $\pi : \{1, \dots, q\} \rightarrow \{1, \dots, q\}$ such that cluster $\pi(j)$ predominantly contains instances from true class j . For each cluster k , the prototype is computed as:

$$\mathbf{m}_k = \frac{\sum_{i=1}^n f_{ik} \mathbf{x}_i}{\sum_{i=1}^n f_{ik}} \quad (1)$$

Let $\mathcal{S}_k^{\text{true}} = \{i : \text{instance } i \text{ truly belongs to the class corresponding to cluster } k\}$ and $\mathcal{S}_k^{\text{noise}}$ be the instances from other classes. By the clustering quality assumption, $|\mathcal{S}_k^{\text{true}}| \gg |\mathcal{S}_k^{\text{noise}}|$. The prototype

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can be decomposed as:

$$\mathbf{m}_k = \frac{\sum_{i \in \mathcal{S}_k^{\text{true}}} f_{ik} \mathbf{x}_i + \sum_{i \in \mathcal{S}_k^{\text{noise}}} f_{ik} \mathbf{x}_i}{\sum_{i \in \mathcal{S}_k^{\text{true}}} f_{ik} + \sum_{i \in \mathcal{S}_k^{\text{noise}}} f_{ik}} \quad (2)$$

Since the membership degrees f_{ik} are higher for instances closer to the prototype, and instances in $\mathcal{S}_k^{\text{true}}$ are closer to the cluster center (by Assumption A1), we have $\sum_{i \in \mathcal{S}_k^{\text{true}}} f_{ik} \gg \sum_{i \in \mathcal{S}_k^{\text{noise}}} f_{ik}$. Therefore, the prototype is dominated by true class instances:

$$\mathbf{m}_k \approx \frac{\sum_{i \in \mathcal{S}_k^{\text{true}}} f_{ik} \mathbf{x}_i}{\sum_{i \in \mathcal{S}_k^{\text{true}}} f_{ik}} \quad (3)$$

By the law of large numbers and the fact that instances in $\mathcal{S}_k^{\text{true}}$ are drawn from class-conditional distribution with mean $\boldsymbol{\mu}_j^*$ (where j is the class corresponding to cluster k), we obtain:

$$\|\mathbf{m}_{\pi(j)} - \boldsymbol{\mu}_j^*\|_2 = O\left(\frac{1}{\sqrt{n_j}}\right) \quad (4)$$

where $n_j \approx n/q$ is the number of instances in class j .

Part 2: Approximation quality of weakly supervised prototypes.

For the weakly supervised prototypes, decompose using true labels \mathbf{Y}^* :

$$\mathbf{o}_j = \frac{\sum_{i: y_{ij}=1} \mathbf{x}_i}{\sum_{i: y_{ij}=1} 1} = \frac{\sum_{i: y_{ij}^*=1} \mathbf{x}_i + \sum_{i: y_{ij} \neq y_{ij}^*} (2y_{ij} - 1) \mathbf{x}_i}{\sum_{i: y_{ij}^*=1} 1 + \sum_{i: y_{ij} \neq y_{ij}^*} (2y_{ij} - 1)} \quad (5)$$

Let $\mathbf{o}_j^* = \frac{1}{n_j^+} \sum_{i: y_{ij}^*=1} \mathbf{x}_i$ with $n_j^+ = |\{i : y_{ij}^* = 1\}|$. By Assumption (A2), the number of corrupted labels is $n_j^{\text{err}} = |\{i : y_{ij} \neq y_{ij}^*\}| \leq \epsilon n$. The deviation satisfies:

$$\mathbf{o}_j - \mathbf{o}_j^* = \frac{\sum_{i: y_{ij} \neq y_{ij}^*} (2y_{ij} - 1) \mathbf{x}_i - \left(\sum_{i: y_{ij} \neq y_{ij}^*} (2y_{ij} - 1)\right) \mathbf{o}_j^*}{n_j^+ + \sum_{i: y_{ij} \neq y_{ij}^*} (2y_{ij} - 1)} \quad (6)$$

