Supplemental Material: Cluster-Aware Grid Layout

Category: Research

Paper Type: algorithm/technique

1 User Study Details

A user study is presented in Section 3.1 of the paper. We report here the content of the tutorial shown to participants, the trials used in practice session and formal study and the questionnaire.

1.1 Tutorial and practice trials

We present a tutorial video to participants that introduced the definition of convex polygons and the user interface of the study system. Here is the content of the tutorial.

What is a convex polygon? Convex polygons refer to polygons whose internal angles are less than or equal 180 degrees.(Fig. 1) Triangles are convex polygons because all internal angles are less than 180 degrees. Besides, regular polygons are always convex. However, quadrilateral may be non-convex according to the degree of internal angles.(Fig. 2)

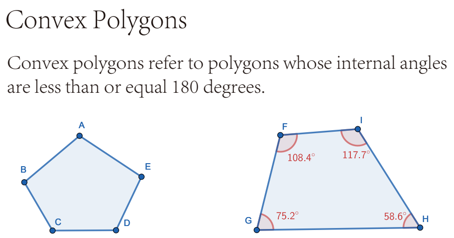

Fig. 1: Convex polygons.

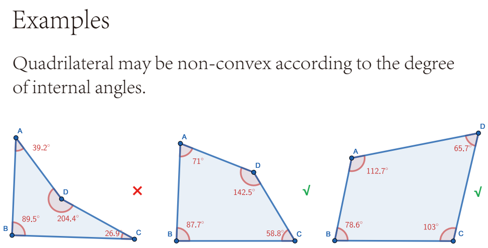

Fig. 2: Example of polygons.

What is convexity? Convexity describes how close a shape is to a convex shape. For non-convex polygons, there are also polygons with better convexity or worse convexity.(Fig. 3) Some examples are given to show polygons with different convexity. It can be seen that as the number and magnitude of depressions become smaller, the convexity of the polygon from left to right becomes better. (Fig. 4)

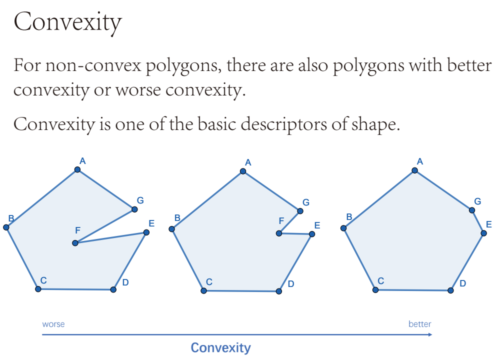

Fig. 3: Convexity.

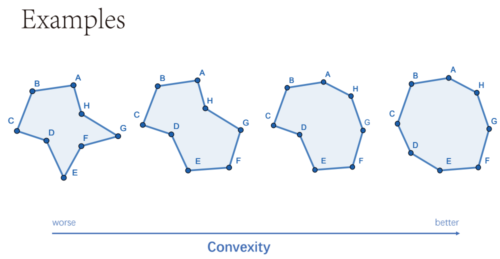

Fig. 4: Example of polygons with different convexity.

How to use the study system? The system of user study is introduced in the tutorial. (Fig. 5) Four different grid visualizations are displayed in the system. Users need to click and sort grid visualizations according to their understanding of convexity. The sorting results will be displayed below. Users can drag and drop to modify the sorting results, or click ">" to modify it to "=" which indicate that the convexity of the visualizations on the left and right sides are similar. After completing a question, the user can click the next button to proceed to the next question. If the user wants to modify the previous result, he can click the previous button to return to the previous question. We also provide a clear button to clear current answers.

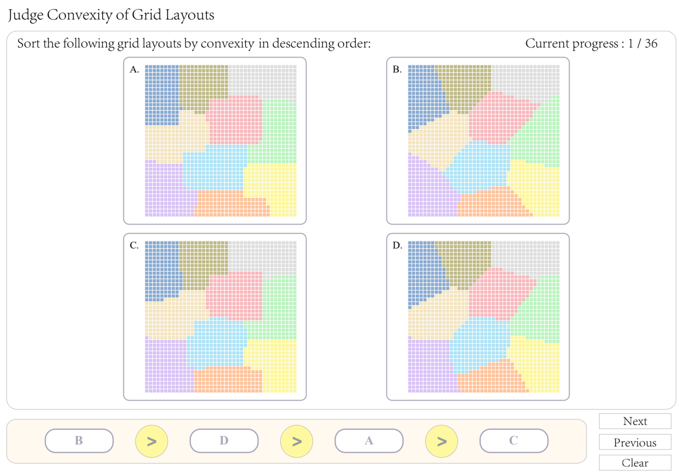

Fig. 5: Example interface of the user study.

Practice trials In the practice session, six practice trials were presented to participants to familiarize them with the concept of convexity and the use of the system. After completing each exercise question, the system will check the answer and present the correct result of the question. At the same time, the positions that mainly affects the convexity of the visualization will be marked in red ink in the figure to help users understand the convexity. Fig. 6 show these practice trials.

