Learning Temporal Transformations From Time-Lapse Videos

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Abstract. Based on life-long observations of physical, chemical, and biologic phenomena in the natural world, humans can often easily picture in their minds what an object will look like in the future. But, what about computers? In this paper, we learn computational models of object transformations from time-lapse videos. In particular, we explore the use of generative models to create depictions of objects at future times. These models explore several different prediction tasks: generating a future state given a single depiction of an object, generating a future state given two depictions of an object at different times, and generating future states recursively in a recurrent framework. We provide both qualitative and quantitative evaluations of the generated results, and also conduct a human evaluation to compare variations of our models.

Keywords: generation, temporal prediction, time-lapse video

1   Introduction

Before they can speak or understand language, babies have a grasp of some natural phenomena. They realize that if they drop the spoon it will fall to the ground (and their parent will pick it up). As they grow older, they develop understanding of more complex notions like object constancy and time. Children acquire much of this knowledge by observing and interacting with the world.

In this paper we seek to learn computational models of how the world works through observation. Specifically, we learn models for natural transformations from video. To enable this learning, we collect time-lapse videos demonstrating four different natural state transformations: melting, blooming, baking, and rotting. Several of these transformations are applicable to a variety of objects. For example, butter, ice cream, and snow melt, bread and pizzas bake, and many different objects rot. We train models for each transformation – irrespective of the object undergoing the transformation – under the assumption that these transformations have shared underlying physical properties that can be learned.

To model transformations, we train deep networks to generate depictions of the future state of objects. We explore several different generation tasks for modeling natural transformations. The first task is to generate the future state depiction of an object from a single image of the object (Sec 3.1). Here the input is a frame depicting an object at time t, and output is a generated depiction

of the object at time t+k, where k is specified as a conditional label input to the network. For this task we explore two auto-encoder based architectures. The first architecture is a baseline algorithm built from a standard auto-encoder framework. The second architecture is a generative adversarial network where in addition to the baseline auto-encoder, a discriminator network is added to encourage more realistic outputs.

For our second and third future prediction tasks, we introduce different ways of encoding time in the generation process. In our two-stack model (Sec 3.2) the input is two images of an object at time t and t+m and the model learns to generate a future image according to the implicit time gap between the input images (ie generate a prediction of the object at time t+2m). These models are trained on images with varying time gaps. Finally, in our last prediction task, our goal is to recursively generate the future states of an object given a single input image of the object. For this task, we use a recurrent neural network to recursively generate future depictions (Sec 3.3). For each of the described future generation tasks, we also explore the effectiveness of pre-training on a large set of images, followed by fine-tuning on time-lapse data for improving performance.

Future prediction has been explored in previous works for generating the next frame or next few frames of a video [1–3]. Our focus, in comparison, is to model general natural object transformations and to model future prediction at a longer time scale (minutes to days) than previous approaches.

We evaluate the generated results of each model both quantitatively and qualitatively under a variety of different training scenarios (Sec 4). In addition, we perform human evaluations of model variations and image retrieval experiments. Finally, to help understand what these models have learned, we also visualize common motion patterns of the learned transformations. These results are discussed in Sec 5.

The innovations introduced by our paper include: 1) A new problem of modeling natural object transformations with deep networks, 2) A new dataset of 1463 time-lapse videos depicting 4 common object transformations, 3) Exploration of deep network architectures for modeling and generating future depictions, 4) Quantitative, qualitative, and human evaluations of the generated results, and 5) Visualizations of the learned transformation patterns.

1.1   Related work

Object state recognition: Previous works [4–6] have looked at the problem of recognizing attributes, which has significant conceptual overlap with the idea of object state recognition. For example "in full bloom" could be viewed as an attribute of flowers. Parikh and Grauman [5] train models to recognize the relative strength of attributes such as face A is "smiling more" than face B from ordered sets of images. One way to view our work is as providing methods to train relative state models in the temporal domain. Most relevant to our work, given a set of object transformation terms, such as ripe vs unripe, [7] learns visual classification and regression models for object transformations from a collection of photos. In contrast, our work takes a deep learning approach and learns

transformations from video – perhaps a more natural input format for learning temporal information.

Timelapse data analysis: Timelapse data captures changes in time and has been used for various applications. [8] hallucinates an input scene image at a different time of day by making use of a timelapse video dataset exhibiting lighting changes in an example-based color transfer technique. [9] presents an algorithm that synthesizes timelapse videos of landmarks from large internet image collections. In their follow-up work, [10] imports additional camera motion while composing videos to create transformations in time and space.

