ABSTRACT
Visual programming environments are increasingly part of the curriculum in schools. Their potential for promoting creative thinking of students is an important factor in their adoption. However, there does not exist a standard approach for detecting creativity in students’ programming behavior, and analyzing programs manually requires human expertise and is time-consuming. This work provides a computational tool for measuring creativity in visual programming that combines theory from the literature with data mining approaches. It adapts the classical dimensions of creative processes to our setting, as well as considering new aspects such as visual elements of the projects. We apply this approach to the Scratch programming environment, measuring the creativity score of hundreds of projects. We show that current metrics of computational thinking in Scratch fail to capture important aspects of creativity, such as the visual artifacts of projects. Interviews conducted with Scratch teachers validate our approach.

Keywords
Creativity, Computational Thinking, Creativity Tests, Visual Programming Environments

1. INTRODUCTION
Creativity is a dynamic process which generates ideas that are both novel and of value [Cropley (2000)]. There is multiple evidence that exhibiting creativity in the classroom is linked to positive learning gains, increased motivation and to advancements in skill mastery [Wheeler et al. (2002); Schacter et al. (2006)]. Despite their increasing prevalence in schools, technological educational environments do not currently promote creativity in students’ interactions or support teachers’ ability to detect creative thinking by students.

This paper provides a computational approach for detecting creativity in students’ visual programming. We adapt the seminal work of Torrance [Torrance (1965)] who focuses on one aspect of creativity, that of divergent thinking from conventional norms, using four dimensions: fluency (the total number of relevant ideas generated); flexibility (the number of different categories of ideas); originality (the rarity of the ideas generated); and elaboration (the amount of detail in the ideas). We use Torrance’s theory to develop a computational tool for measuring creativity in visual programming. The tool receives as input a set of visual programming projects and returns a creativity score for each of the projects in the set. Our tool measures divergent thinking in students’ interactions from many different aspects, including programming skills and visual dimensions of the project. We combine data-driven approaches (neural nets and clustering) with Torrence’s theory to measure these aspects.

We apply our approach in Scratch, a block-based visual programming language and online community targeted primarily at children. Users of Scratch can create online projects using a block-like interface. The service is developed by the MIT Media Lab, has been translated into more than 70 languages, and is used in most parts of the world [1]. Scratch is taught and used in after-school centers, schools, and colleges, as well as other public knowledge institutions.

We measure creativity in two different Scratch project collections (studios) and compare the computed creativity score to existing metrics of computational thinking (CT) in Scratch. We show that while the existing CT metric capture some aspects of creativity, they fail to capture other important aspects captured by our tool that do not depend on programming skills. Supplying teachers in such schools and institutions with our tool can have a positive impact on advancing this essential capability for the 21st century.

2. RELATED WORK
Our approach builds on prior work in modeling computational thinking and creativity in visual programming environments.

Computational Thinking (CT) expresses problems and their solutions in terms of abstraction, decomposition, and algorithmic thinking [Romero et al. (2017)]. There is an increasing awareness that computational thinking skills can improve decision making in everyday life [Wing (2006)], and programming classes are increasingly becoming part of the curricu-

1https://scratch.mit.edu/statistics
In many schools, Lye and Koh (2014) review the use of several studies that use programming in K-12 classrooms to improve computational thinking skills, most of the studies reported positive outcomes. Past work has developed tools to analyze Computational Thinking (CT) in Scratch. Dr. Scratch is an open-source web toolkit that measures computational thinking within Scratch projects. It examines the following seven components within each project: abstraction and problem decomposition, logical thinking, synchronization, parallelism, algorithmic notions of flow control, user interactivity and data representation [Moreno-León et al., 2015].

Hershkovitz studied the relationship between creativity and computational thinking in a block-based multi level game framework for children’s programming [Hershkovitz et al. (2019)]. They measured computational thinking in terms of game performance. They showed that demonstrating originality when designing the early stages of the game is associated with succeeding in this stage relatively easily, however negatively associated with progressing farther in the game.

