OrigamiSet1.0: Two New Datasets for Origami Classification and Difficulty Estimation

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January 15, 2021

Abstract

Origami is becoming more and more relevant to research. However, there is no public dataset yet available and there hasn’t been any research on this topic in machine learning. We constructed an origami dataset using images from the multimedia commons and other databases. It consists of two subsets: one for classification of origami images and the other for difficulty estimation. We obtained 16000 images for classification (half origami, half other objects) and 1509 for difficulty estimation with 3 different categories (easy: 764, intermediate: 427, complex: 318). The data can be downloaded at: https://github.com/multimedia-berkeley/OriSet

Finally, we provide machine learning baselines.

1 Introduction

Origami is the art of paperfolding. The term arises specifically from the Japanese tradition, but that tradition has been practiced around the world for several centuries now [4]. In addition to being a recreational art form, in recent years, origami has increasingly often been incorporated into the work and research of mathematicians and engineers.

In the 1970s for example to solve the problem of packing large, flat membrane structures to be sent into space, Koryo Miura used origami: he developed a method for collapsing a large flat sheet to a much smaller area so that collapsing or expanding the sheet would only require pushing or pulling at the opposite corners of the sheet [13]. Similarly, Robert Lang is using computational origami-based research to help the Lawrence Livermore National Laboratory to design a space telescope lens ("Eyeglass") that can collapse down from 100 meters in diameter to a size that will fit in a rocket with roughly 4 meters in diameter [7, 11]. In the field of mathematics, Thomas Hull is investigating enumeration of the valid ways to fold along a crease pattern (i.e., a diagram containing all the
creases needed to create a model) such that it will lie flat. He uses approaches from coloring in graph theory to solve the problem [6]. In medicine, Kuribayashi et al. used origami to design a metallic heart stent that can be easily threaded through an artery before expanding where it needs to be deployed [10].

In other words, origami is becoming an established part of science. To support research on origami, we decided to generate a new large origami dataset. Part of it comes from filtering it out from the multimedia commons [2]. The multimedia commons comprise information about a dataset of 99 Million images and 800000 videos that have been uploaded on Flickr under creative commons license (YFCC100M) [19]. This work is part of a bigger project that creates a framework around this data to support multimedia big data field studies [9].

Datasets are crucial for new developments and major progress in machine learning. In particular, datasets of images have allowed researchers to make significant advances in the field of computer vision. For example, ImageNet [3], a dataset of millions of images and corresponding noun labels, has been a useful resource in creating and benchmarking large-scale algorithms for image classification. The German Traffic Sign Detection Benchmark Dataset [5] has a practical use for self-driving vehicles to detect traffic signs in order for them to act appropriately. The MNIST database [12], a vast database of handwritten numeric digits, has been used for training and testing various classification techniques on image recognition.

Here, we introduce two new datasets which we collectively call OrigamiSet1.0. The two datasets together consist of more than 15,000 images. In this paper, we first describe the properties of the datasets themselves in Section 2. Next, we provide baseline evaluations for distinguishing images of origami from images that contain no origami (Section 3.1) as well as image-based difficulty estimation of origami models (Section 3.2). We conclude in Section 4.

2 OrigamiSet1.0

First, we describe the dataset to distinguish origami images from normal images and then we introduce the dataset for difficulty estimation. The data can be downloaded at: https://github.com/multimedia-berkeley/OriSet

2.1 Origami Image Classification

This dataset consists of 8,011 images containing origami and 7,976 images that do not contain origami. The majority of the origami images were scraped from two major origami databases: Oriwiki [13] and GiladOrigami [1]. Before scraping both websites for images, we contacted the administrators of both databases, asking for permission to scrape the images. The Oriwiki administrators are unreachable, but Gilad Aharoni gave us permission to use his images in our dataset (Gallery only).
2.1.1 Scraping procedure

To scrape the images from Oriwiki, we found that each model’s page was assigned a Model ID number included in the URL of the page, so we wrote a Python script that iterated through every Model ID number between 0 and 99,999, retrieving the image from the corresponding model’s page. Afterwards, we noticed that a significant portion of the retrieved images were placeholder images. So we removed those, which resulted in 3,934 images from Oriwiki. As for GiladOrigami, unlike Oriwiki, each model image did not have its own page or model ID number. Instead, we went through the gallery section of the site and scraped all the origami images from each page in the gallery by hand. We note that the gallery does not contain all of the images of the site, but scraping from GiladOrigami has produced 2,140 images of origami.