Future prediction: Future prediction has been applied to various tasks such as estimating the future trajectories of cars[11], pedestrians[12], or general objects[13] in images or videos. In the ego-centric activity domain, [14] encodes the prediction problem as a binary task of selecting which of two video clips is first in temporal ordering. Given large amounts of unlabeled video data from the internet, [15] trains a deep network to predict visual representations of future images, enabling them to anticipate both actions and objects before they appear.

Image/Frame generation: Generative models have attracted extensive attention in machine learning [16–21]. Recently many works have focused on generating novel natural or high-quality images. [22] applies deep structure networks trained on synthetic data to generate 3D chairs. [23] combines variational auto-encoders with an attention mechanism to recurrently generate different parts of a single image. Generative adversarial networks (GANs) have shown great promise for improving image generation quality [24]. GANs are composed of two parts, a generative model and a discriminative model, to be trained jointly. Some extensions have combined GAN structure with multi-scale laplacian pyramid to produce high-resolution generation results [25]. Recently [26] incorporated deep convolutional neural network structures into GANs to improve image quality. [27] proposed a network to generate the contents of an arbitrary image region according to its surroundings. Some related approaches [1–3] have trained generation models to reconstruct input video frames and/or generate the next few consecutive frames of a video. We also explore the use of DCGANs for future prediction, focusing on modeling object transformations over relatively long time scales.

2   Object-centric timelapse dataset

Given the high-level goal of understanding temporal transformations of objects, we require a collection of videos showing temporal state changes. Therefore, we collect a large set of object-centric timelapse videos from the web. Timelapse videos are ideal for our purposes since they are designed to show an entire transformation (or a portion of a transformation) within a short period of time.

2.1   Data collection

We observe that time-lapse photography is quite popular due to the relative ease of data collection. A search on YouTube for "time lapse" results in over

Rotting: 185	Melting: 453	Baking: 242	Blooming: 583
Strawberry: 35	Ice cream: 128	Cookies: 55	Flower: 583
Watermelon: 9	Chocolate: 18	Bread: 57	
Tomato: 25	Butter: 9	Pizza: 59	
Banana: 26	Snow: 54	Cake: 48	
Apple: 23	Wax: 60	Other: 23	
Peach: 8	Ice: 184		
Other: 59			

Table 1. Statistics of our transformation categories. Some categories contain multiple objects (e.g. ice cream, chocolate, etc melting) while others apply only to a specific object (e.g. flowers blooming). Values indicate the total number of videos collected for each category.

11 million results. Anyone with a personal camera, GoPro, or even a cell phone can capture a simple time-lapse video and many people post and publicly share these videos on the web. We collect our object-based timelapse video dataset by directly querying keywords through the YouTube API. For this paper, we query 4 state transformation categories: Blooming, Melting, Baking and Rotting, combined with various object categories. This results in a dataset of more than 5000 videos. This dataset could be extended to a wider variety of transformations or to more complex multi-object transformations, but as a first step we focus on these 4 as our initial goal set of transformations for learning.

For ease of learning, ideally these videos should be object-centric with a static camera capturing an entire object transformation. However, many videos in the initial data collection stage do not meet these requirements. Therefore, we clean the data using Amazon Mechanical Turk (AMT) as a crowdsourcing platform. Each video is examined by 3 Turkers who are asked questions related to video quality. Videos that are not timelapse, contain severe camera motion or are not consistent with the query labels are removed. We also manually adjust parts of the videos which are playing backwards (a technique used in some time-lapse videos), contain more than one round of the specified transformation, and remove irrelevant prolog/epilog. Finally our resulting dataset contains 1463 high quality object based timelapse videos. Table. 1 shows the statistics of transformation categories and their respective object counts. Fig. 1 shows example frames of each transformation category.

2.2 Transformation degree annotation

To learn natural transformation models of objects from videos, we need to first label the degree of transformation throughout the videos. In language, people use text labels to describe different states, for instance, fresh vs rotted apple. However, the transformation from one state to another is really a continuous evolution. Therefore, we represent the degree of transformation with a real number, assigning the start state a value of 0 (not at all rotten) and the end state

Fig. 1. Example frames from our dataset of each transformation category: Blooming, Melting, Baking, and Rotting. In each column, time increases as you move down the column, showing how an object transforms.