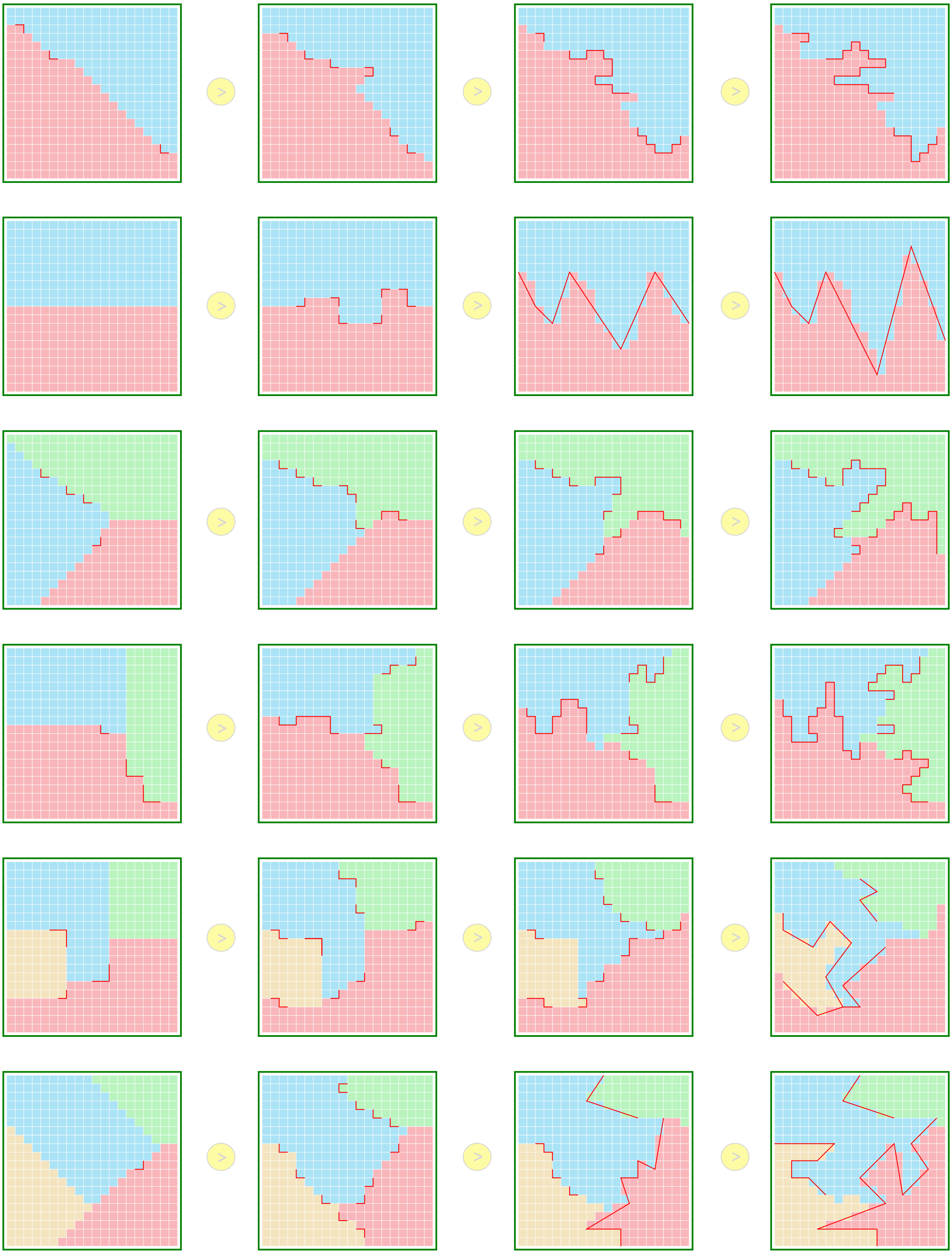

Fig. 6: Practice trials.

1.2 Formal study trials

In the formal session, a total of 36 trials (3 grid sizes × 3 cluster numbers × 4 datasets) were evaluated. Fig. 7 - Fig. 10 show these trials.

Fig. 7: Trials from dataset Animals [4].

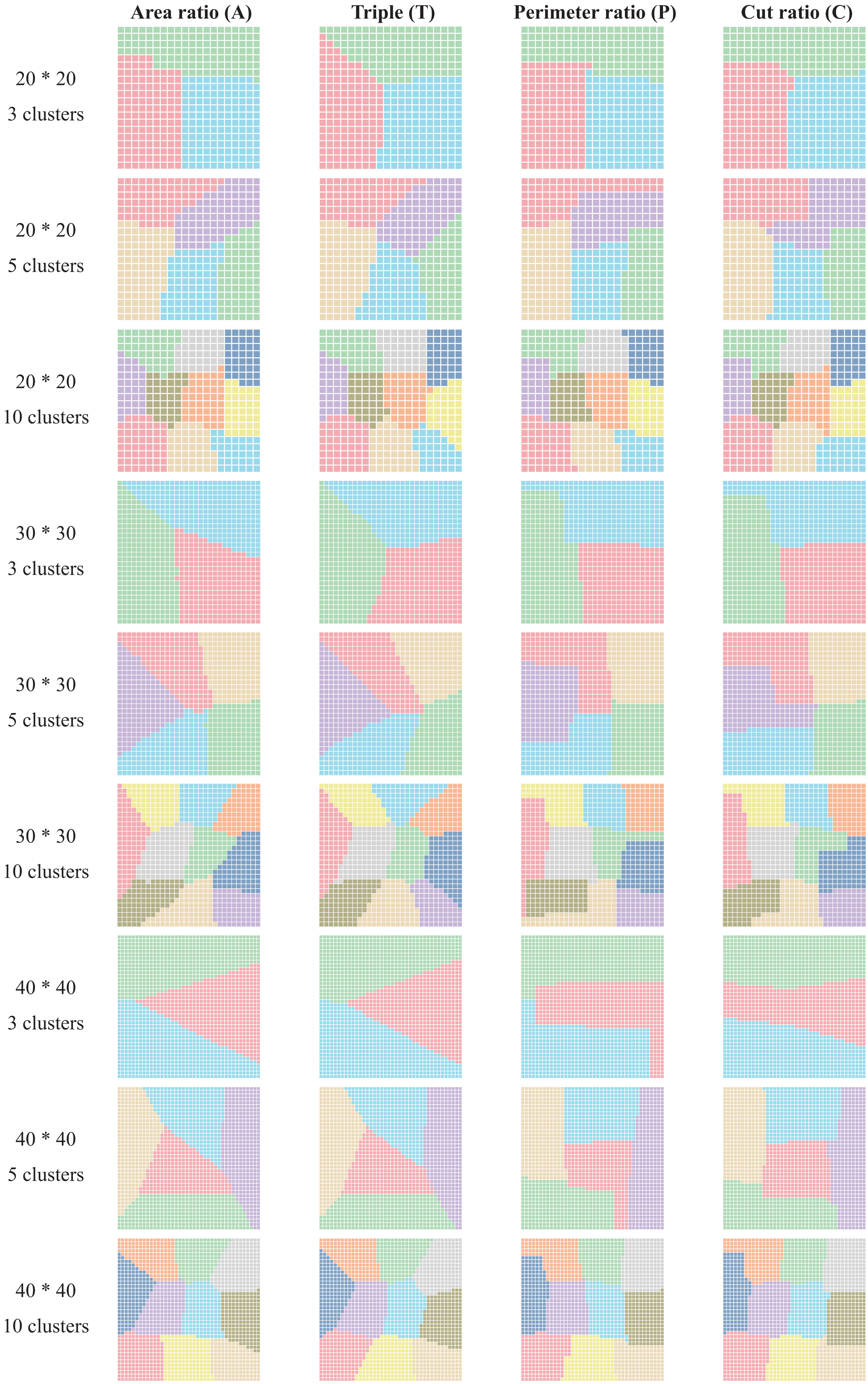

Fig. 8: Trials from dataset Cifar10 [9].