Romero et al. (Romero et al., 2017) developed a model to assess CT in students’ Scratch programming and identified modeling, problem identification, code literacy and digital creativity capabilities. In their work the authors noted the existence of creative concepts in participants’ projects such as using untaught and relevant Scratch elements. The projects assessment was done by experts and by Dr. Scratch. The researchers compared the differences between the scores given by the experts and the evaluation done with Dr. Scratch. In their findings they emphasized the importance of developing automatic tools for measuring creativity in Scratch projects similarly to the evaluation done with Dr. Scratch for computational thinking.

We extend these works in several ways. First, by considering an open-ended programming environment in which students can program a wide range of different projects. Second, by including additional dimensions of creativity from the literature, including visual flexibility and elaboration. Third, by showing the generalizability of our results to hundreds of projects belonging to two different project groups and themes. Forth, we propose an automatic tool to achieve creativity assessment.

3. THE SCRATCH VISUAL PROGRAMMING ENVIRONMENT

Scratch is an online block-based multi-language programming environment designed for children from elementary school to university. The environment allows users to create interactive stories, games, and animations with a focus of creating an interactive, accessible environment for all [2].

Scratch blocks are shaped to fit together in ways that make syntactic sense and the environment enables the use of external data by importing photos, music clips, recorded voices and users’ own graphics [Resnick et al. (2009)]. Sharing projects with the community and learning from other projects is easy and intuitive, creating a thriving and growing community of users from all over the world. As of today, more than 52 million people have shared more than 50 million projects in Scratch. Each project in Scratch is encoded into one JSON file describing the Scratch project and several additional files including the media components used in the project (e.g., sounds, images etc.). These files can be freely downloaded from the Scratch environment.

3.1 Scratch Studios

Many Scratch projects are created in the context of a Scratch Studio: an area where users share projects with the same topic or theme (e.g., Mazes, Breakout games, Explore the jungle, etc.) There are currently more than 25 million studios created by Scratch users.

For this study we specifically chose two studios that are open ended and assign minimal constraints on the programmer: Maze Games (206 projects) and Code-Your-Hero (205 projects). The Maze Games Studio was created by users in Scratch (seventh and eighth graders). Users in this studio were asked to develop a maze based game, including a collection of paths. The goal of the developed game is to find a path from an entrance to an end goal.

The Code-Your-Hero studio was opened as part of the Hour-of-Code activities [3]. Users in this studio were required to produce activities (games or stories) starring their superhero. Users were given a base project that they could choose to extend, as well as a list of tutorials.

As a running example, we present a project from the Maze studio called The Room (Project ID 109884920). In this project, players need to move between different rooms, collect objects and activate them in order to reveal new paths towards the goal (e.g., turn on an engine to open a door).

3.2 Scratch Elements

Scratch projects are created by composing elements that can broadly be divided into the following seven categories: Blocks are pieces of code such as GoTo, MouseDown, WaitUntil. Costumes contain elements for manipulating characters and backdrops and are commonly used for animations. Sounds contain audible elements that are pre-included (e.g., Pop, Meow) or designed by the user. Monitors include values of variables or lists. Arguments accept user input, such

[2] http://www.drscratch.org
[3] https://scratch.mit.edu/about

Figure 1: Script in Scratch
as Message, Color, Direction etc. Action keys trigger actions in the program, and contain the English alphabet, the number keys, the arrow keys and the space key. Extensions, refer to external hardware or blocks allowing for more advanced functionality in the program including the ones created by the user (e.g., Video, Text to Speech etc.). In all, the size of the possible set of elements across all categories is 413 in the Code-Your-Hero projects and 652 in the Maze projects.

A script in Scratch is a collection of ordered blocks that generate a program logic. Figure 1 shows one of the scripts of The Room project. It contains elements from the Block category (WhenGreenFlagClicked), the Argument category (a Number variable with value “75” and X and Y variables with value “0”).

Scratch projects vary widely in the use of elements from each category. To illustrate, Figure 2 shows a histogram of the major categories in the projects of our two studios, shown in the y axis. The x axis lists the number of projects that contain elements of each category, averaged over the number of elements in the category. As shown by the figure, in both studios, arguments and blocks categories are widely used, while sounds and extensions are much more rare. Many of the elements in the sound and extension categories are designed by the users themselves, rather than prepackaged by Scratch.