(completely rotten) a value of 1. To annotate objects from different videos we could naively assign the first frame a value of 0 and the last frame a value of 1, interpolating in between. However, we observe that some time-lapse videos may not depict entire transformations, resulting in poor alignments.

Therefore, we design a labeling task for people to assign degrees of transformation to videos. Directly estimating a real value for frames turns out to be impractical as people may have different conceptions of transformation degree. Instead our interface displays reference frames of an object category-transformation and asks Turkers to align frames from a target video to the reference frames according to degree of transformation. Specifically, for each object category-transformation pair we select 5 reference frames from a reference video showing: transformation degree values of 0, 0.25, 0.5, 0.75, and 1. Then, for the rest of the videos in that object-transformation category, we ask Turkers to select frames visually displaying the same degree of transformation as the reference frames. If the displayed video does not depict an entire transformation, Turkers may align less than 5 frames with the reference. Each target video is aligned by 3 Turkers and the median of their responses is used as annotation labels(linearly interpolating degrees between labeled target frames). This provides us with consistent degree annotations between videos.

3   Future state generation Tasks & Approaches

Our goal is to generate depictions of the future state of objects. In this work, we explore frameworks for 3 temporal prediction tasks. In the first task (Sec 3.1), called pairwise generation, we input an object-centric frame and the model generates an image showing the future state of this object. Here the degree of the future state transformation – how far in the future we want the depiction to show – is controlled by a conditional term in the model. In the second task (Sec 3.2) we have two inputs to the model: two frames from the same video showing a state transformation at two points in time. The goal of this model is to generate a third image that continues the trend of the transformation depicted by the first and second input. We call this "two stack" generation. In the
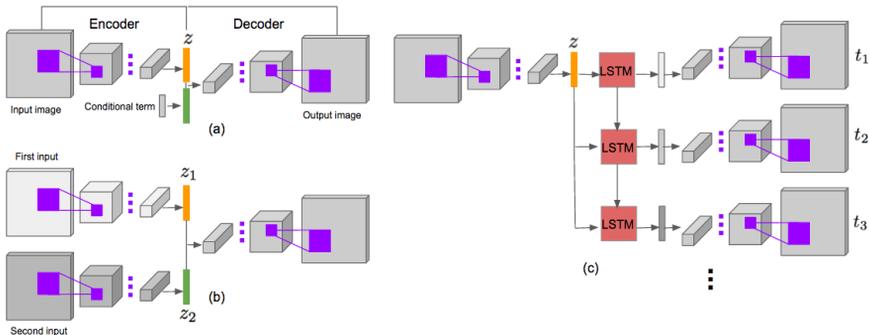
Fig. 2. Model architectures of three generation tasks: (a) Pairwise generator; (b) Two stack generator; (c) Recurrent generator.

third task (Sec 3.3), called "recurrent generation", the input is a single frame and the goal is to recursively generate images that exhibit future degrees of the transformation in a recurrent model framework.

3.1   Pairwise generation

In this task, we input a frame and generate an image showing the future state. We model the task using an autoencoder style convolutional neural network. The model architecture is shown in Fig. 2(a), where the input and output size are 64x64 with 3 channels and encoding and decoding parts are symmetric. Both encoding and decoding parts consists of 4 convolution/deconvolution layers with the kernel size 5x5 and a stride of 2, meaning that at each layer the height and width of the output feature map decreases/increases by a factor of 2 with 64, 128, 256, 512/512, 256, 128, 64 channels respectively. Each conv/deconv layer, except the last layer, is followed by a batch normalization operation[28] and ReLU activation function[29]. For the last layer we use Tanh as the activation function. The size of the hidden variable z (center) is 512. We represent the conditional term encoding the degree of elapsed time between the input and output as a 4 dimensional one-hot vector, representing 4 possible degrees. This is connected with a linear layer (512) and concatenated with z to adjust the degree of the future depiction. Below we describe experiments with different loss functions and training approaches for this network.

p_mse: As a baseline, we use pixel-wised mean square error(p_MSE) between prediction output and ground truth as the loss function. Previous image generation works[1, 2, 30, 3, 27] postulate that pixel-wised l_2 criterion is one cause of output generation blurriness. We also observe this effect in the outputs produced by this baseline model.