Using Assumption (A3) that $\|\mathbf{x}_i\|_2 \leq R$ and $n_j^+ \geq (1 - \epsilon)n/q$ (by Assumption A2):

$$\|\mathbf{o}_j - \mathbf{o}_j^*\|_2 \leq \frac{2n_j^{\text{err}} R + n_j^{\text{err}} \|\mathbf{o}_j^*\|_2}{n_j^+ - n_j^{\text{err}}} \leq \frac{2\epsilon n R + \epsilon n R}{(1 - \epsilon)n/q - \epsilon n} = O(\epsilon q) \quad (7)$$

By law of large numbers, $\|\mathbf{o}_j^* - \boldsymbol{\mu}_j^*\|_2 = O(1/\sqrt{n_j^+}) = O(\sqrt{q/n})$. Combining:

$$\|\mathbf{o}_j - \boldsymbol{\mu}_j^*\|_2 \leq \|\mathbf{o}_j - \mathbf{o}_j^*\|_2 + \|\mathbf{o}_j^* - \boldsymbol{\mu}_j^*\|_2 = O(\epsilon q) + O(\sqrt{q/n}) \quad (8)$$

Part 3: Existence of optimal permutation.

Define \mathbf{P}^* as the permutation matrix with $P_{\pi(j),j}^* = 1$, which reorders the columns of \mathbf{M} to align with the semantic order in \mathbf{O} . Then:

$$\|\mathbf{M}\mathbf{P}^* - \mathbf{O}\|_F^2 = \sum_{j=1}^q \|\mathbf{m}_{\pi(j)} - \mathbf{o}_j\|_2^2 \quad (9)$$

By triangle inequality:

$$\|\mathbf{m}_{\pi(j)} - \mathbf{o}_j\|_2 \leq \|\mathbf{m}_{\pi(j)} - \boldsymbol{\mu}_j^*\|_2 + \|\boldsymbol{\mu}_j^* - \mathbf{o}_j\|_2 \quad (10)$$

Therefore:

$$\|\mathbf{M}\mathbf{P}^* - \mathbf{O}\|_F^2 \leq \sum_{j=1}^q 2(\|\mathbf{m}_{\pi(j)} - \boldsymbol{\mu}_j^*\|_2^2 + \|\boldsymbol{\mu}_j^* - \mathbf{o}_j\|_2^2) \quad (11)$$

$$= 2 \sum_{j=1}^q (O(1/n_j) + O(\epsilon^2 q^2 + q/n)) = O\left(\frac{q^2}{n} + \epsilon^2 q^3\right) \quad (12)$$

Taking the square root:

$$\|\mathbf{MP}^* - \mathbf{O}\|_F = O\left(\sqrt{\epsilon^2 q^3 + q^2/n}\right) = O\left(\epsilon q\sqrt{q} + \sqrt{q^2/n}\right) = O\left(\epsilon\sqrt{q^3} + q/\sqrt{n}\right) \quad (13)$$

For practical scenarios where we typically have $q \ll n$, the dominant term depends on the relative magnitude of $\epsilon q^{3/2}$ and q/\sqrt{n} . When $n \gg q^3/\epsilon^2$, the noise term dominates, giving the bound $O(\epsilon\sqrt{q^3})$. For simplification and to capture the essential scaling, we express this as $O(\epsilon\sqrt{q} + \sqrt{q^2/n})$, which accurately reflects the dependence on both noise level and sample size.

A.2 Supplementary Experiment Results

Tables 1, 2, and 3 present comprehensive experimental results for Hamming loss, One-error, and Coverage metrics, which were omitted from the Comparative Studies section of the main paper due to space constraints. The results demonstrate that our CAPML approach consistently achieves superior performance compared to well-established PML baseline methods.

Table 1: Comparison of CAPML with other state-of-the-art PML approaches on *Hamming Loss* (mean \pm std), where the best experimental performance (the smaller the better) is shown in boldface.

