Paper Dreams: Real-Time Human and Machine Collaboration for Visual Story Development

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Abstract

Increasing human potential is the underlying incentive for all technological advances. In creativity, technology can be used to facilitate faster design and construction, to improve human creative capability through learning and training, and to enable novel and innovative ways to create. The capacity to express our thoughts with visual mechanisms provides the foundation for meaningful creative practices, including art, design, and science. Here we present Paper Dreams explores how the real-time generation of ideas and visuals based on multi-modal user input can encourage divergent thinking, specifically in graphical story development, while also providing enough agency for users to feel that they have creative ownership over the final output of the collaboration.
This paper, thus, makes the following contributions: we have expanded upon the existing state-of-the-art machine learning models used in recognizing sketches and creates personalized suggestions for new elements and colors. We have developed a Text-to-Sketch component, which is not typical to most canvases, that can further assist in populating the canvas. We have also improved upon conventional ways of finding relations between objects by grouping relations into different categories and limiting objects to the sketches in our dataset.

Introduction

Human-machine collaboration has the capacity to augment creativity in a wide variety of ways. Throughout the collaboration stage, ideas emerge from both the users and the system that can assist and encourage creativity[33]. As collaborators make unexpected and novel contributions, their output can lead to new artifacts that otherwise might not have produced individually. The field of intelligent interactive systems has recently gained a fair amount of traction with the rapid increases in the field of AI, especially in so-called co-creative systems that feature human users creatively collaborating with intelligent agents.
These systems have been implemented in numerous domains, including art [10] [18], music [36] and robotics [11]. In addition, these systems are designed to encourage creative thoughts for both novice and expert human users. These novel representations of co-creative systems are proposed as innovation, inspire and motivate the user

to continue the task, and help users achieve shared goals.
The study of how or why something is deemed creative can be challenging due to the lack of cohesive definitions and the ambiguity of what constitutes an idea as creative.
The inspiration features of Paper Dreams have based on principles of Divergent

Thinking [30] as a source of creativity. Divergent thinking can be defined as the process of freely exploring different combinations of related ideas starting from an initial problem state. We base the design of the Paper Dream features to take advantage of the motivators of divergent thinking, like the presentation of new ideas and visuals that go beyond a user's current mental model of possible elements to add to the story. By constantly stimulating the user with new elements of inspiration based off of each interaction, the user can perceive more possibilities for different combinations of ideas. We also use Divergent Thinking as an evaluation metric of successful Paper Dreams that can assist with promoting creative cognition. We measure this by observing the users' perception of how much their final story diverged from their original idea.
Paper Dreams can be potentially used by multiple audiences. Storyboard artists who are afflicted with writer's block, a condition that debilitates them and prevents them to produce any work because he/she has run out of ideas can use Paper Dreams to augment their creativity. The elderly can use Paper Dreams to tell a story and keep themselves engaged, potentially preventing the early onset of dementia.
Though there exist separate methods for recognizing sketches, finding relations between objects, and automatic colorization, to our knowledge, there is no one unifying tool that connects these deep learning models, assists in creative storytelling and relies on the feedback process between the neural net and the user. This paper, thus, makes the following contributions: we have expanded upon the existing state-of-the-art machine learning models used in recognizing sketches. We have developed a Text-to-Sketch component, which is not typical to most canvases, that can further assist in populating the canvas. We have also improved upon conventional ways of finding relations between objects by grouping relations into different categories and limiting objects to the sketches in our dataset.

Creativity

The concept of creativity has different meanings across various mediums, and in many cases is highly subjective to the individual. We felt that it would be helpful to provide a reference to the term creativity as perceived by the authors. Design studies have defined creativity as the "ability to create ideas, solutions or products that are novel and valuable" [32], and creativity is frequently used to signify specific types of divergent [9] and flexible thinking[30] that emerge in an iterative mental process. Studies have widely accepted the view that creative products should be "novel" and "useful," as Sternberg and Lubart [35] suggested.

Related Work

Here we review the opportunities and challenges for the development of such a system, with a specific focus on sketching, Texturizing with AI, and narrative formation using natural language processing (NLP).
Finally, we review the concept of structure imagination from the field of creative

cognition and discuss ways of inducing it in our work.