p_mse+adv: Following the success of recent image generation works[24, 26], which make use of generative adversarial networks (GANs) to generate better quality images, we explore the use of this network architecture for temporal

generation. For their original purpose, these networks generate images from randomly sampled noise. Here, we use a GAN to generate future images from an image of an object at the current time. Specifically, we use the baseline autoencoder previously described and incorporate an adversarial loss in combination with the pixel-wise MSE. During training this means that in addition to the auto-encoder, called the generator (G), we also train a binary CNN classifier, called the discriminator (D). The discriminator takes as input, the output of the generator and is trained to classify images as real or fake (i.e. generated). These two networks are adversaries because G is trying to generate images that can fool D into thinking they are real, and D is trying to determine if the images generated by G are real. Adding D helps to train a better generator G that produces more realistic future state images. The architecture of D is the same as the encoder of G, except that the last output is a scalar and connect with sigmoid function. D also incorporates the conditional term by connecting a one-hot vector with a linear layer and reshaping to the same size as the input image then concatenating in the third dimension. The output of D is a probability, which will be large if the input is a real image and small if the input is a generated image. For this framework, the loss is formulated as a combination of the MSE and adversarial loss:

$$L_G = L_{p\_mse} + \lambda_{adv} * L_{adv} \tag{1}$$

where L_{p_mse} is the mean square error loss, where x is the input image, c is the conditional term, G(.) is the output of the generation model, and y is the ground truth future image at time = current time + c.

$$L_{p\_mse} = |y - G(x,c)|^2 \tag{2}$$

And, L_{adv} is a binary cross-entropy loss with $\alpha = 1$ that penalizes if the generated image does not look like a real image. D[.] is the scalar probability output by the discriminator.

$$L_{adv} = -\alpha \log(D[G(x,c),c]) - (1-\alpha)\log(1 - D[G(x,c),c]) \tag{3}$$

During training, the binary cross-entropy loss is used to train D on both real and generated images. For details of jointly training adversarial structures, please refer to [24].

p_g_mse+adv: Inspired by [2], where they introduce gradient based l_1 or l_2 loss to sharpen generated images. We also evaluate a loss function that is a combination of pixel-wise MSE, gradient based MSE, and adversarial loss:

$$L_G = L_{p\_mse} + L_{g\_mse} + \lambda_{adv} * L_{adv} \tag{4}$$

where L_{g_mse} represents mean square error in the gradient domain defined as:

$$L_{g\_mse} = (g_x[y] - g_x[G(x,c)])^2 + (g_y[y] - g_y[G(x,c)])^2 \tag{5}$$

$g_x[.]$ and $g_y[.]$ are the gradient operations along the x and y axis of images. We could apply different weights to L_{p_mse} and L_{g_mse}, but in this work we simply weight them equally.

p_g_mse+adv+ft: Since we have limited training data for each transformation, we investigate the use of pre-training for improving generation quality. In this method we use the same loss function as the last method, but instead of training the adversarial network from scratch, training proceeds in two stages. The first stage is a reconstruction stage where we train the generation model using random static images for the reconstruction task. Here the goal is for the output image to match the input image as well as possible even though passing through a bottleneck during generation. In the second stage, the fine-tuning stage, we fine-tune the network for the temporal generation task using our timelapse data. By first pre-training for the reconstruction task, we expect the network to obtain a good initialization, capturing a representation that will be useful for kick-starting the temporal generation fine-tuning.

3.2   Two stack generation

In this scenario, we want to generate an image that shows the future state of an object given two input images showing the object in two stages of its transformation. The output should continue the transformation pattern demonstrated in the input images, i.e. if the input images depict the object at time t and t+m, then the output should depict the object at time t+2m. We design the generation model using two stacks in the encoding part of the model as shown in Fig. 2(b). The structures of the two stacks are the same and are also identical to the encoding part of the pairwise generation model. The hidden variables z_1 and z_2 are both 512 dimensions, and are concatenated together and fed into the decoding part, which is also the same as the previous pairwise generation model. The two stacks are sequential, trained independently without shared weights.

Given the blurry results of the baseline for pairwise generation, here we only use three methods **p_mse+adv**, **p_g_mse+adv**, and **p_g_mse+adv+ft**. The structure of the discriminator is the same. For the fine-tuning method, during the reconstruction training, we make the two inputs the same static image. The optimization procedures are the same as for the pairwise generation task, but we do not have conditional term here (since time for the future generation is implicitly specified by the input images).