4. INTERVIEWING SCRATCH EDUCATORS

To better understand how Scratch educators are considering creativity in their students’ work, we have conducted interviews with three Scratch teachers working with students between the ages of 9 to 14. Two of the teachers work with Scratch as part of the curriculum in school, and the third teacher uses Scratch in after school computer science lessons. All teachers identified creativity as an important element in their Scratch teachings. They described creativity as an ability they look at, support and encourage in addition to focusing on computational thinking skills. This stresses the need for a creativity focused metric to assist teachers in their work.

The teachers emphasized the importance of novelty with respect to students’ project, whether in context to the history of a specific student, or the class. One teacher also mentioned the importance of measuring creativity as an evolving aspect for each student in separation, i.e. comparing a student’s project to earlier projects they did.

Teachers view creativity in Scratch as being expressed in two manners: (1) in the Scratch code itself - the blocks and other Scratch elements and (2) in the Scratch project output as expressed in the visual and textual artifacts presented when the project is executed. Teachers stressed the importance of creativity in the design process. Projects are considered more creative if they diverted from baseline projects presented in the classroom. Additionally, two teachers described wit and humor in the project outcome (specifically in the text messages and images presented) as creative elements.

All teachers also emphasized the plurality of scripts, characters and blocks used as an indication of the creative capabilities of projects created by students. This connects with the Torrance’s elaboration dimension which considers the quantity of the elements created.

All teachers expressed the need to combine a computational tool for creativity with the personal connection and familiarity of an educator with the students and their learning process. The teachers emphasized the need to view any such score as an auxiliary tool that may assist teachers, always leaving decision making and final call in the human hands of the teacher.

5. MODELING CREATIVITY IN SCRATCH

We now describe the development of a computational tool for measuring creativity in Scratch. Our goal was to provide computational measures of the dimensions given by Torrance in Scratch and to compute a creativity score for any project. The tool receives as input a set of Scratch projects from a given studio and returns a creativity score for each of the projects in the set. The set of projects can belong to the same user or to different users. The metric should support the analysis of creativity in a wide range of Scratch projects across multiple project topics and themes. We describe a separate score for each of the three dimensions originality, flexibility and elaboration. As our metrics score is given to each project individually and not to a user we will not refer to the fluency dimension as it refers to the quantity of user-delivered products.

The originality score of a Scratch project $j$ is measured with relation to all projects in the studio $(D)$. A Scratch project is more original if it uses more elements that are rarely used by other projects in the studio.
Let $E_l$ be the set of elements in project $j$. For each element $e_i$, let #($e_i$) denote the number of studio projects that this element appears in. The uniqueness of each element is $O(e_i) = 1/#(e_i)$. For example, the Block element \texttt{When-GreenFlagClicked} that is used in all maze projects gains a low uniqueness score of 0.004 while the Action key element \texttt{m} (with the purpose of showing the full map of the game) that is used only in 3 maze projects gains a higher uniqueness score of 0.333.

The originality of the project $j$ is the sum of the uniqueness scores of all its elements as given by $O_j = \sum_{e_i \in E_l} O(e_i) / Z$, where $Z$ is a normalization factor over all of the projects in the studio. For example, the project The Room uses 51 elements that are used in less than 15% of the projects, leading to the highest originality score in the Maze studio.

The \textit{elaboration} score of a Scratch project $j$ is based on the number of occurrences of elements in the different categories as well as the structure of the scripts making up the project. First, we count how often elements from each of the seven categories appears in a project (Blocks $B$, Costumes $C$, Sounds $S$, Action keys $K$, Extensions $Ext$, Monitors $M$ and Arguments $A$). To illustrate, the room project uses 65 unique elements from the block category but many of them are used more than once, so overall it contains 2742 block elements.