Interfaces for Sketching

Sketching, or the production of once ideas, is a physical activity that we naturally perform in our daily lives to assist in the development of visual ideas is one of the earliest and most frequent activities of artists and designers. The influences of sketching can be seen as a tool for various domains like in expression, communication, but also an extension of once cognitive process and cognitive load management. Humans of load memory into a piece of paper when we do math or write a to-do list, we construct and develop new ideas as we doodle on a piece of paper. There is still great potential in incorporating sketching as an interaction for augmenting creativity and cognition [23]. One of the determinants limiting research advancement in the area of generative hand drawings is the lack of publicly available datasets. Google's team had made available one of the largest available dataset made from human sketches [46] This enabled for a larger-scale investigation of human sketches. Unfortunately, the people that created this dataset were are asked to draw objects belonging to a distinct object type in less than 20 seconds, resulting in a dataset with drawings with very low fidelity.

Generative Adversarial Network

A Generative Adversarial Network, or GAN, is a generative model approach based on differentiable generator networks. A differentiable generator network is a generative model that transforms a sample from a latent variable z to a sample x using a differentiable function [15]. GANs are a combination of two neural networks, specifically a network generator and network discriminator, that work hand in hand to optimize each other.
Based on the concept that creativity can be viewed as a unique combination of ideas, GANs are particularly useful in exploring creativity in a computational manner. The generative model of part of a GAN essentially is a function of the vector interpolation of the inputs in the given data. The latent space in this interpolation provides different combinations of base inputs.

Our primary motivation in studying GANs was to try to apply a GAN-derived model to the generation of novel art. Much of the work in deep learning that has concerned itself with art generation has focused on style, and specifically the style of particular art pieces. Interactive GAN [?] models exist that aim to create a simple but effective layer for synthesizing photorealistic images given an input semantic layout. This model allows users to control the style and content of image synthesis.

Our implementation uses Pix2PixHD [39], NVIDIA's Pytorch [26] implementation of image-to-image translation. A deep learning neural network calculates object boundaries and incorporates that semantic information into creating more realistic and higher definition textures. Pix2PixHD grew from Pix2pix[17], a U-net architecture that relies on conditional adversarial networks to provide a general-purpose solution to image-to-image translation problems. Pix2pix has become a popular state-of-the-art algorithm for image translation with a GAN architecture.
By building off of the GAN model described above, we propose to build a deep neural network that is not only capable of learning a distribution of the

varying styles and content components of many different illustrative pieces but also is able to combine these components in a sophisticated manner to create new pieces of art.

Creative Cognition

The work presented in this paper is an interdisciplinary effort between the fields of computational creativity, creativity support tools, and human-computer interaction (HCI). The field of computational creativity is a sub-field of artificial intelligence that focuses on developing agents that generate creative products autonomously[1] [40] [8]. Creativity support tools, on the other hand, are technologies designed to enhance and augment the user's creativity, typically aiming to improve the quality of the final product. By combining core concepts from computational creativity and creativity support tools, we can develop computer applications that collaborate with human users on a shared creative task. Co-creative systems can adopt different roles to foster human creativity, such as coach, pen-pal, and collaborator [24]. The co-creative tool for visual communication presented here can be considered a computational partner that utilizes a computational model of conceptual shifts [28] to design alongside a user and inspire creativity. In response to the constant information overload that humans have to deal with each moment, current information retrieval tools such as Google Search have evolved for returning near-exact precise matches.

However, such technologies run the danger of entirely losing the benefit of serendipitous findings: unexpected yet valuable discoveries that are divergent or completely unrelated to an inquiry [14] [7]. Our determination to support serendipitous discovery is grounded on the reality that creators tend to browse existing repositories for creative simulation [3] [13]. By constantly stimulating the user with new elements of inspiration based off of each interaction, the user can perceive more possibilities for different combinations of ideas.

System Description

Paper Dreams runs on the web browser; this was chosen over a native application (i.e., one downloaded directly onto a device) to increase accessibility to a larger subset of our target population. Our application can be used by anyone with access to an electronic device with internet and a browser, such as a laptop or a tablet. In addition, this circumvents the need to develop distinct apps for different mobile devices, e.g., a Swift-based app for iOS and a Java-based app for Android, and allows us to more effectively collect data on what users are drawing in order to improve our database.