3.3   Recurrent generation

In this scenario, we would like to recursively generate future images of an object given only a single image of its current temporal state. In particular, we use a recurrent neural network framework for generation where each time step generates an image of the object at a fixed degree interval in the future. This model structure is shown in Fig. 2(c). After hidden variable z, we add a LSTM[31] layer. For each time step, the LSTM layer takes both z and the output from the previous time step as inputs and sends a 512 dimension vector to the decoder. The structure of the encoder and decoder are the same as in the previous scenarios, where the decoding portions for each time slot share the same weights.

We evaluate three loss functions in this network: **p_mse+adv**, **p_g_mse+adv** and **p_g_mse+adv+ft**. The structure of the discriminator is again the same without the conditional term (as in the two-stack model). For fine-tuning, during reconstruction training, we train the model to recurrently output the same static image as the input at each time step.

4   Experiments

In this section, we discuss the training process and parameter settings for all experiments (Sec 4.1). Then, we describe dataset pre-processing and augmentation (Sec 4.2). Finally, we discuss quantitative and qualitative analysis of results for: pairwise generation (Sec 4.3), two-stack generation (Sec 4.4), and recurrent generation (Sec 4.5).

4.1   Training & Parameter settings

Unless otherwise specified training and parameter setting details are applied to all models. During training, we apply Adam Stochastic Optimization[32] with learning rate 0.0002 and minibatch of size 64. The models are implemented using the Tensorflow deep learning toolbox[33]. In the loss functions where we combine mean square error loss with adversarial loss (as in equation(1)), we set the weight of the adversarial loss to $\lambda_{adv} = 0.2$ for all experiments.

4.2   Dataset preprocessing & augmentation

Timelapse dataset: Some of the collected videos depict more than one object or the object is not located in the center of the frames. In order to help the model concentrate on learning the transformation itself rather object localization, for each video in the dataset, we obtain a cropped version of the frames centered on the main object. We randomly split the videos into training and testing sets in a ratio of 0.85 : 0.15. Then, we sample frame pairs (for pairwise generation) or groups of frames (for two-stack and recurrent generation) from the training and testing videos. Frames are resized to 64x64 for generation. To prevent overfitting, we also perform data augmentation on training pairs or groups by incorporating frame crops and left-right flipping.

Reconstruction dataset: This dataset contains static images used to pre-train our models on reconstruction tasks. Initially, we tried training only on objects depicted in the timelapse videos and observed performance improvement. However, collecting images of specific object categories is a tedious task at large-scale. Therefore, we also tried pre-training on random images (scene images or images of random objects) and found that the results were competitive. This implies that the content of the images is not as important as encouraging the networks to learn how to reconstruct arbitrary input images well. We randomly download 50101 images from ImageNet[34] as our reconstruction dataset. The advantage of this strategy is that we are able to use the same group of images for every transformation model and task.
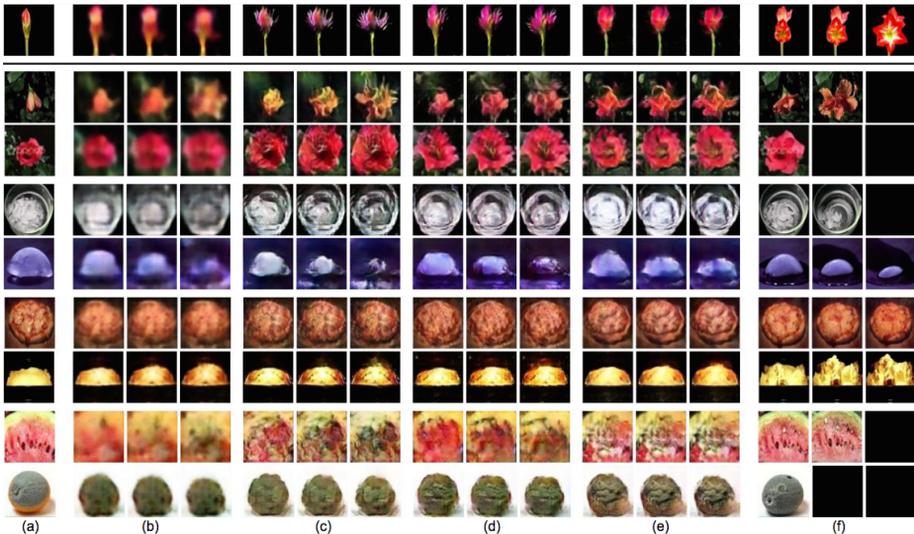
Fig. 3. Pairwise generation results for: Blooming (rows 1-3), Melting (rows 4-5), Baking (rows 6-7) and Rotting (rows 8-9). Input(a), p_mse(b), p_mse+adv(c), p_g_mse+adv(d), p_g_mse+adv+ft(e), Ground truth frames(f). Black frames in the ground truth indicate video did not depict transformation that far in the future.

