Humans' Perceptions of Handwritten Digits Generated by a Generative Adversarial Network

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Abstract

Generative Adversarial Network has been the center of attention in the domain of artificial generative knowledge processes, such as handwriting, painting, and the creative field in general. In this paper, we focus on the human-AI relationship and study how humans perceive and interpret the generative process and outcome of a Generative Adversarial Network that generates handwritten digits. Specifically, we explore the outputs of the handwritten digits generated by the Generative Adversarial Network via NVIDIA DIGITS, as they are perceived by humans. The analysis suggests that humans do perceive the handwritten digits generated by the Generative Adversarial Network to be better over time. Further, the study suggests that human does relate to the handwritten digits generated by a Generative Adversarial Network to a certain extent with around 81.25% of the study participants indicated that the handwritings were written by children who are 9 years and above. We present implications for future interdisciplinary research at the intersection of artificial and human intelligence.

Keywords
Artificial Intelligence, Generative Adversarial Network, Human-AI Interaction, Cognition and Perception.

1. Introduction

Generative Adversarial Network (Goodfellow 2014) has been the center of attention in the domain of artificial generative knowledge processes. Through the efforts of artificial intelligence researchers, neural networks like Generative Adversarial Network have been advancing exponentially (Eghbal-zadeh and Gerhard 2017, Gan et al. 2017). Various technical means have been employed to determine the effectiveness of neural networks in generating better outputs over time (Creswell and Anil 2016, Liu and Oncel 2016, Wang 2016). However, humans' perceptions on the outputs of neural networks like Generative Adversarial Network are rarely employed to judge the outputs of the neural networks to be better over time. Also, humans' perceptions on the level of expertise the Generative Adversarial Network has reached based on the humans' perceptions on its final generated outputs such as the perceived age of humans who produced the handwritten digits are rarely studied. With the prevalence of the debates in the domain of artificial and human intelligence (Wagman 1997, Ge et al. 2008, Servick 2018, Ulman 2019), it is critical to obtain humans' perceptions in regard to the maturity of a neural network to better judge the current state of advancements in artificial intelligence. Questions like "Do you think this alphabet is written by a human? If so, how old do you think the human who wrote this alphabet?" and "Do you think this piece of art is drawn by a human? If so, what is the level of expertise of the human who drew this art?" need to be raised more often. To examine the outputs of handwriting by a Generative Adversarial Network as they are perceived by humans, we pose our research question as follows: What are the humans' perceptions of handwritten digits produced by a Generative Adversarial Network?

2. Methods

In order to examine the humans' perceptions of the handwritten digits generated by the Generative Adversarial Network (GAN) via NVIDIA DIGITS, we recruited 34 mTurkers from Amazon Mechanical Turk to evaluate the 10 digits ranging from the digit 0 to the digit 9 (Figure. 1) generated from a Generative Adversarial Network through NVIDIA DIGITS. We broke down the sequence of 10 digits (Figure. 1) into a set of 10 distinct digits that branched into 10 separate survey questions and randomized the questions to avoid bias when mTurkers gave us the best guess on the digits that they perceived. For each digit displayed on the survey, we gave them the options from digit 0 to digit 9 to choose from. The mTurkers will then choose the digit that they perceive based on the digit generated through GAN displayed to them. 32 mTurkers successfully passed our screening question, where we ask them to give the correct digit that will complete the number line, so we performed the data analysis on the 32 mTurkers that passed our screening question. The goal of the simple screening question is to test the mTurkers' numeracy skills (Reder and Bynner 2009). The results from the Amazon Mechanical Turk study is portrayed in the "Figures and Tables" section.

3. Figures and Tables

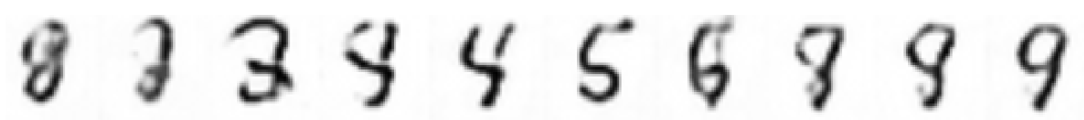

Figure. 1 Handwritten digits ranging from digit 0 to digit 9 (in consecutive sequence) generated by Generative Adversarial Network through NVIDIA DIGITS. Note that we broke down and randomized these 10 distinct digits as 10 separate questions in the survey to avoid bias. (Image of handwritten digits extracted from NVIDIA DIGITS)

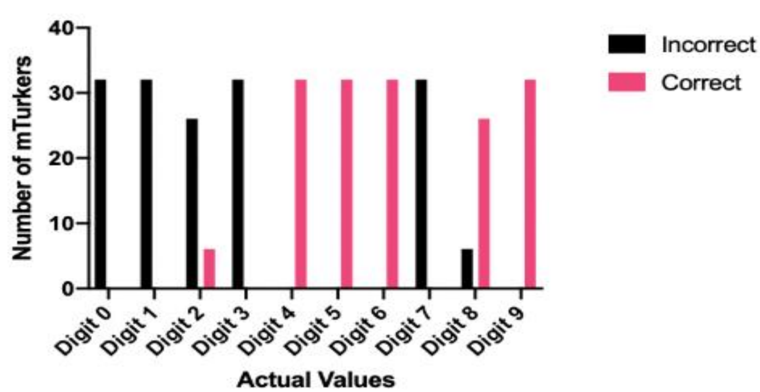

Figure. 2 Histogram of Whether Perceived Value Equals Actual Value.