Second, we count the amount of scripts ($Sc$) in the project and their max depth ($Md$). The elaboration score of a project is given by $E_j = (\#(B_j) + \#(Sc_j) + \#(K_j) + \#(A_j) + \#(Ext_j) + \#(M_j) + \#(C_j) + \#(S_j) + \#(Md_j)) / Z$, where $Z$ is a normalization factor.

To illustrate, The Room project is built from 90 scripts with max depth of 42. Over all it has an elaboration score of 0.637 and is ranked 4th in the Maze studio by this metric.

The \textit{flexibility} score of a Scratch project is based on the diversity that is embedded in the textual and visual outputs of the project. Figure 3 presents this diversity with examples from the Code-Your-Hero studio. While all outcomes demonstrate the adherence to the requirements of presenting their hero. In each project presented, characters and backgrounds differ, as well as various textual outputs depicting the hero’s role.

We measure the diversity of the visual outputs by clustering the images of all projects in the studio into different groups. To this end we used a ResNet50 convolutional neural network [He et al. (2016)] to transform each image in this collection to a 2048 vector representation. ResNet50 is a neural network trained on more than a million images from the ImageNet database [Deng et al. (2009)]. The network is 50 layers deep and can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals. Figure 4 presents the architecture of the ResNet50 neural network.

To group together projects with similar image designs, we applied a K-Means clustering algorithm on the image vectors, which produces the different image clusters for the given studio. Finally, the visual flexibility score of a project $j$ was computed as the number of different clusters to which this project’s images belong. Algorithm 1 summarizes this process. Line 1 embeds a set of vectors from all of the images of the projects in the studio. Line 2 applies a Means clustering algorithm on the vectors. Each image is assigned to a cluster. Lines 3-5 assign to each project $j$, a visual flexibility score that is the cardinality of the set of unique clusters that match all of its images.

To illustrate, Figure 5 shows two projects in the Maze studio with different visual flexibility scores, as determined by the algorithm. Project A (left) and Project B (right) both have four maze images. The images of Project A are visually similar to each other. They are clustered into one group and the project gets a low visual flexibility score. The images of Project B are visually different from each other (colors and graphics wise). The images are clustered into four groups and the project gets a high visual flexibility score.

Similarly, we measure the diversity of the textual outputs by clustering the textual elements that appeared in the studio projects into different groups. The textual elements based on the Argument elements such as Message, Broadcast, Question etc and they converted to vectors using TF-IDF model [Ramos et al. (2003)].

The flexibility score of project $j$ is the sum of the textual...
\begin{algorithm}
\textbf{Algorithm 1: Computing Visual Flexibility Score}
\begin{algorithmic}[1]
\State \textbf{Data:} Studio images - Images; Studio projects - Projects
\State \textbf{Result:} Visual flexibility scores for all projects in studio
\begin{algorithmic}
\State \textbf{begin}
\State \quad \textbf{vectors} $\leftarrow$ ResNet50(Images);
\State \quad \textbf{clusters} $\leftarrow$ KMeans(vectors);
\For {$P_j \in$ Projects do}
\State \quad \textbf{clusterIDS} $\leftarrow$ Set(clusters[Images[j]]);
\State \quad \textbf{Vf}_j \leftarrow [\text{clusterIDS}];
\State \quad \textbf{Vf}.insert(\textbf{Vf}_j);
\EndFor
\State \Return \textbf{Vf};
\State \textbf{end}
\end{algorithmic}
\end{algorithmic}
\end{algorithm}

$(\#T_f_j)$ and visual $(\#V_f_j)$ flexibility scores given by $F_j = (\#T_f_j + \#V_f_j)/Z$ where $Z$ is a normalization factor. For the project The Room the over all visual and textual amount of categories is 17 resolving the highest flexibility score in the Maze studio.

Finally, the Combined Creativity Score (CCS) is the normalized summation of the originality, elaboration and flexibility scores, as given in Equation (1).

\begin{equation}
CCS = \frac{(O_j + E_j + F_j)}{Z} \tag{1}
\end{equation}

where $Z$ is a normalization factor. The Room project received the highest score in the Maze studio.