	Pairwise			Two stack			Recurrent		
	PSNR	SSIM	MSE	PSNR	SSIM	MSE	PSNR	SSIM	MSE
p_mse+adv	17.0409	0.5576	0.0227	17.7425	0.5970	0.0185	17.2758	0.5747	0.0211
p_g_mse+adv	17.0660	0.5720	0.0224	17.9157	0.6122	0.0177	17.2951	0.5749	0.0214
p_g_mse+adv+ft	17.4784	0.6036	0.0207	18.6812	0.6566	0.0153	18.3357	0.6283	0.0166

Table 2. Quantitative Evaluation of: Pairwise generation, Two stack generation, and Recurrent tasks. For PSNR and SSIM larger is better, while for MSE lower is better.

4.3   Pairwise generation

In the pairwise generation task, we input an image of an object and the model outputs depiction of the future state of the object, where the degree of transformation is controlled by a conditional term. The conditional term is a 4 dimensional one-hot vector which indicates whether the predicted output should be 0, 0.25, 0.5 or 0.75 degrees in the future from the input frame. We sample frame pairs from timelapse videos based on annotated degree value intervals. A 0 degree interval means that the input and output training images are identical. We consider 0 degree pairs as auxiliary pairs, useful for two reasons: 1) They help augment the training data with video frames (which display different properties from still images), and 2) The prediction quality of image reconstruction is highly correlated with the quality of future generation. Pairs from 0 degree transformations can be easily be evaluated in terms of reconstruction quality
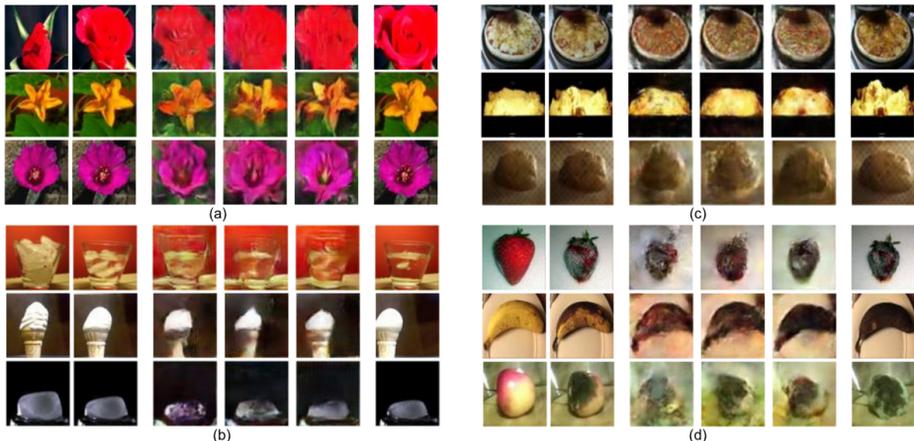
Fig. 4. Two stack generation results for Blooming (a), Melting (b), Baking (c) and Rotting (d). For each we show the two input frames (col 1-2), and results for: p_mse+adv (col 3), p_g_mse+adv (col 4), p_g_mse+adv+ft (col 5) and ground truth (col 6)

since the prediction should ideally exactly match the ground truth image. Predictions for future degree transformations are somewhat more subjective. For example, from a bud the resulting generated bloom may look like a perfectly valid flower, but may not match the exact flower shape that this particular bud grew into (an example is shown in Fig. 3 row 1).

We train pairwise generation models separately for each of the 4 transformation categories using **p_mse**, **p_mse+adv** and **p_g_mse+adv** methods, trained for 12500 iterations on timelapse data from scratch. For the **p_g_mse+adv+ft** method, the models are first trained on the reconstruction dataset for 5000 iterations with the conditional term fixed as '0 degree' and then fine-tuned on timelapse data for another 5500 iterations. We observe that the fine-tuning training converges faster than training from scratch (example results with 3 different degree conditional terms in Fig. 3). We observe that the baseline suffers from a high degree of blurriness. Incorporating other terms into the loss function improves results, as does pre-training with fine-tuning. Table. 2 (cols 2-4) shows evaluations of pairwise-generation reconstruction. For evaluation, we compute the Peak Signal to Noise Ratio(PSNR), Structural Similarity Index(SSIM) and Mean Square Error (MSE) values between the output and ground truth. We can see that incorporating gradient loss slightly improves results while pre-training further improves performance. This agrees with the qualitative visual results.