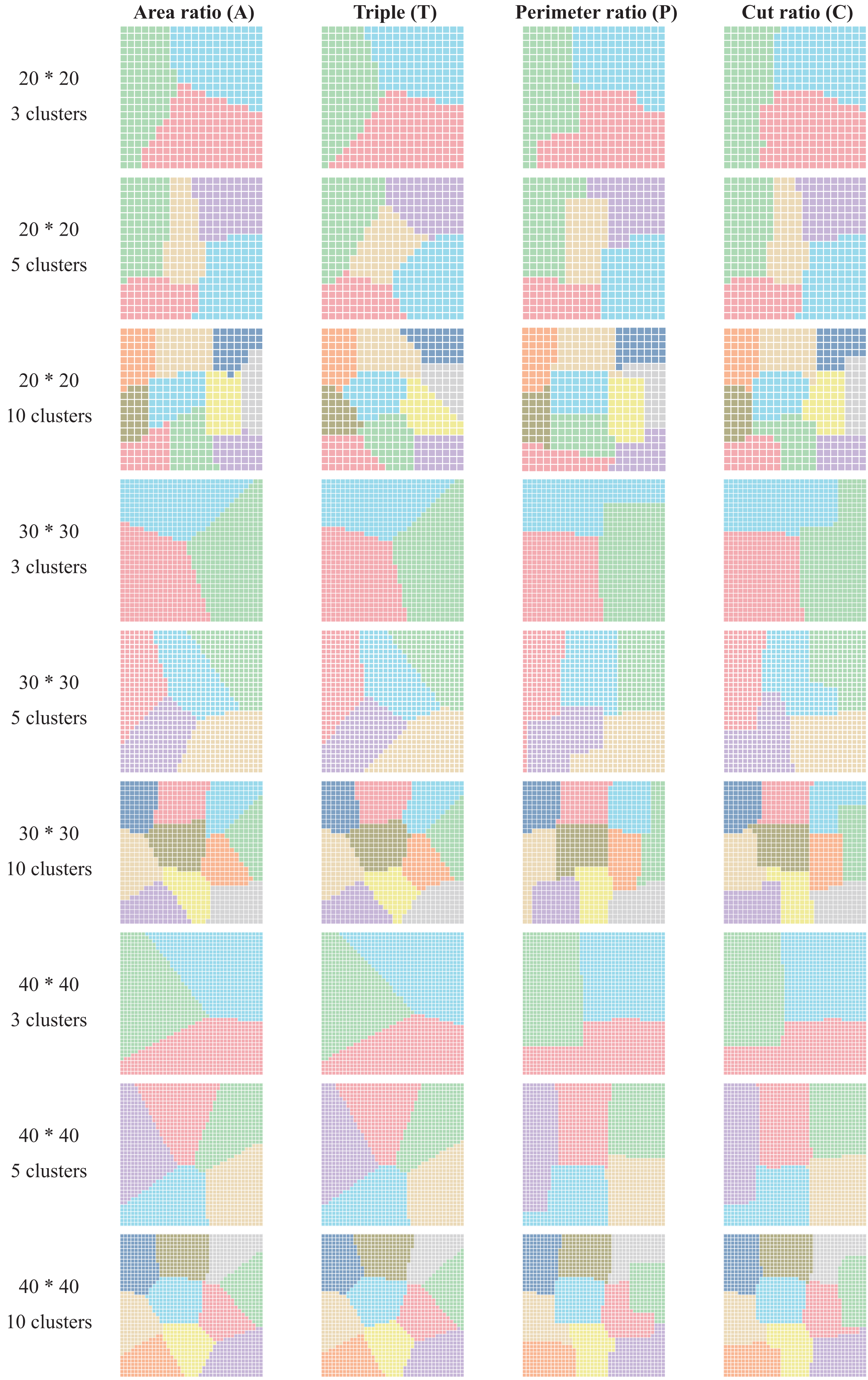

Fig. 9: Trials from dataset Mnist [10].

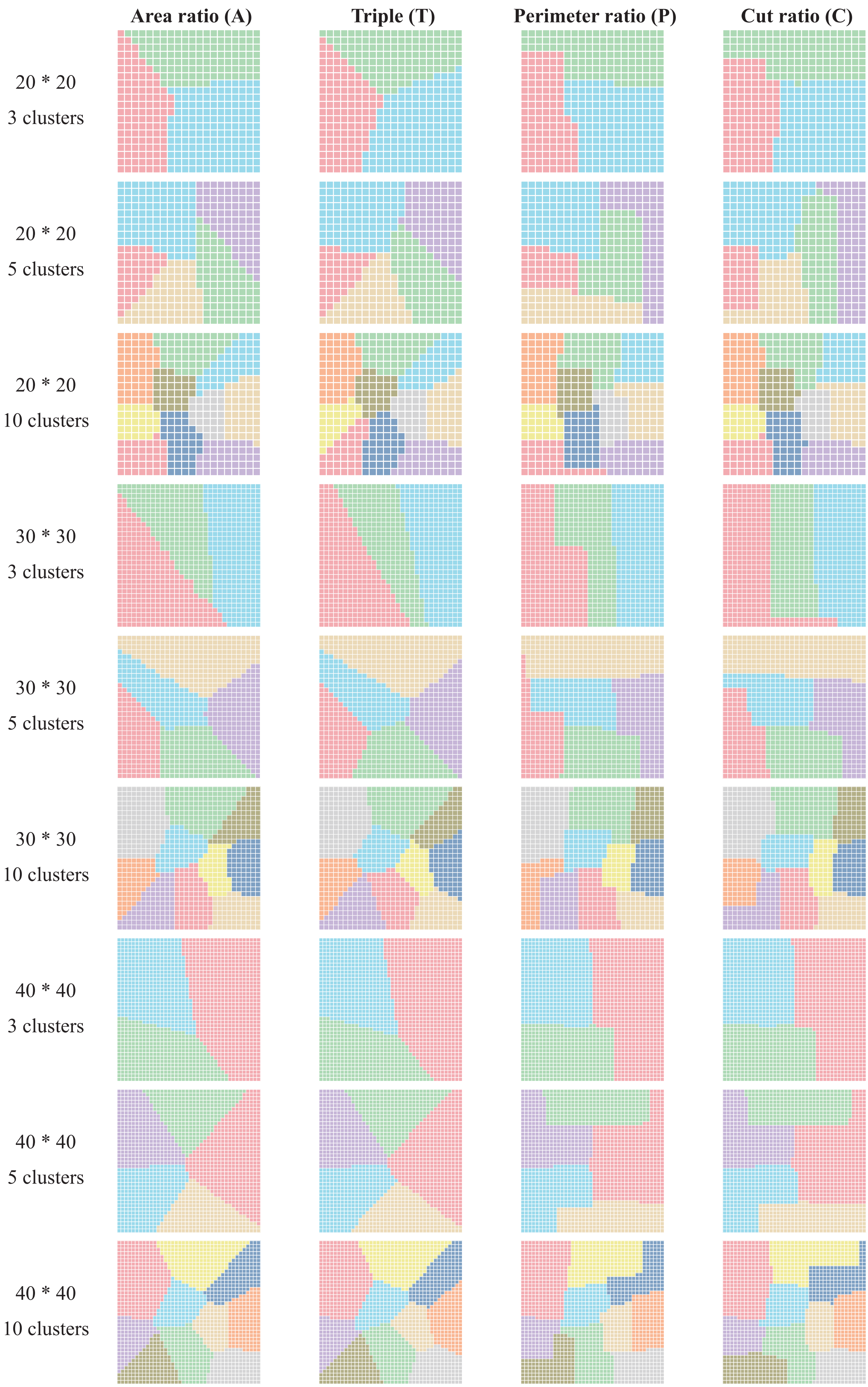

Fig. 10: Trials from dataset USPS [7]

1.3 Questionnaire

Following the completion of all trials, participants were asked to fill out a questionnaire that included personal information and a question asking them to explain how they compare the convexity of different grid visualizations.