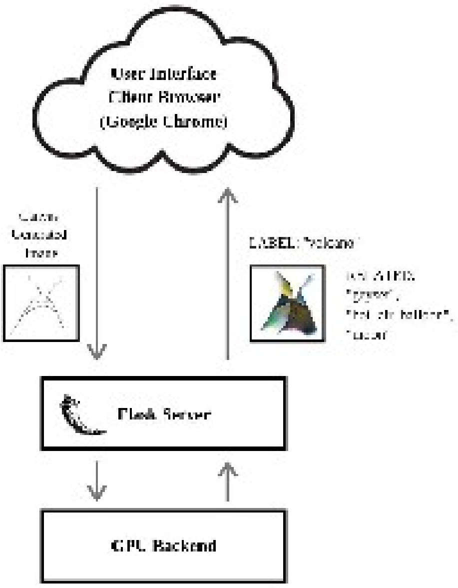

Figure 1. ***shows the system architecture, with the front-end client-side browser (e.g., Google Chrome) making requests to and from a back-end web server. The web server was built using Flask [29], a lightweight and easily customizable Python***

System Architecture

server framework. The user interface in the browser was built with HTML, Javascript, and CSS, with an HTML5 canvas as the primary drawing surface. The Flask server currently runs locally on a computer with a GPU (Graphics Processing Unit), allowing the server to use the GPU for the computing needed for the sketch recognition and the adaptive Texturizing.

General Workflow

The Paper Dreams workflow can be represented by a state model consisting of three mutually exclusive modalities: Sketch, Query and Composition, as shown in Figure 1.

The user can sketch on the screen in a free-form manner or they can choose for the system to recognize what they have sketched.
As Paper Dreams currently is unable to detect when the user has completed their drawing, the user must press the "Sketch Recognition" button to allow the system to know when the user is finished with their current sketch. A label is then processed and shown to the user from the sketch recognition, identifying the current sketch. There are 125 possible classes for the label to be chosen from, as the sketch recognition was trained on the 125-class Sketchy dataset.
Alternatively, the user can interact with Paper Dreams by speaking to it instead of drawing on it or typing a query into the search bar. The nouns are parsed from the spoken phrase and are then mapped to the different sketch categories using spaCy. The most related words (i.e. highest similarity) are shown on the sidebar for inspiration, and can then be selected and placed on the canvas. After the user requests that the system recognizes the sketch or prompts the system with a query, a list of related nouns is displayed to the user in the inspiration bar on the right side of the interface. The user can then select one of the words, pulling up a grid of sketches of that word, any of which can then be placed into the canvas to add more details and elements to the current scene.

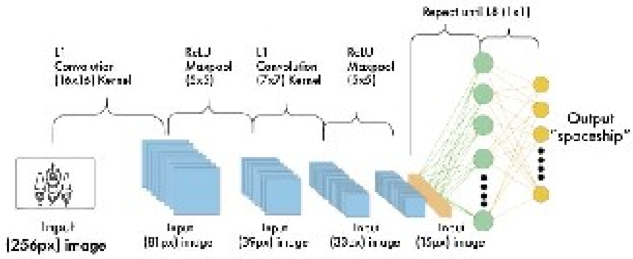

Figure 2. Our custom-made eight-layer convolutional neural network trained on sketches from Sketchy Dataset.

Sketch Recognition

We have trained an eight-layer convolutional neural net (CNN) on the 125 classes on the publicly available Sketchy dataset [31] (as shown in Figure 2). Our present recognition architecture is based on deep learning network Sketch-a-net, which claims one of the highest accuracy rates on human sketches [41]. However, at its current size, the dataset is too small to train a high-performing CNN. This type of network performs best with a large number of samples; therefore, we used a data augmentation technique for machine learning called Augmentor [6] to augment the Sketchy dataset. After augmentation, we found that we had an approximately 75% accuracy rate across those 125 classes. While we can use our architecture for recognizing incomplete or "partial" sketches, the resulting labels are often incorrect until enough defining features are drawn.
The sketch recognition model works best on a finished sketch- however, Paper Dreams cannot tell when the user has completed their drawing. Therefore, the user must press the "Sketch Recognition" button to allow the system to know when the user is finished with their current sketch.
The sketch-identified label (e.g., "hedgehog") is associated with a model (e.g., "animal"), and then the active user sketch is processed by that model to return an appropriate texture. Other models include "plants", "buildings", "transportation", ""flowers", "appliances" and “fruit".