4.4   Two stack generation

For two stack generation, the model generates an image showing the future state of an object given two input depictions at different stages of transformation. As training data, we sample frame triples from videos with neighboring frame degree intervals: 0, 0.1, 0.2, 0.3, 0.4, and 0.5. We train two stack generation models

Fig. 5. Two stack generation with varying time between input images. For each example we show: the two input images (col 1-2), p_mse+adv (col 3), p_g_mse+adv (col 4), p_g_mse+adv+ft (col 5) and ground truth (col 6). The models are able to vary their outputs depending on elapsed time between inputs.

for each of the 4 transformation categories, trained for 12500 iterations for the **p_mse+adv** and **p_g_mse+adv** methods. For the **p_g_mse+adv+ft** method, the models are first pre-trained on the reconstruction dataset for 4000 iterations and then fine-tuned on timelapse data for 6500 iterations (Fig. 4 shows example prediction results). We observe that **p_g_mse+adv+ft** generates improved results in terms of both image quality and future state prediction accuracy. We further evaluate the reconstruction accuracy off these models in Table. 2 (cols 5-7). Furthermore, in this task we expect that the models can not only predict the future state, but also learn to generate the correct time interval based on the input images. Fig. 5 shows input images with different amounts of elapsed time. We can see that the models are able to vary how far in the future to generate based on the input image interval.

4.5   Recurrent generation

For our recurrent generation task, we want to train a model to generate multiple future states of an object given a single input frame. Due to limited data we recursively generate 4 time steps. During training, we sample groups of frames from timelapse videos. Each group contains 5 frames, the first being the input, and the rests having 0, 0.1, 0.2, 0.3 degree intervals from the input. As in the previous tasks, the reconstruction outputs are used for quantitative evaluation.

We train the models separately for the 4 transformation categories. The models for the **p_mse+adv** and **p_g_mse+adv** methods are trained for 8500 iterations on timelapse data from scratch. For the **p_g_mse+adv+ft** method, models are pre-trained on the reconstruction dataset for 5000 iterations then fine-tuned for another 5500 iterations. Fig. 6 shows prediction results (outputs of $2^{nd}, 3^{rd}$ and 4th time steps) of the three methods. Table. 2 (cols 8-10) shows the reconstruction evaluation.

5   Additional experiments

Human Evaluations: As previously described, object future state prediction is sometimes not well defined. Many different possible futures may be considered reasonable to a human observer. Therefore, we design human experiments to
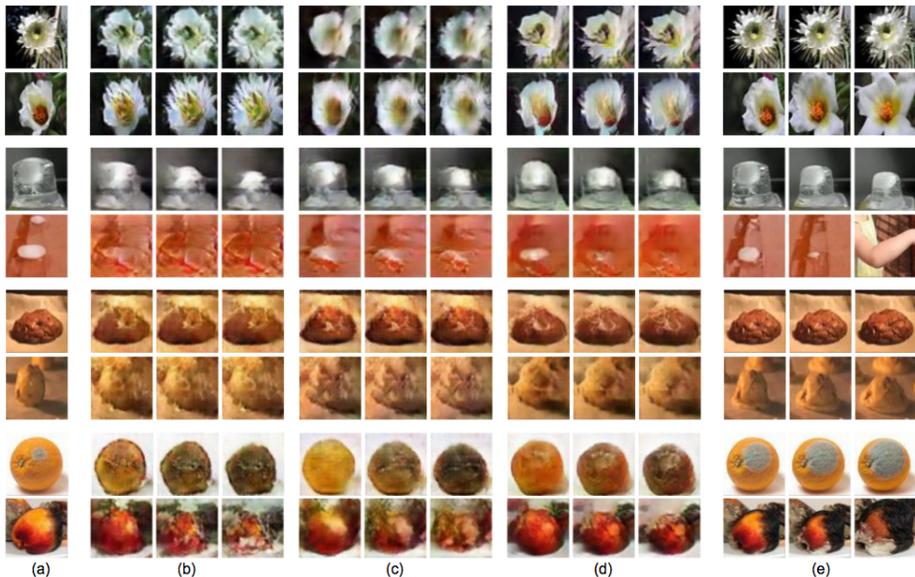
Fig. 6. Recurrent generation results for: Blooming (rows 1-2), Melting (rows 3-4), Baking (rows 5-6) and Rotting (rows 7-8). Input(a), p_mse+adv(b), p_g_mse+adv(c), p_g_mse+adv+ft(d), Ground truth frames(e).

judge the quality of our generated future states. For each transformation category and generation task, we randomly pick 500 test cases. Human subjects are shown one (or two for two stack generation) input image and future images generated by each method (randomly sorted to avoid biases in human selection). Subjects are asked to choose the image that most reasonably shows the future object state.