Part One: Basic Information

1. **Please select the range of your age.**
   - ☐ 16 - 20
   - ☐ 21 - 25
   - ☐ 26 - 30
   - ☐ 31 - 35
   - ☐ 36 - 40
   - ☐ 41 - 45
   - ☐ 46 - 50
   - ☐ 51 - 55
   - ☐ 56 - 60
   - ☐ More than 60

2. **Please select your gender.**
   - ☐ Male
   - ☐ Female

3. **Please select your education background.**
   - ☐ High school and below
   - ☐ Bachelor
   - ☐ Master's degree
   - ☐ Doctoral degree

4. **Whether you have color blindness, color weakness or other diseases that affect visual judgment?**
   - ☐ No
   - ☐ Yes, illegible colors: ____________________

5. **Please specify your contact information. (telephone/email)**

   ____

Part Two: Professional background

6. **Are you familiar with the concepts of convexity and convex polygons?**

   Unfamiliar / Slightly familiar / Moderately familiar / Familiar / Very familiar

   Unfamiliar ☐ — ☐ — ☐ — ☐ — ☐ Very familiar

7. **Are you familiar with grid layouts?**

   Unfamiliar ☐ — ☐ — ☐ — ☐ — ☐ Very familiar

Part Three: Open question

8. **How did you judge the convexity of graphics in the formal trials?**

   For example, in the example below, among the factors such as the slope of the edge, the degree of curvature, the number of serrations, the number and size of the depressions, etc., which help you judge whether the grid layout has better/worse convexity?

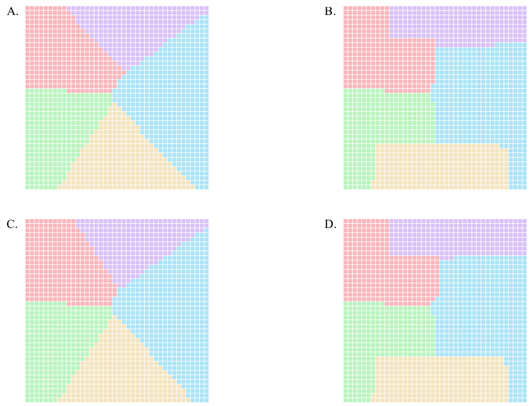

Fig. 11: Example

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2 EXPERIMENTS DETAILS

2.1 Datasets

Ten datasets we used are from Xia *et al.*'s work [12]. They are Animals [4], CIFAR10 [9], Indian Food [11], Isolet [5], MNIST [10], Stanford Dogs [3], Texture [1], USPS [7], Weather [6] and Wifi [2].
We also used an additional dataset, OoD-Animals, which is from a real-world application [3].
It is about different images of different animals: cat, dog, rabbit, wolf, and tiger. The information of datasets are shown in Table 1.

Table 1: Datasets information.

Dataset	Size	Clusters	Type
Animals [4]	26179	10	Image
CIFAR10 [9]	60000	10	Image
Indian Food [11]	3625	11	Image
Isolet [5]	2352	8	Text
MNIST [10]	70000	10	Image
Stanford Dogs [8]	1291	7	Image
Texture [1]	5500	11	Text
USPS [7]	9298	10	Image
Weather [6]	1156	4	Image
Wifi [2]	2000	4	Tabular
OoD-Animals [3]	26683	5	Image

2.2 Pearson Correlations Between Convexity Measures

The correlation between convexity measures is calculated based on a set of diverse cluster shapes. Therefore, the key is to generate a diverse set of cluster shapes that are similar to those that appear in a grid layout. To achieve this, we generated multiple grid layouts using the baseline method and then extracted the shape of each cluster. Specifically, we used the ten datasets from Xia *et al.*'s work [12], and generated 60 grid layouts using the baseline with each grid size (20x20, 30x30, 40x40). Thus, we obtained 10x60x3=1800 grid layouts and then extracted corresponding cluster shapes. If a cluster contained multiple disconnected components, we would only choose the largest connected one because those disconnected components usually have poor convexity at all measures, which cannot help evaluate the correlation between different measures. In total, 9,689 different shapes are selected to evaluate the correlations between convexity measures.

2.3 Full Experiment Results in Evaluation

Layout generation. For each dataset, we began by sampling 20x20, 30x30, and 40x40 samples for each dataset. We then generated t-SNE projections from these samples and used them as input for the baseline layout method. However, because different rotations of the same t-SNE projection can produce different grid layouts, we rotated each projection with degrees $\pi/16 * k, k = 0, 1, \ldots, 7$. To reduce the randomness in sampling, we repeated this entire process five times. As a result, we generated a total of 120 layouts for each dataset (3 sizes x 8 rotations x 5 repetitions).
Results. In the ablation study, Tables 2 to 7 show the comparison of proximity, compactness, area ratio, triple ratio, perimeter ratio, and cut ratio of all the methods on 11 datasets. The results are averaged over different grid sizes. To demonstrate the effectiveness of our method, Tables 8 to 10 show the comparison of proximity, compactness, area ratio, triple ratio, perimeter ratio, and cut ratio between baseline and Ours-T/Ours-P on 11 datasets with 3 different grid sizes.

2.4 Examples

Here are examples of layouts generated by baseline method and our method, from different datasets.