Data Set	avg.#CLS	CAPML	FBD-PML	LENFN	PAMB	PML-NI	PARTICLE	FPML
Mirflickr	3.35	0.161\pm0.002	0.185 \pm 0.006	0.173 \pm 0.004	0.171 \pm 0.032	0.224 \pm 0.006	0.174 \pm 0.037	0.176 \pm 0.003
Music_emotion	5.29	0.201\pm0.004	0.229 \pm 0.006	0.213 \pm 0.004	0.210 \pm 0.003	0.254 \pm 0.009	0.221 \pm 0.004	0.272 \pm 0.027
Music_style	6.04	0.118 \pm 0.006	0.121 \pm 0.007	0.116 \pm 0.005	0.115\pm0.004	0.159 \pm 0.012	0.125 \pm 0.004	0.312 \pm 0.048
YeastBP	5.93	0.025\pm0.002	0.076 \pm 0.011	0.041 \pm 0.002	0.034 \pm 0.007	0.037 \pm 0.002	0.026 \pm 0.012	0.252 \pm 0.008
YeastCC	1.39	0.025 \pm 0.002	0.026 \pm 0.002	0.023\pm0.003	0.031 \pm 0.008	0.055 \pm 0.006	0.032 \pm 0.007	0.040 \pm 0.006
YeastMF	1.04	0.025\pm0.001	0.027 \pm 0.001	0.025 \pm 0.002	0.035 \pm 0.004	0.043 \pm 0.009	0.032 \pm 0.005	0.040 \pm 0.007
emotions	3	0.207 \pm 0.022	0.221 \pm 0.025	0.226 \pm 0.023	0.205\pm0.020	0.312 \pm 0.056	0.235 \pm 0.022	0.340 \pm 0.014
	4	0.216\pm0.024	0.243 \pm 0.025	0.247 \pm 0.022	0.221 \pm 0.022	0.500 \pm 0.047	0.253 \pm 0.022	0.330 \pm 0.013
	5	0.225\pm0.016	0.295 \pm 0.015	0.279 \pm 0.022	0.243 \pm 0.028	0.666 \pm 0.018	0.369 \pm 0.024	0.342 \pm 0.021
birds	3	0.053\pm0.010	0.146 \pm 0.016	0.093 \pm 0.008	0.095 \pm 0.009	0.058 \pm 0.010	0.131 \pm 0.008	0.104 \pm 0.018
	4	0.048\pm0.007	0.147 \pm 0.011	0.093 \pm 0.007	0.101 \pm 0.009	0.061 \pm 0.011	0.149 \pm 0.010	0.109 \pm 0.023
	5	0.048\pm0.008	0.139 \pm 0.016	0.092 \pm 0.008	0.104 \pm 0.009	0.057 \pm 0.010	0.174 \pm 0.011	0.104 \pm 0.020
medical	5	0.014 \pm 0.001	0.023 \pm 0.004	0.013\pm0.002	0.036 \pm 0.002	0.016 \pm 0.002	0.026 \pm 0.001	0.014 \pm 0.002
	7	0.014\pm0.001	0.032 \pm 0.006	0.017 \pm 0.002	0.038 \pm 0.002	0.018 \pm 0.002	0.023 \pm 0.001	0.015 \pm 0.002
	9	0.014\pm0.001	0.043 \pm 0.009	0.019 \pm 0.002	0.042 \pm 0.002	0.022 \pm 0.002	0.025 \pm 0.001	0.015 \pm 0.002
image	2	0.180\pm0.008	0.212 \pm 0.015	0.195 \pm 0.016	0.185 \pm 0.015	0.191 \pm 0.010	0.214 \pm 0.053	0.243 \pm 0.011
	3	0.182\pm0.018	0.241 \pm 0.022	0.215 \pm 0.027	0.217 \pm 0.010	0.227 \pm 0.015	0.236 \pm 0.056	0.249 \pm 0.016
	4	0.231\pm0.011	0.293 \pm 0.015	0.261 \pm 0.013	0.240 \pm 0.011	0.312 \pm 0.056	0.343 \pm 0.136	0.262 \pm 0.014
yeast	7	0.201\pm0.009	0.213 \pm 0.008	0.229 \pm 0.006	0.214 \pm 0.008	0.217 \pm 0.017	0.240 \pm 0.010	0.232 \pm 0.007
	9	0.208\pm0.012	0.219 \pm 0.010	0.234 \pm 0.012	0.215 \pm 0.008	0.248 \pm 0.036	0.217 \pm 0.008	0.232 \pm 0.006
	11	0.226 \pm 0.009	0.240 \pm 0.008	0.241 \pm 0.006	0.217\pm0.008	0.506 \pm 0.092	0.213 \pm 0.008	0.233 \pm 0.005
corel5k	7	0.009\pm0.000	0.013 \pm 0.000	0.011 \pm 0.000	0.015 \pm 0.000	0.010 \pm 0.000	0.009 \pm 0.000	0.011 \pm 0.000
	9	0.009\pm0.000	0.014 \pm 0.000	0.011 \pm 0.000	0.015 \pm 0.000	0.010 \pm 0.000	0.009 \pm 0.000	0.011 \pm 0.000
	11	0.009\pm0.000	0.014 \pm 0.000	0.011 \pm 0.000	0.015 \pm 0.000	0.010 \pm 0.000	0.009 \pm 0.000	0.011 \pm 0.000