The remainder of the origami images were taken from the YFCC100M data browser [8]. Starting with the search term origami resulted in over 13,000 images, but more than 30% of the images did not contain origami. Due to a tag cloud visualization, we used papiroflexia and origamiforum as search terms which generated a more reliable, albeit smaller set of results. After some minor hand-cleaning, which involved removing non-origami images as well as images containing people, we obtained 1,937 origami images.

2.1.2 Data properties and non-origami class creation

In this section, the properties of the origami images in our dataset are described. In our diverse set, each of the models itself is the main focus of the image. For example, all of these images do not contain humans or human body parts. Furthermore, there is generally only one model in the center of the image. In addition, there were many images of models that were meant to represent the same topic. For example, there were multiple instances of dragons; some were very simplistic, while others incorporated much more details in the wings, head, and appendages of the model (see Figure 1).

To explore the diversity of the dataset as well as its relation to the ImageNet dataset, we applied a VGG16 neural network [17] to the YFCC100M origami images that was trained on ImageNet with 1000 common classes. ImageNet does not include the class origami.

We found that the top-1 predictions were spread among 263 different classes, while the top-5 predictions were spread among 529 classes. The most common classes that appeared are shown in Table 1. As one can tell, our origami images were very often classified as items that are similar to paper-folding and origami (such as envelope or handkerchief) as well as things that involve paper (such as paper towel or carton). In some cases, some images were classified as objects that an origami model was meant to represent such as flowers, candles, or bugs.

With these labels in mind, we generated a non-origami class by using the ILSVRC2011 validation data [10]. For each label, excluding pinwheel, envelope, carton, paper towel, packet, and handkerchief, we gathered the first 8 examples, producing 7976 non-origami images.

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2.2 Difficulty Estimation

To the best of our knowledge, there is no single useful standard for defining the difficulty of an origami model. Some heuristics to estimate the difficulty of folding a model include the number of creases involved or the number of steps included in the diagrams in the model. However, such data is not easily available for a large number of models and collecting such data might be infeasible. Instead, we estimate difficulty based on the appearance of the model.

At first, we used difficulty levels that were assigned to the origami images that we scraped from the Oriwiki database \cite{14}. These difficulty levels were assigned by the uploading user. Each difficulty label was a value between 1 and 5, where 1 represents low difficulty and 5 represents high difficulty. Again, we used the VGG16 features. However this time, we trained an algorithm to predict the difficulty of an origami model. However, training a classifier could not produce any useful result (see Section 3.2). A likely reason for the low performance is that the labeling of difficulties by users is inconsistent or even wrong. This can be seen in Figure 2 where the images show a clear discrepancy between the difficulty label and the perceived difficulty. Thus, we provide our own difficulty labels.

We picked a subset of 1509 images of origami from the set of images used for origami image classification, hand-assigning each image a difficulty of 0 (easy), 1 (intermediate), or 2 (complex). In the end, there were 764 easy images, 427 intermediate images and 318 complex images. Several assumptions and
Table 1: Top-1 predictions for our extracted YFCC100M subset ($n =$ number of occurrences).

|         | Top-1 | | Top-5 |
|---------|-------|---|-------|
| name    | n     |   | name  | n     |
| pinwheel| 243   |   | envelope | 788  |
| envelope| 243   |   | pinwheel | 518  |
| carton  | 117   |   | carton | 499   |
| paper towel | 76   |   | packet | 328   |
| honeycomb | 71   |   | handkerchief | 314  |
| lampshade | 41   |   | paper towel | 302  |
| rubber eraser | 39   |   | rubber eraser | 238  |
| handkerchief | 37  |   | candle | 218   |
| pencil sharpener | 35  |   | lampshade | 192  |
| shower cap | 34  |   | wall clock | 168  |

Guidelines were followed in labeling the difficulty of the models in these images. In particular, each image was assigned a difficulty based on the assumption that the model in the image was made from a single sheet of paper. Images containing modular models (i.e., models made from multiple pieces of paper) and tessellations (i.e., models with repeating patterns), as complex as they appear, usually involve folding an easy sequence of folds repetitively. Table 2 contains general guidelines that were used for assigning a difficulty to each model and Figure 3 provides some examples.