Results are shown in Table 3, where numbers indicate the fraction of cases where humans selected results from each method as the best future prediction. For pairwise generation (cols 2-5), the **p_g_mse+adv+ft** method achieves the most human preferences, while the baseline performs worst by a large margin. For both two stack generation (cols 6-8) and recurrent generation (cols 9-11), **p_mse+adv** and **p_g_mse+adv** are competitive, but again making use of pre-training plus fine-tuning obtains largest number of human preferences.

Image retrieval: We also add a simple retrieval experiment on Pairwise generation results using pixelwise similarity. We count retrievals within reasonable distance (20% of video length) to the ground truth as correct, achieving average accuracies on top-1/5 of **p_mse+adv**: 0.68/0.94; **p_g_mse+adv**: 0.72/0.95; and **p_g_mse+adv+ft**: 0.90/0.98.

Visualizations: Object state transformations often lead to physical changes in the shape of an object. To further understand what our models have learned, we provide some simple visualizations of motion features computed on generated images. Visualizations are computed on results of the **p_g_mse+adv+ft**

	Pairwise				Two stack			Recurrent		
	BL	ADV	Grad	Ft	ADV	Grad	Ft	ADV	Grad	Ft
Blooming	0.1320	0.2300	0.2880	0.3500	0.3080	0.3240	0.3680	0.3320	0.2860	0.3820
Melting	0.1680	0.2520	0.2760	0.3040	0.3400	0.3120	0.3480	0.3180	0.3220	0.3600
Baking	0.1620	0.2600	0.2840	0.2940	0.3120	0.3200	0.3680	0.2780	0.3540	0.3680
Rotting	0.1340	0.2020	0.2580	0.4060	0.3040	0.2640	0.4320	0.2940	0.2900	0.4160
Average	0.1490	0.2360	0.2765	**0.3385**	0.3160	0.3050	**0.3790**	0.3055	0.3130	**0.3815**

Table 3. Human evaluation results: BL stands for p_mse method, ADV (p_mse+adv), Grad(p_g_mse+adv) and Ft(p_g_mse+adv+ft)
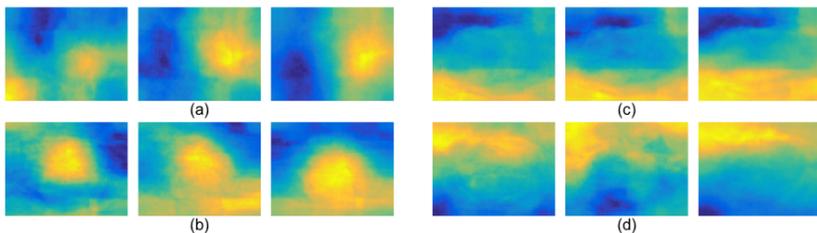
.

Fig. 7. Visualization results of learned transformations: x axis flows of blooming (a), y axis flows of melting (b), y axis flows of baking (c) and y axis flows of rotting (d)

recurrent model since we want to show the temporal trends of the learned transformations. For each testing case, we compute 3 optical flow maps in the x and y directions between the input image and the second, third, and fourth generated images. We cluster each using kmeans (k=4). Then, for each cluster, we average the optical flow maps in the x and y directions.

Fig. 7 shows the flow visualization: (a) is the x axis flow for the blooming transformation. From the visualization we observe the trend of the object growing spatially. (b) shows the y axis flows for the melting transformation, showing the object shrinking in the y direction. (c) shows baking, consistent with the object inflating up and down. For rotting (d), we observe that the upper part of the object inflates with mold or shrinks due to dehydration.

6   Conclusions

In this paper, we have collected a new dataset of timelapse videos depicting temporal object transformations. Using this dataset, we have trained effective methods to generate one or multiple future object states. We evaluate each prediction task under a number of different loss functions and show improvements using adversarial networks and pre-training. Finally, we provide human evaluations and visualizations of the learned models. Future work includes applying our methods to additional single-object transformations and to more complex transformations involving multiple objects.

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