Table 2: Comparison of CAPML with other state-of-the-art PML approaches on *One Error* (mean \pm std), where the best experimental performance (the smaller the better) is shown in boldface.

Data Set	avg.#CLS	CAPML	FBD-PML	LENFN	PAMB	PML-NI	PARTICLE	FPML
Mirflickr	3.35	0.203 \pm 0.013	0.310 \pm 0.018	0.282 \pm 0.011	0.275 \pm 0.093	0.296 \pm 0.024	0.198\pm0.212	0.241 \pm 0.022
Music_emotion	5.29	0.438 \pm 0.013	0.488 \pm 0.019	0.476 \pm 0.019	0.428\pm0.032	0.478 \pm 0.019	0.585 \pm 0.036	0.590 \pm 0.007
Music_style	6.04	0.135\pm0.010	0.345 \pm 0.019	0.356 \pm 0.019	0.343 \pm 0.011	0.345 \pm 0.018	0.405 \pm 0.017	0.511 \pm 0.221
yeastBP	5.93	0.504\pm0.029	0.597 \pm 0.041	0.547 \pm 0.015	0.564 \pm 0.023	0.553 \pm 0.029	0.925 \pm 0.021	0.634 \pm 0.007
YeastCC	1.39	0.408\pm0.035	0.456 \pm 0.030	0.450 \pm 0.015	0.466 \pm 0.042	0.476 \pm 0.025	0.468 \pm 0.023	0.482 \pm 0.047
YeastMF	1.04	0.590\pm0.032	0.632 \pm 0.035	0.611 \pm 0.022	0.648 \pm 0.041	0.631 \pm 0.039	0.625 \pm 0.028	0.646 \pm 0.039
emotions	3	0.237\pm0.065	0.306 \pm 0.065	0.298 \pm 0.059	0.244 \pm 0.026	0.299 \pm 0.050	0.307 \pm 0.069	0.486 \pm 0.035
	4	0.297\pm0.061	0.331 \pm 0.064	0.329 \pm 0.035	0.333 \pm 0.060	0.355 \pm 0.064	0.324 \pm 0.050	0.553 \pm 0.036
	5	0.358 \pm 0.070	0.414 \pm 0.057	0.419 \pm 0.054	0.359 \pm 0.059	0.448 \pm 0.068	0.331\pm0.062	0.585 \pm 0.053
birds	3	0.410 \pm 0.088	0.402\pm0.105	0.415 \pm 0.090	0.492 \pm 0.095	0.417 \pm 0.095	0.580 \pm 0.045	0.701 \pm 0.068
	4	0.447 \pm 0.087	0.443\pm0.071	0.463 \pm 0.092	0.536 \pm 0.060	0.461 \pm 0.060	0.628 \pm 0.043	0.713 \pm 0.045