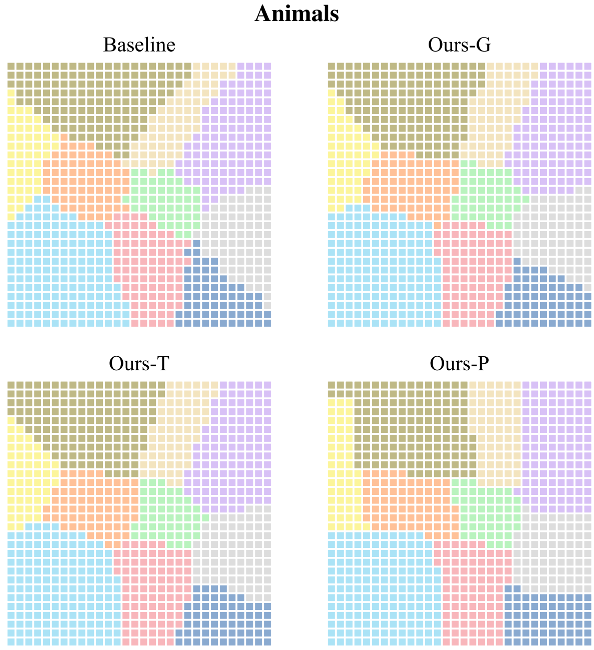

Fig. 12

Fig. 13

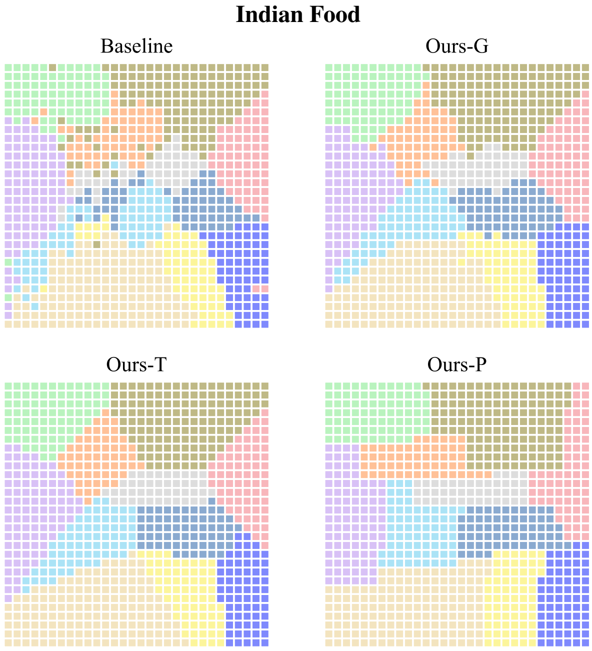

Fig. 14

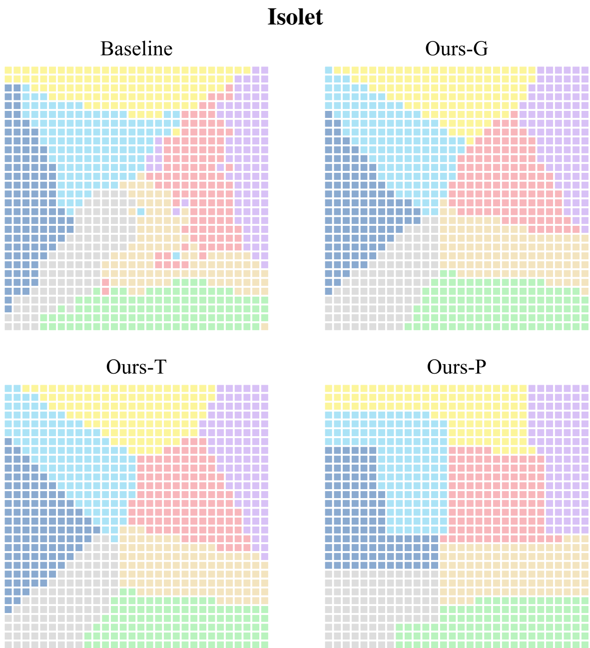

Fig. 15

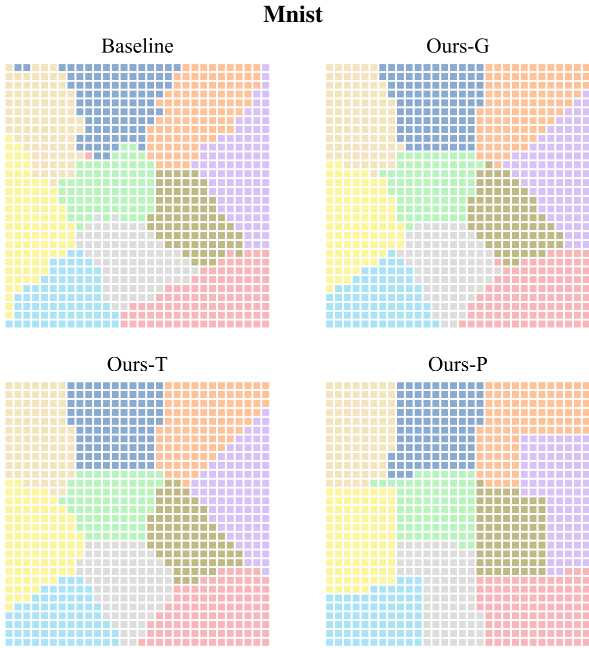

Fig. 16

Fig. 17

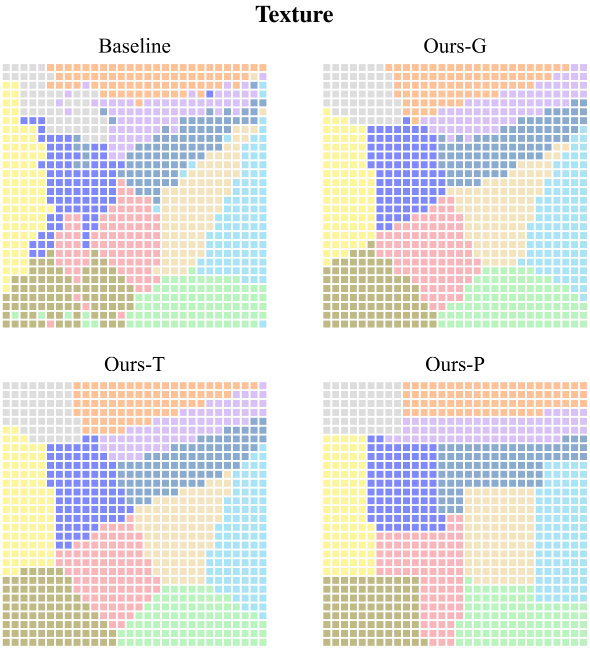

Fig. 18

Fig. 20

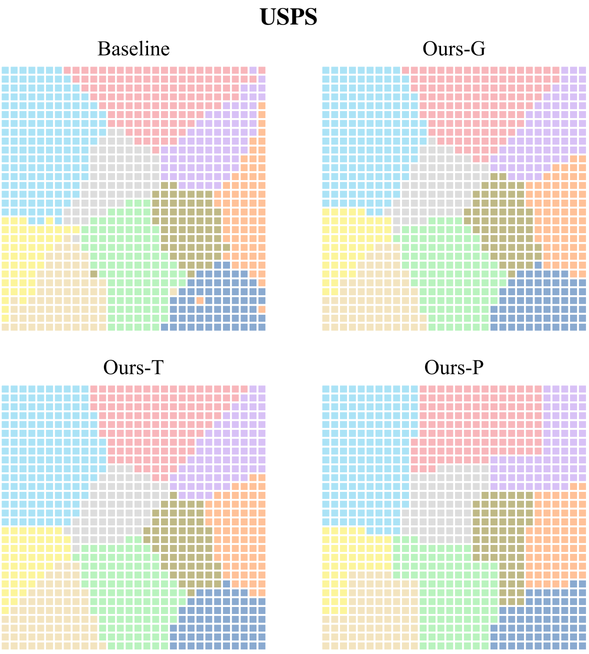

Fig. 19

Fig. 21

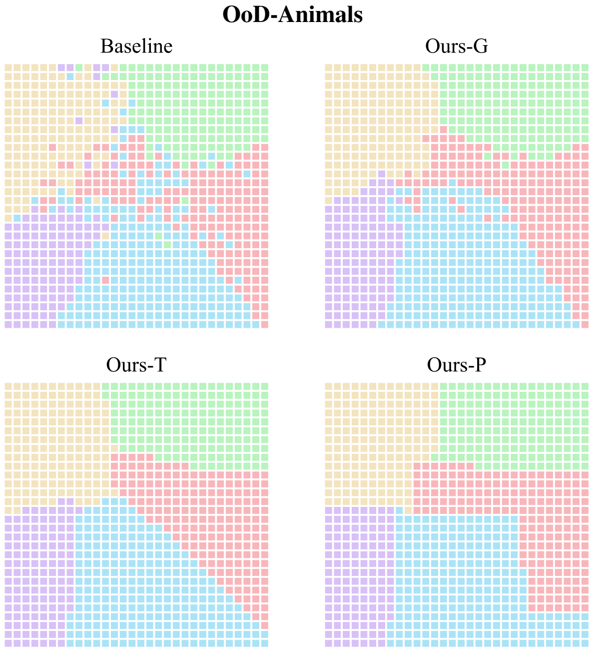

Fig. 22

Table 2: Comparison of proximity of all the methods. G: global; L: local; T: triple ratio; P: perimeter ratio.