Table 2: Guidelines for assigning difficulty levels (see also Figure 3).

| Difficulty | Description |
|------------|-------------|
| Easy (0)   | Contains very little detail |
|           | Appears very “flat”, i.e. has very few layers of paper |
|           | Appearance may consist of a collection of simple geometric shapes |
|           | Has very few appendages, most of which are wide |
|           | Boxes and airplanes in most cases fall under this difficulty |
| Intermediate (1) | Moderate amount of detail |
|             | Moderate number of appendages that are somewhat narrow |
|             | Inclusion of toes or fingers to appendages |
|             | Contain two objects in a single model, although one object may be significantly smaller than the other (e.g. man with violin) |
|             | Some shaping to add curves and a 3D appearance to the model |
| Complex (2) | Highly detailed |
|             | Large number of appendages |
|             | High resemblance to the subject the model is supposed to represent |
|             | Contains several objects in a single model |
|             | If a model contains only two objects, the two objects are about the same size |
|             | Significant amount of shaping |
|             | Insects tend to fall in this category, especially if the models have long, narrow appendages |

Table 2: Guidelines for assigning difficulty levels (see also Figure 3).
Figure 2: Examples of wrong difficulty assignment in the Oriwiki database [14]. On the left are images of models that are ranked as very difficult when they appear to actually be easy or intermediate models. On the right are images of models that are rated as very easy when they actually appear to be complex.

One concern regarding our difficulty estimation is that in the process of hand-labeling difficulty, some models are actually more difficult or easier than they appear. For example, a model with many appendages will be classified as difficult according to our heuristic, but the actual difficulty of the model may be intermediate instead. Here, future contributions to the dataset are welcome to provide corrections or new variants. Note, however, that visual judgement of the difficulty cannot be as accurate as a real estimated related to the folding procedure.

3 Machine Learning Evaluation

Apart from the creation of the datasets, we also want to present and explore two machine learning challenges on this data to encourage data analysis and algorithm development for this kind of data. It is meant to be seen as a first baseline and to quantify the challenges.

3.1 Origami Classification

In the first setting, we want to distinguish origami from non-origami images.
3.1.1 General Processing Setup

For generating features of all our images we used the VGG16 neural network model implemented in MXNet. In particular, each image's features were generated by taking the output right before the last layer of the model. In addition, a list of labels was created to denote whether the resulting feature vector belongs to an origami image (1) or to a non-origami image (-1). With these features and labels, we evaluated multiple classifier models using Scikit-learn's 5-fold cross-validation function.

3.1.2 Classifier Comparison Results

We compared multiple kernels of SVC models as well as the logistic regression model provided by scikit-learn, all on default settings. Table 3 shows the accuracy scores for each model.

3.1.3 Discussion

We note that a majority of the classifiers' accuracy scores are actually quite close, so it is difficult to say which classifier has the best performance. However, the results indicate that a good classification is possible with our data and that with further tuning, scores around 99% should be possible.
Table 3: Origami classification estimation: 5-fold cross-validation scores for different models on default settings

| Classifier    | Accuracy Score       |
|---------------|----------------------|
| SVC: Linear Kernel | 0.9674 ± 0.0049     |
| SVC: RBF Kernel    | 0.9705 ± 0.0051     |
| SVC: Poly Kernel   | 0.9746 ± 0.0063     |
| SVC: Sigmoid Kernel| 0.9215 ± 0.0128     |
| Logistic Regression| 0.9707 ± 0.0071     |

3.2 Origami Difficulty Estimation

Similar to the Origami Image Classification setup, we again used the output vector right before the last layer of the VGG-16 neural network as the feature for each image. As before, we looked at how well several models on default settings could predict the difficulty based on the values provided by the users of the Oriwiki [13] database. We performed a 5-fold cross-validation on the same classifiers that we used earlier in Section 3.1 but produced $R^2$ scores as well as balanced accuracy scores to account for the fact that the images are not distributed very evenly across the different difficulty labels [18].