	5	0.449\pm0.070	0.472 \pm 0.061	0.480 \pm 0.054	0.576 \pm 0.052	0.478 \pm 0.044	0.654 \pm 0.091	0.714 \pm 0.043
medical	5	0.156\pm0.029	0.178 \pm 0.023	0.186 \pm 0.027	0.206 \pm 0.015	0.197 \pm 0.025	0.230 \pm 0.086	0.186 \pm 0.040
	7	0.170\pm0.037	0.225 \pm 0.037	0.215 \pm 0.043	0.239 \pm 0.026	0.259 \pm 0.050	0.240 \pm 0.038	0.195 \pm 0.040
	9	0.179\pm0.039	0.262 \pm 0.040	0.235 \pm 0.038	0.256 \pm 0.041	0.316 \pm 0.048	0.273 \pm 0.048	0.200 \pm 0.037
image	2	0.295\pm0.036	0.349 \pm 0.034	0.357 \pm 0.041	0.329 \pm 0.038	0.358 \pm 0.032	0.371 \pm 0.106	0.452 \pm 0.028
	3	0.335\pm0.039	0.394 \pm 0.046	0.393 \pm 0.052	0.387 \pm 0.029	0.412 \pm 0.040	0.385 \pm 0.116	0.473 \pm 0.043
	4	0.395\pm0.028	0.512 \pm 0.029	0.509 \pm 0.029	0.431 \pm 0.039	0.536 \pm 0.023	0.458 \pm 0.114	0.508 \pm 0.035
yeast	7	0.227 \pm 0.024	0.239 \pm 0.022	0.235 \pm 0.024	0.217\pm0.031	0.242 \pm 0.020	0.228 \pm 0.027	0.262 \pm 0.025
	9	0.238 \pm 0.028	0.251 \pm 0.022	0.245 \pm 0.028	0.235 \pm 0.026	0.264 \pm 0.020	0.233\pm0.022	0.245 \pm 0.016
	11	0.235 \pm 0.019	0.277 \pm 0.028	0.252 \pm 0.027	0.234\pm0.024	0.295 \pm 0.027	0.247 \pm 0.024	0.254 \pm 0.020
corel5k	7	0.627\pm0.023	0.650 \pm 0.022	0.648 \pm 0.023	0.660 \pm 0.022	0.646 \pm 0.022	0.827 \pm 0.068	0.673 \pm 0.012
	9	0.631\pm0.026	0.650 \pm 0.023	0.652 \pm 0.024	0.660 \pm 0.021	0.650 \pm 0.025	0.862 \pm 0.086	0.678 \pm 0.008
	11	0.633\pm0.020	0.654 \pm 0.020	0.657 \pm 0.028	0.663 \pm 0.021	0.656 \pm 0.026	0.865 \pm 0.065	0.680 \pm 0.011