Natural Language Processing

In natural language processing (NLP), cosine similarity is a classic metric for measuring the similarity between two words [25]. Each of the words (or concepts) is first turned into an n-dimensional vector, based on its frequency in the training set of documents. The value of n is dependent on the model used but generally is in the hundreds or thousands. The similarity between two-word vectors, A and B, can then be calculated according to Equation 1, where ||A|| and ||B|| are the L2 norms of A and B respectively.

$$Similarity(\vec{A},\vec{B}) = \frac{\vec{A}\cdot\vec{B}}{||A||\cdot||B||} \qquad (1)$$

Because the speech/text modality in the user interface is built with the spaCy software library [16], we originally used spaCy’s vectorization for each word to calculate the similarity between words/labels.
However, there was an issue: spaCy is built to process on the single word level. Approximately 15% of our labels are compound words, i.e. multi-word phrases such as "hot air balloon" that have a single meaning that is more than "hot", "air", and "balloon" by themselves. (For reference, a full list of the available classes in the Paper Dreams dataset can be found in Appendix 6.) This can have a significant impact on the overall results; the relationship between "mouse" and "cat" is very different from the relationship between "computer mouse" and "cat." The spaCy library would return two values for the relationship between "computer mouse" and "cat": one for "computer" and "cat" and another for "mouse" and "cat."

To resolve this, we attempted to use the Natural Language Toolkit (NLTK) library [22], which does support some bi and tri-gram words (such as "computer mouse" and "hot air balloon", respectively), but found that it was not robust enough to process a significant portion of our compound word classes (as the words have to be defined in the NLTK library.) For example, "t shirt" is not in the NLTK library.

Finally, we used sense2vec, a Python library trained on Red- dit comments designed to extract multiple possible meanings (or "senses") and subsequent embeddings from the input word/label [38]. Sense2vec was able to calculate similarity values for nearly all classes in our dataset, with the exception of unusual noun phrases such as "person walking." We then calculated the cosine similarities between the main label and all other classes in order to generate a mapping such as the one seen in Figure 3, where 9 is the most closely related value and 0 is unrelated. This graph is then used for the serendipity wheel.

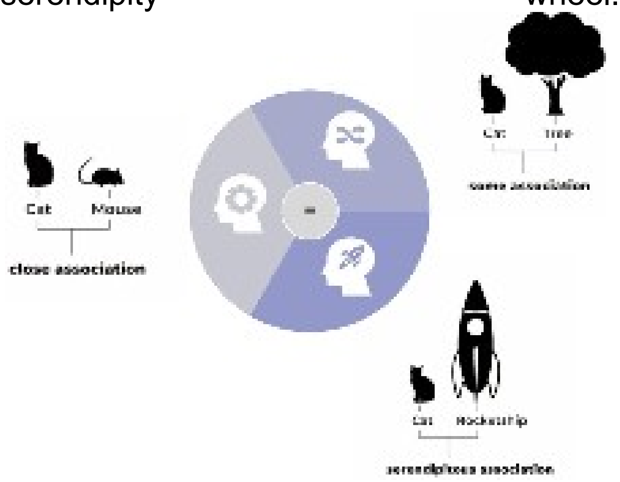

Figure 3. *An example of the relationship between "cat" and eight other classes of varying similarity (9 being most closely related). In practice, there are 185 total other classes in each graph for a label.*

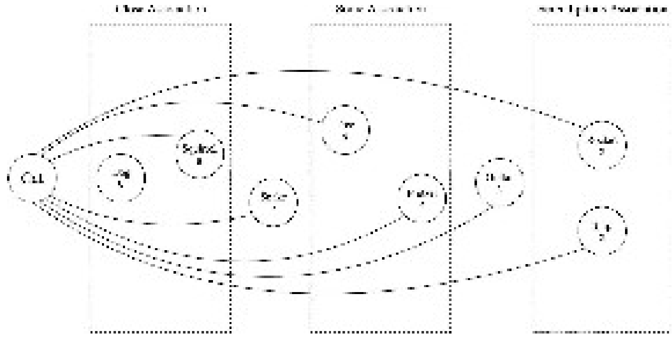

Figure 4. Serendipity Wheel, with an example of the associations it would suggest for each tab when given the label "cat".

Serendipity Wheel

The serendipity wheel, as seen in Figure 4, uses the label from the sketch recognition to generate a list of classes that the user can add to their sketch, and allows the user to control how closely associated the list is. The three tabs in the wheel correspond to increasing unrelatedness (lighter being closely related, darker being less related.) For example, from the label "cat", a closely related list could contain ["dog", "mouse", "squirrel"] and a relatively unrelated or serendipitous list could contain ["rocket", "ship", "teapot"]. These lists are generated from the similarity map for the label; if the user requests classes that are very related from the label, the system will pull from the objects with high similarity values with the label.

Texturizing

In order to train the Paper Dreams model, we collect 2000 unique images that consisted of
80% illustration art and 20% watercolor or similar medium these images where either collected from the Internet with a crawler or generated by our team. Paper Dreams currently supports coloring 186 distinct

classes of sketches. It would be impractical to train and store a single model for each individual class.