Dataset	Baseline	Ours-G	Ours-L(A)	Ours-L(B)	Ours-L(A)-G	Ours-L(B)-G	Ours-G-L(A)	Ours-G-L(B)
Animals	**1.000**	0.998	0.999	0.995	0.999	0.998	0.998	0.996
CIFAR10	**1.000**	0.999	0.999	0.996	0.999	0.999	0.999	0.997
Indian Food	**1.000**	0.996	0.997	0.989	0.997	0.996	0.995	0.994
Isolet	**1.000**	0.995	0.997	0.992	0.995	0.995	0.995	0.993
MNIST	**1.000**	0.998	0.999	0.993	0.999	0.998	0.998	0.996
Stanford Dogs	**1.000**	0.996	0.996	0.988	0.996	0.996	0.995	0.992
Texture	**1.000**	0.996	0.998	0.990	0.996	0.996	0.995	0.994
USPS	**1.000**	0.998	0.999	0.994	0.999	0.998	0.998	0.996
Weather	**1.000**	0.992	0.998	0.991	0.997	0.992	0.991	0.987
Wifi	**1.000**	0.991	0.998	0.994	0.992	0.991	0.991	0.989
OoD-Animals	**1.000**	0.998	0.998	0.989	0.998	0.997	0.997	0.994
Average	**1.000**	0.996	0.998	0.992	0.997	0.996	0.996	0.994

Table 3: Comparison of compactness of all the methods. G: global; L: local; T: triple ratio; P: perimeter ratio.

Dataset	Baseline	Ours-G	Ours-L(A)	Ours-L(B)	Ours-L(A)-G	Ours-L(B)-G	Ours-G-L(A)	Ours-G-L(B)
Animals	0.974	**0.977**	0.975	0.973	0.976	**0.977**	**0.977**	0.976
CIFAR10	0.980	**0.981**	0.980	0.978	**0.981**	**0.981**	**0.981**	0.980
Indian Food	0.970	**0.978**	0.976	0.970	0.977	**0.978**	**0.978**	0.976
Isolet	0.965	**0.973**	0.969	0.963	**0.973**	**0.973**	**0.973**	0.971
MNIST	0.977	**0.980**	0.979	0.975	**0.980**	**0.980**	**0.980**	0.979
Stanford Dogs	0.960	**0.969**	0.967	0.960	**0.969**	**0.969**	**0.969**	0.967
Texture	0.973	**0.979**	0.976	0.970	**0.979**	**0.979**	**0.979**	0.977
USPS	0.976	**0.979**	0.977	0.974	0.978	**0.979**	**0.979**	0.978
Weather	0.936	**0.944**	0.939	0.937	0.940	0.942	**0.944**	0.941
Wifi	0.939	**0.950**	0.942	0.937	0.949	0.949	**0.950**	0.948
OoD-Animals	0.953	**0.960**	0.959	0.952	**0.960**	**0.960**	**0.960**	0.958
Average	0.964	**0.970**	0.967	0.963	0.969	**0.970**	**0.970**	0.968

Table 4: Comparison of area ratio of all the methods. G: global; L: local; T: triple ratio; P: perimeter ratio.

Dataset	Baseline	Ours-G	Ours-L(A)	Ours-L(B)	Ours-L(A)-G	Ours-L(B)-G	Ours-G-L(A)	Ours-G-L(B)
Animals	0.775	0.893	0.897	0.872	0.884	0.896	**0.910**	0.900
CIFAR10	0.786	0.893	0.899	0.869	0.885	0.893	**0.910**	0.901
Indian Food	0.555	0.846	0.889	0.818	0.832	0.840	**0.901**	0.885
Isolet	0.593	0.867	0.886	0.827	0.855	0.870	**0.905**	0.891
MNIST	0.718	0.886	0.899	0.868	0.862	0.884	**0.908**	0.901
Stanford Dogs	0.577	0.860	0.907	0.846	0.851	0.858	**0.919**	0.890
Texture	0.617	0.856	0.877	0.819	0.851	0.858	**0.889**	0.870
USPS	0.739	0.892	0.896	0.875	0.877	0.891	**0.910**	0.904
Weather	0.738	0.903	0.906	0.872	0.874	0.918	**0.926**	0.877
Wifi	0.724	0.921	0.916	0.845	0.915	0.921	**0.936**	0.916
OoD-Animals	0.534	0.889	0.924	0.862	0.877	0.886	**0.932**	0.914
Average	0.669	0.882	0.900	0.852	0.869	0.883	**0.913**	0.895

Table 5: Comparison of triple ratio of all the methods. G: global; L: local; T: triple ratio; P: perimeter ratio.

Dataset	Baseline	Ours-G	Ours-L(A)	Ours-L(B)	Ours-L(A)-G	Ours-L(B)-G	Ours-G-L(A)	Ours-G-L(B)
Animals	0.977	0.995	0.996	0.973	0.994	0.995	**0.997**	0.983
CIFAR10	0.975	0.994	0.996	0.961	0.993	0.994	**0.997**	0.979
Indian Food	0.889	0.986	0.996	0.947	0.985	0.984	**0.997**	0.981
Isolet	0.893	0.986	0.993	0.936	0.983	0.987	**0.996**	0.974
MNIST	0.963	0.993	0.996	0.964	0.989	0.991	**0.997**	0.982
Stanford Dogs	0.909	0.984	0.997	0.949	0.983	0.983	**0.998**	0.976
Texture	0.893	0.985	0.991	0.929	0.983	0.985	**0.994**	0.964
USPS	0.968	0.995	0.996	0.971	0.992	0.994	**0.997**	0.985
Weather	0.952	0.993	0.995	0.963	0.989	0.996	**0.997**	0.965
Wifi	0.953	0.997	0.996	0.944	0.996	0.997	**0.998**	0.982
OoD-Animals	0.925	0.993	**0.998**	0.961	0.993	0.993	**0.998**	0.984
Average	0.936	0.991	0.995	0.954	0.989	0.991	**0.997**	0.978

Table 6: Comparison of perimeter ratio of all the methods. G: global; L: local; T: triple ratio; P: perimeter ratio.