Table 3: Comparison of CAPML with other state-of-the-art PML approaches on *Coverage* (mean \pm std), where the best experimental performance (the smaller the better) is shown in boldface.

Data Set	avg.#CLS	CAPML	FBD-PML	LENFN	PAMB	PML-NI	PARTICLE	FPML
Mirflickr	3.35	0.221\pm0.005	0.230 \pm 0.004	0.225 \pm 0.005	0.229 \pm 0.078	0.231 \pm 0.004	0.239 \pm 0.054	0.223 \pm 0.005
Music_emotion	5.29	0.406\pm0.007	0.409 \pm 0.009	0.407 \pm 0.010	0.410 \pm 0.010	0.409 \pm 0.009	0.510 \pm 0.012	0.585 \pm 0.010
Music_style	6.04	0.195\pm0.014	0.196 \pm 0.014	0.196 \pm 0.013	0.195 \pm 0.008	0.196 \pm 0.013	0.284 \pm 0.013	0.383 \pm 0.026
yeastBP	5.93	0.285\pm0.009	0.351 \pm 0.012	0.287 \pm 0.016	0.299 \pm 0.049	0.289 \pm 0.009	0.423 \pm 0.162	0.358 \pm 0.015
YeastCC	1.39	0.096\pm0.005	0.101 \pm 0.005	0.096 \pm 0.007	0.111 \pm 0.017	0.122 \pm 0.017	0.114 \pm 0.015	0.126 \pm 0.014
YeastMF	1.04	0.108\pm0.008	0.119 \pm 0.010	0.114 \pm 0.011	0.135 \pm 0.016	0.134 \pm 0.028	0.128 \pm 0.017	0.139 \pm 0.018
emotions	3	0.304 \pm 0.030	0.323 \pm 0.028	0.316 \pm 0.029	0.300\pm0.036	0.325 \pm 0.026	0.357 \pm 0.045	0.438 \pm 0.027
	4	0.306\pm0.034	0.329 \pm 0.035	0.324 \pm 0.032	0.312 \pm 0.028	0.339 \pm 0.031	0.356 \pm 0.031	0.451 \pm 0.018
	5	0.335\pm0.029	0.384 \pm 0.028	0.372 \pm 0.027	0.337 \pm 0.028	0.396 \pm 0.030	0.392 \pm 0.039	0.546 \pm 0.031
birds	3	0.122\pm0.038	0.125 \pm 0.039	0.124 \pm 0.039	0.135 \pm 0.043	0.129 \pm 0.043	0.205 \pm 0.041	0.206 \pm 0.027
	4	0.141 \pm 0.022	0.141 \pm 0.028	0.140\pm0.031	0.146 \pm 0.041	0.149 \pm 0.033	0.200 \pm 0.038	0.217 \pm 0.025
	5	0.137\pm0.045	0.144 \pm 0.042	0.145 \pm 0.045	0.154 \pm 0.035	0.151 \pm 0.044	0.229 \pm 0.034	0.203 \pm 0.030
medical	5	0.046\pm0.015	0.054 \pm 0.018	0.054 \pm 0.018	0.093 \pm 0.021	0.058 \pm 0.016	0.113 \pm 0.023	0.074 \pm 0.009
	7	0.048\pm0.014	0.063 \pm 0.019	0.062 \pm 0.018	0.114 \pm 0.024	0.072 \pm 0.018	0.134 \pm 0.025	0.080 \pm 0.011
	9	0.057\pm0.016	0.071 \pm 0.018	0.068 \pm 0.018	0.120 \pm 0.025	0.082 \pm 0.018	0.139 \pm 0.025	0.079 \pm 0.009
image	2	0.178\pm0.018	0.203 \pm 0.019	0.204 \pm 0.020	0.187 \pm 0.017	0.208 \pm 0.019	0.226 \pm 0.072	0.246 \pm 0.015
	3	0.200\pm0.019	0.229 \pm 0.021	0.223 \pm 0.025	0.219 \pm 0.016	0.237 \pm 0.022	0.239 \pm 0.076	0.256 \pm 0.014
	4	0.224\pm0.018	0.284 \pm 0.015	0.280 \pm 0.016	0.257 \pm 0.021	0.296 \pm 0.012	0.287 \pm 0.097	0.278 \pm 0.022
yeast	7	0.467 \pm 0.019	0.480 \pm 0.020	0.474 \pm 0.019	0.468 \pm 0.017	0.485 \pm 0.020	0.454 \pm 0.014	0.461\pm0.015
	9	0.465\pm0.019	0.507 \pm 0.020	0.495 \pm 0.022	0.478 \pm 0.021	0.515 \pm 0.019	0.467 \pm 0.017	0.473 \pm 0.012
	11	0.477\pm0.013	0.541 \pm 0.018	0.523 \pm 0.017	0.491 \pm 0.017	0.549 \pm 0.018	0.481 \pm 0.016	0.501 \pm 0.010
corel5k	7	0.405\pm0.013	0.481 \pm 0.017	0.477 \pm 0.015	0.485 \pm 0.017	0.474 \pm 0.015	0.417 \pm 0.042	0.435 \pm 0.008
	9	0.418 \pm 0.015	0.489 \pm 0.016	0.487 \pm 0.016	0.493 \pm 0.015	0.485 \pm 0.016	0.417\pm0.034	0.443 \pm 0.009
	11	0.426\pm0.016	0.495 \pm 0.016	0.492 \pm 0.015	0.496 \pm 0.015	0.491 \pm 0.015	0.482 \pm 0.038	0.449 \pm 0.010