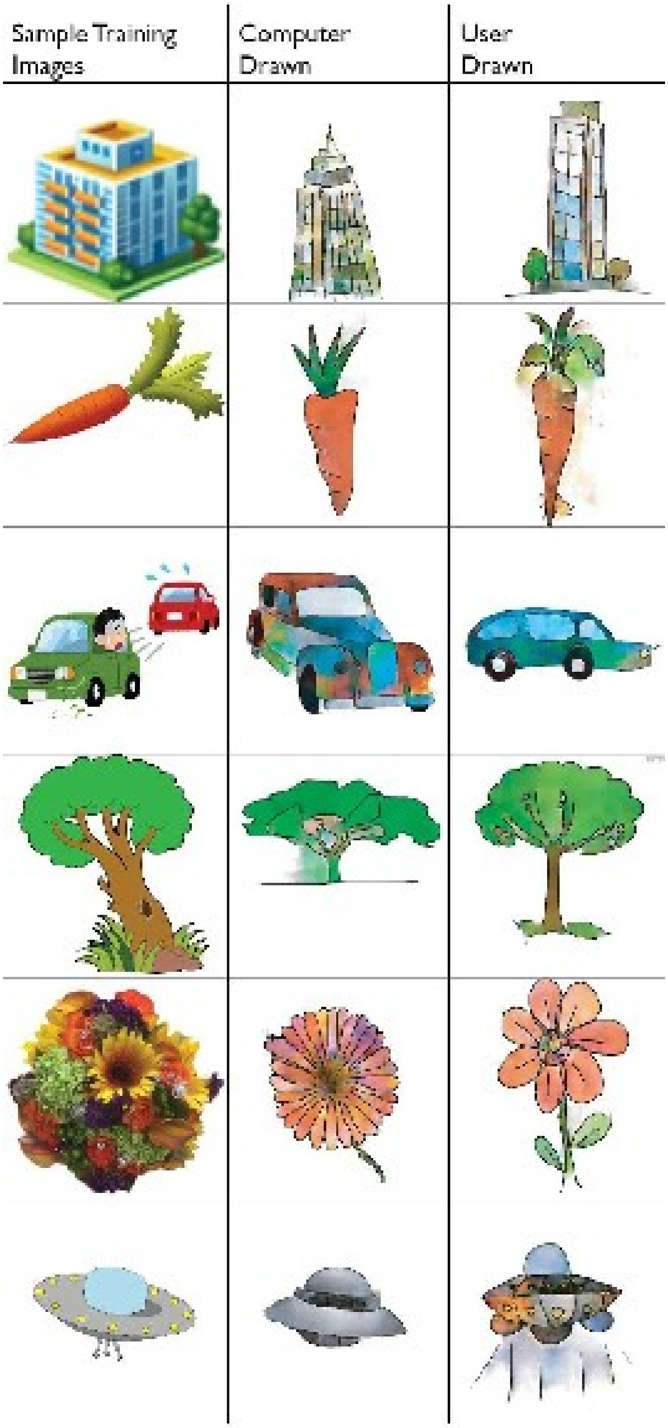

Figure 5. Six examples of the fifteen distinct trained Texturizing models, each encompassing a relevant subset of the classes available as part of the sketch recognition and the inspiration bar while using Paper Dreams. From left to right, Sample images used on the training dataset, Textured images that have been drawing by the machine as on of the features for Paper Dreams, Sample images from user sketches texturized with the system aid

Therefore, the classes are separated into fifteen different models, each encompassing a relevant subset of the classes. For example, "butterfly", "scorpion", "hedgehog", and "cat" are all processed by the "animal" model; other models include "plants", "buildings", "transportation", and "fruit". The sketch-the identified label is associated with a model, and then the Canvas Generate Image is processed by that model to return an appropriate texture. Figure 5 shows six of the fifteen distinct trained Texturizing models, each encompassing a relevant subset of the classes available as part of the sketch recognition and the inspiration bar while using Paper Dreams.