Dataset	Baseline	Ours-G	Ours-L(A)	Ours-L(B)	Ours-L(A)-G	Ours-L(B)-G	Ours-G-L(A)	Ours-G-L(B)
Animals	0.830	0.859	0.853	0.926	0.851	0.861	0.872	**0.935**
CIFAR10	0.834	0.855	0.850	0.925	0.850	0.853	0.868	**0.934**
Indian Food	0.807	0.804	0.854	0.916	0.809	0.800	0.861	**0.929**
Isolet	0.784	0.818	0.858	0.921	0.818	0.824	0.864	**0.936**
MNIST	0.852	0.845	0.858	0.926	0.844	0.844	0.864	**0.933**
Stanford Dogs	0.868	0.773	0.854	0.926	0.777	0.772	0.868	**0.933**
Texture	0.794	0.828	0.857	0.922	0.828	0.833	0.850	**0.927**
USPS	0.861	0.851	0.854	0.930	0.846	0.850	0.865	**0.933**
Weather	0.790	0.858	0.863	**0.940**	0.849	0.880	0.864	0.937
Wifi	0.784	0.867	0.861	0.929	0.867	0.867	0.875	**0.948**
OoD-Animals	0.724	0.812	0.862	0.929	0.825	0.807	0.873	**0.944**
Average	0.812	0.834	0.857	0.926	0.833	0.835	0.866	**0.935**

Table 7: Comparison of cut ratio of all the methods. G: global; L: local; T: triple ratio; P: perimeter ratio.

Dataset	Baseline	Ours-G	Ours-L(A)	Ours-L(B)	Ours-L(A)-G	Ours-L(B)-G	Ours-G-L(A)	Ours-G-L(B)
Animals	0.838	0.887	0.872	0.920	0.879	0.888	0.895	**0.936**
CIFAR10	0.843	0.890	0.876	0.920	0.883	0.889	0.899	**0.937**
Indian Food	0.763	0.849	0.867	0.893	0.846	0.844	0.885	**0.925**
Isolet	0.776	0.858	0.868	0.901	0.855	0.861	0.885	**0.932**
MNIST	0.848	0.887	0.889	0.918	0.882	0.886	0.900	**0.936**
Stanford Dogs	0.786	0.836	0.872	0.912	0.835	0.835	0.893	**0.931**
Texture	0.781	0.856	0.860	0.898	0.855	0.860	0.870	**0.921**
USPS	0.839	0.888	0.878	0.922	0.879	0.887	0.898	**0.937**
Weather	0.803	0.862	0.856	**0.927**	0.852	0.889	0.868	**0.927**
Wifi	0.800	0.890	0.866	0.910	0.889	0.890	0.896	**0.947**
OoD-Animals	0.744	0.868	0.892	0.920	0.870	0.865	0.904	**0.946**
Average	0.802	0.870	0.872	0.913	0.866	0.872	0.890	**0.934**

Table 8: Comparison of four convexity measures on 11 datasets with grid size of 20x20.

Dataset	Proximity			Compactness			Area ratio			Triple ratio			Perimeter ratio			Cut ratio		
	Basel.	Ours-T	Ours-P	Basel.	Ours-T	Ours-P	Basel.	Ours-T	Ours-P	Basel.	Ours-T	Ours-P	Basel.	Ours-T	Ours-P	Basel.	Ours-T	Ours-P
Animals	**1.000**	0.998	0.995	0.975	**0.977**	0.975	0.833	**0.893**	**0.893**	0.981	**0.995**	0.980	0.840	0.878	**0.935**	0.860	0.896	**0.932**
CIFAR10	**1.000**	0.999	0.996	0.980	**0.981**	0.979	0.831	**0.892**	0.891	0.979	**0.995**	0.973	0.832	0.873	**0.934**	0.859	0.897	**0.932**
Indian Food	**1.000**	0.997	0.995	0.975	**0.979**	0.977	0.720	0.893	**0.898**	0.944	**0.996**	0.983	0.843	0.874	**0.936**	0.831	0.899	**0.934**
Isolet	**1.000**	0.995	0.994	0.968	**0.974**	0.972	0.696	**0.893**	0.888	0.920	**0.994**	0.973	0.838	0.874	**0.935**	0.826	0.894	**0.931**
MNIST	**1.000**	0.998	0.995	0.977	**0.980**	0.978	0.746	**0.891**	**0.891**	0.957	**0.995**	0.975	0.863	0.873	**0.934**	0.860	0.901	**0.932**
Stanford Dogs	**1.000**	0.995	0.991	0.961	**0.969**	0.967	0.644	**0.907**	0.895	0.912	**0.997**	0.978	0.898	0.876	**0.937**	0.819	0.901	**0.934**
Texture	**1.000**	0.995	0.994	0.974	**0.980**	0.977	0.733	**0.869**	0.865	0.925	**0.990**	0.956	0.848	0.857	**0.929**	0.837	0.874	**0.920**
USPS	**1.000**	0.997	0.995	0.976	**0.979**	0.978	0.777	**0.895**	**0.895**	0.969	**0.995**	0.981	0.867	0.876	**0.932**	0.860	0.902	**0.933**
Weather	**1.000**	0.995	0.988	0.939	**0.942**	0.940	0.824	**0.909**	0.907	0.973	**0.995**	0.977	0.844	0.877	**0.949**	0.847	0.878	**0.944**
Wifi	**1.000**	0.991	0.989	0.942	**0.950**	0.948	0.824	**0.924**	0.912	0.974	**0.997**	0.979	0.834	0.884	**0.947**	0.844	0.901	**0.945**
OoD-Animals	**1.000**	0.997	0.993	0.953	**0.960**	0.958	0.624	**0.918**	0.915	0.922	**0.997**	0.985	0.767	0.879	**0.944**	0.781	0.907	**0.947**
Average	**1.000**	0.996	0.993	0.965	**0.970**	0.968	0.750	**0.898**	0.896	0.951	**0.995**	0.976	0.843	0.875	**0.938**	0.839	0.895	**0.935**

Table 9: Comparison of four convexity measures on 11 datasets with grid size of 30x30.

Dataset	Proximity			Compactness			Area ratio			Triple ratio			Perimeter ratio			Cut ratio		
	Basel.	Ours-T	Ours-P	Basel.	Ours-T	Ours-P	Basel.	Ours-T	Ours-P	Basel.	Ours-T	Ours-P	Basel.	Ours-T	Ours-P	Basel.	Ours-T	Ours-P
Animals	**1.000**	0.998	0.996	0.974	**0.977**	**0.977**	0.767	**0.912**	0.900	0.976	**0.997**	0.983	0.834	0.871	**0.934**	0.838	0.896	**0.936**
CIFAR10	**1.000**	0.999	0.997	0.980	**0.981**	**0.981**	0.799	**0.914**	0.904	0.978	**0.997**	0.981	0.839	0.870	**0.934**	0.849	0.901	**0.939**
Indian Food	**1.000**	0.996	0.995	0.971	**0.978**	0.977	0.542	**0.905**	0.892	0.893	**0.997**	0.985	0.808	0.861	**0.929**	0.758	0.887	**0.927**
Isolet	**1.000**	0.995	0.993	0.965	**0.973**	0.971	0.592	**0.906**	0.892	0.888	**0.996**	0.975	0.775	0.861	**0.936**	0.772	0.883	**0.932**
MNIST	**1.000**	0.998	0.997	0.978	**0.981**	0.980	0.738	**0.911**	0.907	0.973	**0.997**	0.985	0.856	0.865	**0.934**	0.857	0.902	**0.939**
Stanford Dogs	**1.000**	0.995	0.993	0.960	**0.969**	0.967	0.557	**0.922**	0.889	0.911	**0.998**	0.975	0.889	0.868	**0.931**	0.787	0.895	**0.930**
Texture	**1.000**	0.996	0.995	0.973	**0.980**	0.978	0.636	**0.893**	0.877	0.908	**0.995**	0.969	0.805	0.848	**0.928**	0.784	0.871	**0.923**
USPS	**1.000**	0.998	0.997	0.976	**0.979**	0.978	0.758	**0.911**	0.905	0.975	**0.998**	0.986	0.864	0.863	**0.933**	0.845	0.898	**0.937**
Weather	**1.000**	0.990	0.987	0.937	**0.945**	0.942	0.726	**0.930**	0.872	0.951	**0.997**	0.961	0.787	0.861	**0.936**	0.797	0.865	**0.924**
Wifi	**1.000**	0.991	0.988	0.939	**0.950**	0.948	0.702	**0.939**	0.921	0.952	**0.998**	0.986	0.789	0.875	**0.949**	0.795	0.898	**0.950**
OoD-Animals	**1.000**	0.997	0.994	0.953	**0.960**	0.959	0.488	**0.933**	0.914	0.919	**0.998**	0.984	0.731	0.871	**0.944**	0.734	0.903	**0.945**
Average	**1.000**	0.996	0.994	0.964	**0.970**	0.969	0.664	**0.916**	0.897	0.938	**0.997**	0.979	0.816	0.865	**0.935**	0.801	0.891	**0.935**