Table 4: Difficulty Estimation: 5-fold CV Scores of Different Models using Oriwiki Labels

| Classifier    | Balanced Accuracy Score | $R^2$ Score       |
|---------------|-------------------------|-------------------|
| SVC: Linear Kernel | 0.2775 ± 0.0220    | −0.5751 ± 0.0842 |
| SVC: RBF Kernel    | 0.4488 ± 0.0451    | −0.5383 ± 0.1282 |
| SVC: Poly Kernel   | 0.3202 ± 0.0170    | −0.4513 ± 0.1022 |
| SVC: Sigmoid Kernel| 0.2931 ± 0.0470    | −0.737 ± 0.0832  |
| Logistic Regression| 0.3034 ± 0.0233    | −0.4958 ± 0.0879 |

Table 4 clearly shows that useful difficulty estimation is not possible with the labels from the Oriwiki database. For this reason, we decided to label a subset of the origami images by hand (see Section 2.2). With these labels, we again fit the data to several models on default settings and got significantly better accuracy and $R^2$ scores (see Table 5).

Table 5: Difficulty Estimation: 5-fold CV Scores of Different Models using our Labels

| Classifier    | Balanced Accuracy Score | $R^2$ Score |
|---------------|-------------------------|-------------|
| SVC: Linear Kernel | 0.7581 ± 0.0151    | 0.5631 ± 0.0716 |
| SVC: RBF Kernel    | 0.7826 ± 0.0217    | 0.6293 ± 0.1323 |
| SVC: Poly Kernel   | 0.7854 ± 0.0172    | 0.6158 ± 0.0948 |
| SVC: Sigmoid Kernel| 0.7223 ± 0.0281    | 0.5822 ± 0.1516 |
| Logistic Regression| 0.7625 ± 0.0101    | 0.5738 ± 0.0789 |
3.2.1 Evaluation setup

To further improve on this classifier, we decided to tune the kernel and C hyperparameters of the SVC. Hence, we used the GridSearchCV class of the scikit-learn package to find the hyperparameters that provided the highest score. We passed in all the possible default kernels of the SVC as well as powers of 10 ranging from $10^{-4}$ to 10 for the C hyperparameter as arguments to iterate over to find the parameter that provides the highest 5-fold cross-validation balanced accuracy score.

3.2.2 Results

We found that an SVC with a polynomial kernel with $C = 0.1$ provided the highest possible score, giving us a balanced accuracy of $0.7913 \pm 0.0219$. Figure 4 shows several of the images that were classified incorrectly using these parameters for the SVC.

| 0,1 | 1,0 | 1,2 | 2,0 | 2,1 |
|-----|-----|-----|-----|-----|
| ![Image1] | ![Image2] | ![Image3] | ![Image4] | ![Image5] |
| ![Image6] | ![Image7] | ![Image8] | ![Image9] | ![Image10] |
| ![Image11] | ![Image12] | ![Image13] | ![Image14] | ![Image15] |
| ![Image16] | ![Image17] | ![Image18] | ![Image19] | ![Image20] |

Figure 4: A collection of images that were wrongly classified. The first number in each column represents the labeled difficulty, while the second number represents the predicted difficulty.

3.2.3 Discussion

Keeping in mind, that difficulty estimation is a challenging task and that guessing would result in a balanced accuracy of 0.3333, our results show that a difficulty estimation with machine learning and our three difficulty levels is in general possible.
4 Conclusion

In this paper, we introduced OrigamiSet1.0, which provides images for the origami classification as well as difficulty estimation. Our empirical results show that our data can be successfully used for these two machine learning challenges.

Future challenges are to estimate the number of folds that a model contains as well as to classify what an origami model is supposed to represent. Furthermore, the existing approaches can be improved in performance. For example, randomizing background, lighting, and paper texture (if possible) can be helpful augmentation techniques on the training data and also more tailored classification algorithms can improve performance. However, this requires an extension of the dataset in size as well as information content. We hope this paper encourages the interested reader to contribute more data.

Acknowledgments

This work was supported by a fellowship from the FITweltweit program of the German Academic Exchange Service (DAAD), by the Undergraduate Research Apprenticeship Program (URAP) at University of California, Berkeley, and by grants from the U.S. National Science Foundation (1251276 and 1629990). (Findings and conclusions are those of the authors, and do not necessarily represent the views of the funders.)

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