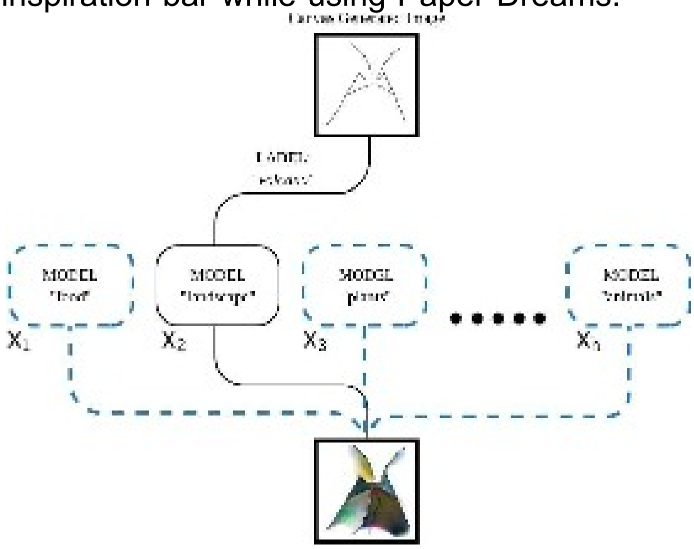

Figure 6. *Using the Canvas Generated Image and the label from the Sketch recognition, the texturizing model passes the image through the appropriate model to get an appropriate texture.*

Our texturizing network follows pix2pixHD[3] with only some small changes. We first train a residual network G1 on lower resolution images. Then, another residual network G2 is appended to G1 and the two networks are trained jointly on high-resolution images. Specifically, the input to the residual blocks in G2 is the element-wise sum of the feature map from G2 and the last feature map from G1.
We use 3 discriminators(D1, D2, and D3.) that have an identical network structure but operate at different image scales. Specifically, we downsample the real and synthesized high-resolution images by a factor of 2 and 4 to create an image pyramid of 3 scales.

Figure 7*. A screenshot from the storyboard feature as part of the Paper Dreams platform*

The discriminators D1, D2, and D3 are then trained to differentiate real and synthesized images at the 3 different scales, respectively. By using a coarse to a fine generator, a multi-scale discriminator architecture, and a robust adversarial learning objective function.

EXPERIMENTAL USER STUDY

To evaluate how effectively Paper Dreams encourages divergent thinking in the context of storytelling, we conducted a formative user study where we compared the experience of participants developing stories using Paper Dreams with the experience of those using Adobe Sketch.

Procedure

The objective of the study was to evaluate to what degree the interface supports the user in their creative endeavors and its role in the imagination process for the development of a story. For this study, we requested that the participants compare Paper Dreams with Adobe's Sketch app for iOS [2] The Adobe Sketch app provides virtual drawing brush tools that interact naturally with the canvas, including a graphite pencil, ink pen, and blending markers. In addition, built-in brushes open up even more creative possibilities. We decided to use this app due to its realistic visual qualities to physical mediums such as acrylic paint, watercolor, and graphite.
At the beginning of each study, we asked the participant to pull a piece of paper containing a topic for their story, and randomly assigned whether they started the study by working in the Sketch app or in Paper Dreams. For both scenarios, the participant was offered a chair and desk to rest their tablets and conduct the study. Participants were initially trained for approximately five minutes on both applications, and after the demonstration was allowed the free practice of scribbling, editing, and composing. We recorded the art developed by the participants during the task.

After each task, participants were interviewed about their experience with performing the task of developing a story each interface. Participants were required to respond to a survey that included both Likert scale ratings and open-ended questions about their experience.

Study

To investigate the effects of real-time AI feedback for collaboration, we conducted a formative user study to evaluate how well our collaborative storytelling environment supported the development of stories on demand. We recruited 26 participants (14 female, 12 male) over email, between the ages of 18 to 34 years old. All participants were either undergraduate or graduate students. We requested that all participants had prior experience using a tablet and a stylus-style pen.

User Task

Participants were given an open-ended prompt to develop a story and to create illustrations using the available resources from both apps; the Adobe Sketch app and the Paper Dreams app for fifteen minutes. As part of the experiment, we kept switching the order of assignment of application that they would start the task. There were two main drawing tasks: one collaborating with the Paper Dream system (referred to as the agent condition), and the other collaborating with an iPad using the Adobe Sketch app (referred to as the control condition). Participants were asked to create a story from the topic they had randomly selected and further develop their story by illustrating what they have imagined, using sketch strokes to query and display images that they could use. Participants were also asked to freely use features such as the texturizing, sketch recognition, and the serendipity wheel within Paper Dreams, and features like shapes, colors, and paint brushes available within the Sketch app.