6. COMPARING CCS TO DR. SCRATCH

In this section we study the relationship between CCS, our proposed creativity metric, to Dr. Scratch, which is used to measure computational thinking, over all projects in the studios. We investigate the differences in the ranking of projects created by both metrics. We will refer to the project based on their ID given by Scratch and can be accessed at https://scratch.mit.edu/projects/ID

Table 1 shows the comparison between CCS and Dr. Scratch for the Maze projects and Table 2 presents this comparison for the Code-Your-Hero projects. In each such table we present the top five ranked projects by each metric and the corresponding ranking of every project by the other metric. We also show an image of each project in the table. As can be seen in both tables, projects ranked highest by one metric are not necessarily ranked highest by the other metric.

Table 3 presents the Kendall Rank Correlation Coefficient Abdi (2007) between all the projects in the studio. As shown in the table, there is some correlation between CCS and Dr. Scratch in the two project types, although the metrics do not fully agree. Specifically, we see a higher correlation between the two measures in the Maze projects ($\tau = 0.628$) than in the Code-Your-Hero projects ($\tau = 0.549$). Maze projects are generally more complex than Code-Your-Hero projects from a programming perspective. For projects where creativity is demonstrated in ways other than programming skills in Scratch, such as with images, text and sounds, the correlation between CCS and Dr. Scratch decreases.

For the Maze studio, CCS ranked highest a project from our running example called The Room (ID 109884920). This project was the 4th highest in terms of elaboration, and 1st in terms of flexibility and originality. Clearly, this project exhibits many aspects of creative thinking, yet it was ranked only 8th by Dr. Scratch. In the same studio, CCS ranked at the 4th place a project that Dr. Scratch ranked at 27th place. This project (ID 339733364) is a 3D Maze game where points can be gained by collecting coins and candies. Additionally, there are obstacles represented by other characters with special abilities such as shooting. The only way to reach the target is by collecting keys and reveal new paths by using them. The project ranked 1st in terms of elaboration (122 scripts, 76 costumes, 3416 blocks). This is an original project with varied details (thus high on the originality and flexibility scores - with 12 different visual clusters and 3 textual ones) which was not captured by Dr. Scratch.

Similarly, there is disagreement in the 5 top Code-Your-Hero projects. Although CCS and Dr. Scratch rank 1st the same project, the 2nd project by Dr. Scratch was ranked 19th by CCS. This project (ID 344287265) has low diversity in

| | CCS Ranking | Dr. Scratch Ranking | CCS Rank |
| --- | --- | --- | --- |
| 1 | 8 | 1 | 2 |
| 2 | 1 | 2 | 3 |
| 3 | 2 | 3 | 9 |
| 4 | 27 | 4 | 10 |
| 5 | 9 | 5 | 17 |

| | CCS Top Ranking | Dr. Scratch Top Ranking | CCS Rank |
| --- | --- | --- | --- |
| 1 | 1 | 1 | 1 |
| 2 | 14 | 2 | 19 |
| 3 | 4 | 3 | 3 |
| 4 | 38 | 4 | 5 |
| 5 | 3 | 5 | 156 |
the visual flexibility outputs (4 different clusters out of the possible 17) and is missing textual elements compared to projects ranked higher by CCS in this studio (2 different clusters out of the possible 12). It ranked 14th in terms of elaboration with 1040 elements while the project ranked highest under this metrics uses almost twice as much. The project (ID 35257648) ranked 5th by Dr. Scratch but only 156th according to the CCS metric. In this project the main character is a flying dog trying to catch donuts. It is ranked high by Dr. Scratch due to features such as parallelism and synchronization, but in relation to the other projects, it has minimal textual flexibility with 1 unique cluster. The visual outputs used are limited and taken from the Scratch environment. In addition, it contains no unique elements at all and most of its elements (including 71 blocks, 10 scripts, 3 sounds) are similar to many other projects in the studio. This occurs due the similarity of this game to the tutorials that has been shown in the activity. Thus, while this project is considered high on the list of Dr. Scratch, CCS gives it a relatively low score.