Table 10: Comparison of four convexity measures on 11 datasets with grid size of 40x40.

Dataset	Proximity			Compactness			Area ratio			Triple ratio			Perimeter ratio			Cut ratio		
	Basel.	Ours-T	Ours-P	Basel.	Ours-T	Ours-P	Basel.	Ours-T	Ours-P	Basel.	Ours-T	Ours-P	Basel.	Ours-T	Ours-P	Basel.	Ours-T	Ours-P
Animals	**1.000**	0.998	0.996	0.974	**0.977**	**0.977**	0.726	**0.925**	0.906	0.975	**0.998**	0.986	0.816	0.866	**0.935**	0.816	0.894	**0.939**
CIFAR10	**1.000**	0.999	0.998	0.979	**0.981**	**0.981**	0.727	**0.924**	0.907	0.969	**0.998**	0.984	0.830	0.861	**0.935**	0.820	0.898	**0.940**
Indian Food	**1.000**	0.993	0.992	0.965	**0.977**	0.975	0.403	**0.906**	0.864	0.830	**0.998**	0.976	0.769	0.848	**0.922**	0.701	0.868	**0.913**
Isolet	**1.000**	0.994	0.993	0.963	**0.973**	0.971	0.491	**0.917**	0.892	0.870	**0.997**	0.974	0.740	0.855	**0.938**	0.731	0.877	**0.932**
MNIST	**1.000**	0.998	0.997	0.977	**0.981**	0.980	0.670	**0.922**	0.905	0.960	**0.998**	0.985	0.838	0.855	**0.931**	0.828	0.896	**0.938**
Stanford Dogs	**1.000**	0.995	0.993	0.960	**0.969**	0.968	0.529	**0.928**	0.886	0.904	**0.998**	0.977	0.816	0.858	**0.931**	0.753	0.884	**0.929**
Texture	**1.000**	0.995	0.994	0.970	**0.979**	0.977	0.481	**0.905**	0.869	0.845	**0.996**	0.966	0.729	0.844	**0.925**	0.720	0.867	**0.919**
USPS	**1.000**	0.998	0.997	0.975	**0.979**	0.978	0.682	**0.923**	0.912	0.960	**0.998**	0.988	0.851	0.857	**0.934**	0.813	0.894	**0.940**
Weather	**1.000**	0.988	0.986	0.934	**0.945**	0.942	0.662	**0.939**	0.852	0.931	**0.998**	0.957	0.739	0.856	**0.927**	0.766	0.860	**0.912**
Wifi	**1.000**	0.991	0.989	0.937	**0.949**	0.947	0.645	**0.946**	0.916	0.933	**0.999**	0.982	0.728	0.867	**0.948**	0.761	0.891	**0.946**
OoD-Animals	**1.000**	0.998	0.995	0.954	**0.960**	0.959	0.489	**0.945**	0.914	0.934	**0.999**	0.983	0.672	0.869	**0.943**	0.718	0.902	**0.946**
Average	**1.000**	0.995	0.993	0.962	**0.970**	0.969	0.591	**0.926**	0.893	0.919	**0.998**	0.978	0.775	0.858	**0.933**	0.766	0.885	**0.932**

References

[1] D. Arthur, Asuncion. Uci machine learning repository. https://archive.ics.uci.edu/ml/index.php, 2007. Last accessed 2023-3-31. 8

[2] R. Bhatt. Fuzzy-rough approaches for pattern classification: Hybrid measures, mathematical analysis, feature selection algorithms, decision tree algorithms, neural learning, and applications. *Decision tree algorithms, neural learning, and applications. Amazon books*, 2005. 8

[3] C. Chen, J. Yuan, Y. Lu, Y. Liu, H. Su, S. Yuan, and S. Liu. Oodanalyzer: Interactive analysis of out-of-distribution samples. *IEEE Trans. Vis. Comput. Graphics*, 27(7):3335–3349, 2021. doi: 10.1109/TVCG.2020.2973258 8

[4] A. Corrado. Animals-10 dataset. https://www.kaggle.com/datasets/alessiocorrado99/animals10/, 2019. Last accessed 2023-3-31. 3, 8

[5] M. Fanty and R. Cole. Spoken letter recognition. In *Adv. Neural Inform. Process. Syst.*, 1990. 8

[6] Gupta, Vijay. Weathers. https://www.kaggle.com/datasets/vijaygiitk/multiclass-weather-dataset, 2020. Last accessed 2023-3-31. 8

[7] J. J. Hull. A database for handwritten text recognition research. *IEEE Trans. Pattern Anal. Mach. Intell.*, 16(5):550–554, 1994. doi: 10.1109/34.291440 6, 8

[8] A. Khosla, N. Jayadevaprakash, B. Yao, and F.-F. Li. Novel dataset for fine-grained image categorization: Stanford dogs. In *Proc. CVPR Workshop on Fine-Grained Visual Categorization (FGVC)*, 2011. 8

[9] A. Krizhevsky and G. Hinton. Learning multiple layers of features from tiny images. Technical report, University of Toronto, Toronto, Ontario, 2009. 4, 8

[10] Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner. Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, 86(11):2278–2324, 1998. doi: 10.1109/5.726791 5, 8

[11] Mehta, Anshul. Indian food. https://www.kaggle.com/datasets/anshulmehtakaggl/themassiveindianfooddataset, 2020. Last accessed 2023-3-31. 8

[12] J. Xia, L. Huang, W. Lin, X. Zhao, J. Wu, Y. Chen, Y. Zhao, and W. Chen. Interactive visual cluster analysis by contrastive dimensionality reduction. *IEEE Trans. Vis. Comput. Graphics*, 29(1):734–744, 2023. doi: 10.1109/TVCG.2022.3209423 8