RESULTS

User Study Results

Our study shows promising results in Paper Dreams' ability to promote divergent thinking in storytelling for its users. A majority of users (92%) answered that the interface of Paper Dreams helped positively change their story, which is significantly higher than the 23% of users who said that the interface of Adobe Sketch changed their story. This correlates to our initial intuition- because Adobe's application functions as a highly efficient tool, it would only reflect the user's proficiency with the tool. In addition, Figure 8 shows a positive correlation between how strongly a user identifies as being "creative" and how far they perceived that they diverged from the initial concept. This indicates two potential possibilities: people who perceive themselves as creative may be better at divergent thinking regardless of the interface they use, and divergent thinking is a valid evaluation of creativity.

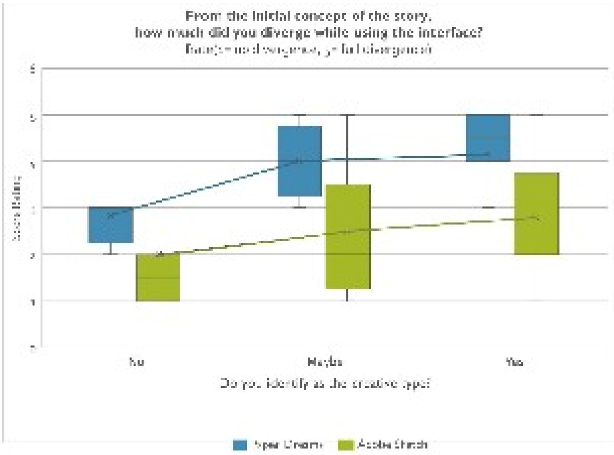

Figure 8. ***On average, users indicated that the Paper Dreams interface helped them diverge their stories from their original idea more than the digital interface of Adobe Sketch.***

In the post-task survey, we prompted the participants to describe their thought process for generating the storyline and describe if and how the Paper Dreams interface influenced their story. The users were asked the same questions regarding their experience with Adobe Sketch. In order to evaluate the most influential features within in Paper Dreams and Adobe Sketch (i.e. features that promoted divergent thinking), we analyzed how many users mentioned specific features when describing their thought process for creating the story.

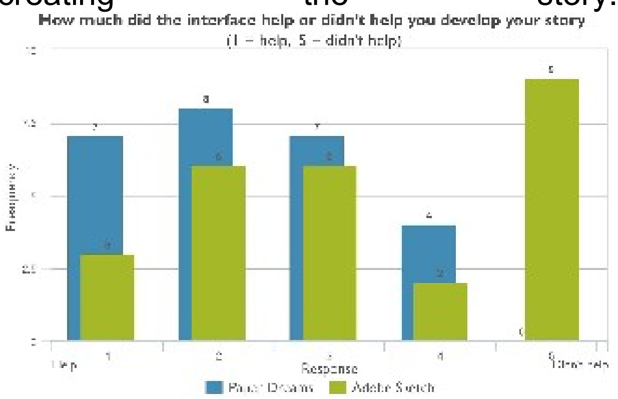

Figure 9. ***Based on the distribution of the Likert scale survey question "How much did the interface help or didn't help you develop your story?", users indicated that the Paper Dreams interface was more helpful in developing their story than Adobe Sketch.***

Of the 6 users who indicated that the interface of Adobe Sketch influenced their storyline, only two mentioned that they got inspiration from the variety of brushes. The others said that they simply had difficulty translating their ideas from concept to drawing due to lack of artistic skill, and therefore were forced to simplify their story.
The most popular feature and source of divergent thinking for Paper Dreams were the Inspiration Panel, which is populated with related or not-so-related objects via the serendipity wheel; Fifteen out of the twenty-six users specifically mentioned that interactions with the Inspiration Panel assisted them in getting and producing new concepts for use in developing their storyline. One of the participants said, *"I had no idea about what I was going to draw, but the different drawing suggestions of the same class gave me some new ideas about moving ahead with the story."* Another commented, *"I think that Paper Dreams really helped in framing the story with popping up random words on the screen which designed my ideas and acted as ink to my blank slate."*

The second most influential feature in Paper Dreams, based on the study, was the adaptive texturization and variety of generated colors. One-third of the participants mentioned the colors in their description of their story-generating thought process. Based on user

responses, the adaptive texturization played the following roles in influencing the storyline of the user:
● Changing the overall mood of the story, or of a character
○ Another user said, *"I was drawing a nice and relaxing landscape but the colors came out very dark (grey, purple, blue) so I came up with a different story which was tenser."*
○ One user commented, *"The colors were super bright and happy, and made me switch from having the dinosaur be destructive (my original thought) to having her be a nice gentle dino."*
Allowing users to more quickly continue in developing the story, as they require less time coloring their visuals in.
● A user said, *"The automatic coloring made things go faster to some extent so I could focus on other things"*
Color the item with an unexpected hue, therefore changing the context of the item.
● A user said, *"I was trying to draw a tear but it came out red, which completely changed the context of the drop I drew."*

We also received feedback that the pre-made drawings in each class helped the users develop their stories more quickly and that they didn't feel limited from their drawing skills.
The features in Paper Dreams not only inspire users to include new ideas to their story, but they also help users develop their story more quickly because they do not need to focus on developing the visual components of their story from scratch, but rather the development of the actual plot.