We note another interesting phenomena observed in the Code-Your-Hero studio. In this studio both metrics ranked two projects that were developed by the same user, one project (ID 353026680) improving the other (ID 352632009) and ranked 11th and 5th respectively. These projects were ranked at the 3rd and 5th place by CCS, with the later improved project ranked higher. However, Dr. Scratch was not able to detect the subtle changes between the projects and ranked them both with the same score (3rd and 4th for Dr. Scratch).

### 7. CONCLUSIONS

In this work we have developed a Combined Creativity score (CCS) to measure creativity in Scratch projects. CCS was developed based on an existing theory of creativity and focused on modeling the originality, elaboration and flexibility dimensions of a Scratch project based on the various elements of the project. We have run CCS on more than 400 Scratch projects taken from two studios, one for Maze game creation and the other for development of personal hero stories and games. We compared CCS to Dr. Scratch, an existing computational framework for measuring computational thinking in Scratch, and demonstrated the potential value of a creativity focused metric in automatically ranking projects based on creativity. Feedback obtained from multiple Scratch teachers through interviews supported the theory used and the computational approach taken in this work. In future work we plan to correlate CCS with creativity scores given by expert Scratch instructors. We will also run CCS on additional Scratch Studios and plan to test its ability to estimate personal creativity progress, i.e. the evolution of one student’s creativity over time.

### References

Abdi, Hervé. 2007. The Kendall rank correlation coefficient. Encyclopedia of Measurement and Statistics. Sage, Thousand Oaks, CA, 508–510.

Cropley, Arthur J. 2000. Defining and measuring creativity: Are creativity tests worth using? Roeper review, **23**(2), 72–79.

Deng, J., Dong, W., Socher, R., Li, L.-J., Li, K., & Fei-Fei, L. 2009. ImageNet: A Large-Scale Hierarchical Image Database. In: CVPR09.

He, Kaiming, Zhang, Xiangyu, Ren, Shaoqing, & Sun, Jian. 2016. Deep residual learning for image recognition. Pages 770–778 of: Proceedings of the IEEE conference on computer vision and pattern recognition.

Hershkovitz, Arnon, Sitman, Raquel, Israel-Fishelson, Rotem, Eguluz, Andoni, Garaizar, Pablo, & Guenaga, Mariluz. 2019. Creativity in the acquisition of computational thinking. Interactive Learning Environments, **27**(5-6), 628–644.

Lye, Sze Yee, & Koh, Joyce Hwee Ling. 2014. Review on teaching and learning of computational thinking through programming: What is next for K-12? Computers in Human Behavior, **41**, 51–61.

Moreno-León, Jesús, Robles, Gregorio, & Román-González, Marcos. 2015. Dr. Scratch: Automatic analysis of scratch projects to assess and foster computational thinking. RED. Revista de Educación a Distancia, **15**(46), 1–23.

Ramos, Juan, et al. 2003. Using tf-idf to determine word relevance in document queries. Pages 133–142 of: Proceedings of the first instructional conference on machine learning, vol. 242. Piscataway, NJ.

Resnick, Mitchel, Maloney, John, Monroy-Hernández, Andrés, Rusk, Natalie, Eastmond, Evelyn, Brennan, Karen, Millner, Amon, Rosenbaum, Eric, Silver, Jay, Silverman, Brian, et al. 2009. Scratch: programming for all. Communications of the ACM, **52**(11), 60–67.

Romero, Margarida, Lepage, Alexandre, & Lille, Benjamin. 2017. Computational thinking development through creative programming in higher education. International Journal of Educational Technology in Higher Education, **14**(1), 42.

Schacter, John, Thum, Yeow Meng, & Zifkin, David. 2006. How much does creative teaching enhance elementary school students’ achievement? The Journal of Creative Behavior, **40**(1), 47–72.

Torrance, E Paul. 1965. Scientific views of creativity and factors affecting its growth. Daedalus, 663–681.

Wheeler, Steve, Waite, SJ, & Bromfield, Carolyn. 2002. Promoting creative thinking through the use of ICT. Journal of Computer Assisted Learning, **18**(3), 367–378.

Wing, Jeannette M. 2006. Computational thinking. Communications of the ACM, **49**(3), 33–35.