Results and Discussion

Discussion

Our formative study helped identify the intuitive and unintuitive interactions that users had with Paper Dreams, and allowed us to be significantly more aware of improvements that need to be made to the interface. Primary suggestions include more intuitive drag handles to move individual images, an addition of an eraser tool, zoom controls for the canvas, and intuitive scaling of images. However, the principal insight gathered from the participants was that the interface was at its best when topics presented on the Inspiration Panel helped them get new ideas of concepts to use to develop their storyline. We propose that the current version of Paper Dreams is the most useful and enjoyable to use as a brainstorming tool for people who do not identify as creative.

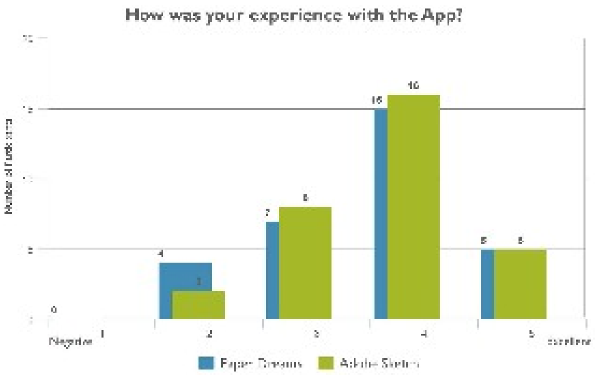

Figure 11. Based on the distribution of the Likert Scale Ratings of the experience of the user sentiment of experience is approximately the same.

Our current evaluation for Paper Dreams in this paper was by necessity a qualitative and exploratory one, rather than controlled, quantitative, and comparative one. Attempting to pin down artistic activities and their outcome is notoriously difficult, if not impossible, and any results from such an analysis would have questionable value. While our evaluation does not allow us to make statements on the superiority (or inferiority) of Paper Dreams over other creative workflows, we nevertheless feel that the results speak to the expressiveness of the system. Earlier, we theorized that the texturizer feature may allow users to more quickly develop their story, as they require less time to coloring their visuals to match the story. However, we are also considering the possibility that this feature potentially prevents the user from engaging in some retrospective dialog with their creation. This type of assessment and ideation could potentially take place while the user engages in automatic actions like coloring. This is visualizations is difficult to measure objectively, as discussed in previous sections.

While the coloring from the texturizing model can be a source of inspiration and evoke new moods in the user's story, some users voiced their frustrations that the abstract coloring of the image can diverge from the user's plan for their story. For example, one user said she tried to draw a tear, but it came out red instead of blue. Because of the user currently does not have agency over manipulating the color output, they may feel like they do not have full creative ownership over their piece.

After a certain point, users often commit to a vision of what they want to produce on the interface, and the system can continue to challenge those expectations. When the system goes against the users' ideas, such as continuing to generate new colors, the users tend to get frustrated. We speculate that people who self-identify as creative commit to a vision earlier. However, despite these challenges, we believe our interface still accomplishes our goal of promoting divergent thinking.

CONCLUSION

We have presented Paper Dream, a platform for assisting a user's visual expression. Paper Dreams incorporates customized machine learning models in a creative workflow for stimulating serendipitous discoveries. The real-time feedback of the system allows for more efficient exploration of new topics of inspiration, thus promoting creativity. Although these serendipitous suggestions are an important part of learning, ideation, and creativity, most existing systems aim towards photo-realistic or geometrically correct content. This means that creative diversity and expression- key ingredients of artistic production- are often neglected. The ease with which users can sketch, edit, and compose using Paper Dreams focuses the control and creative freedom in the hands of the users. We performed a qualitative user study that has informed our work and showcased the utility of our ideas by letting both novices and expert artists create digital imagery using our workflow implementation. The participants found via sketch recognition and text input that Paper Dreams Inspiration Panel was helpful as a source for high-quality and imaginative results when they hit a creative block. We believe that tools such as Paper Dream are uniquely situated to meet these future challenges, but more work is needed in this domain.

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