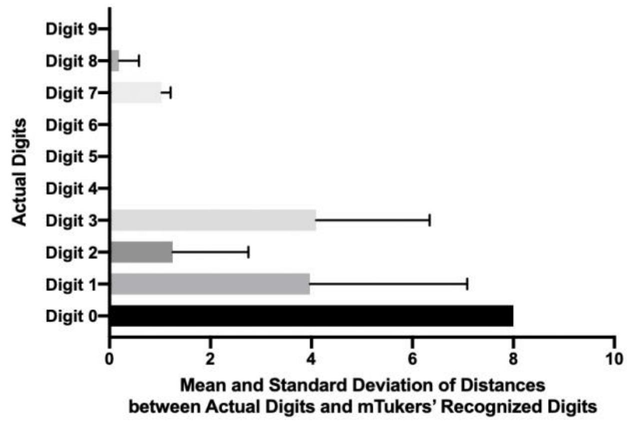

Figure. 3 Histogram of Mean and Standard Deviation of the Differences between Actual Digits Generated from the Generative Adversarial Network through NVIDIA DIGITS and the Perceived Digits by the mTurkers.

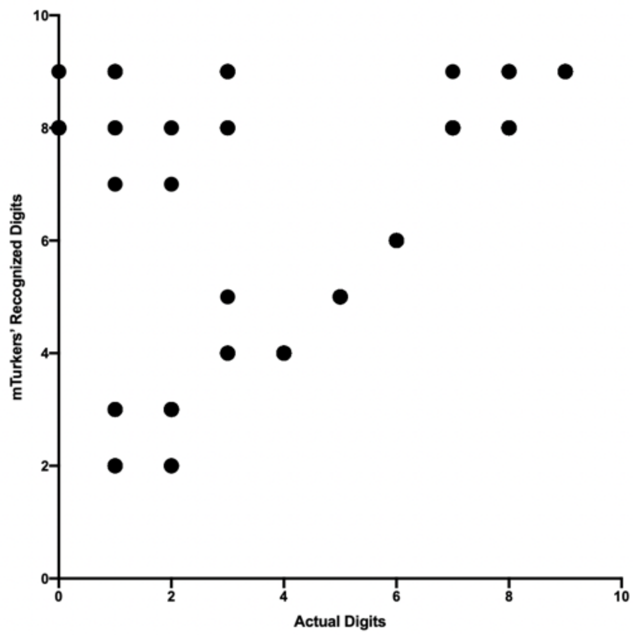

Figure. 4 Scatter Plot of the mTurkers' Perceived Digits Versus Actual Digits.

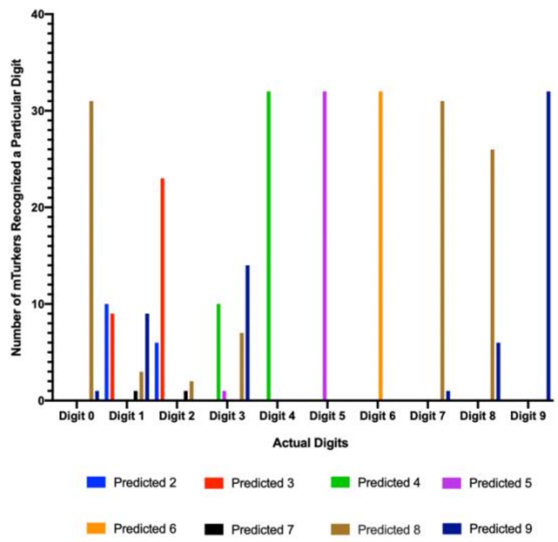

Figure. 5 Histogram of the Number of mTurkers who Perceived a Digit versus the Actual Digit.

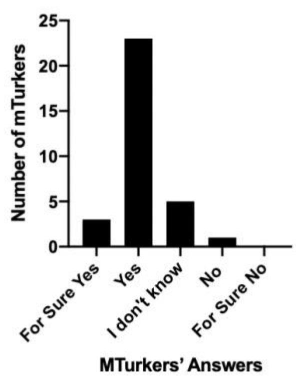

Figure. 6 Histogram for the Question "Are the Digits Written by Human?".

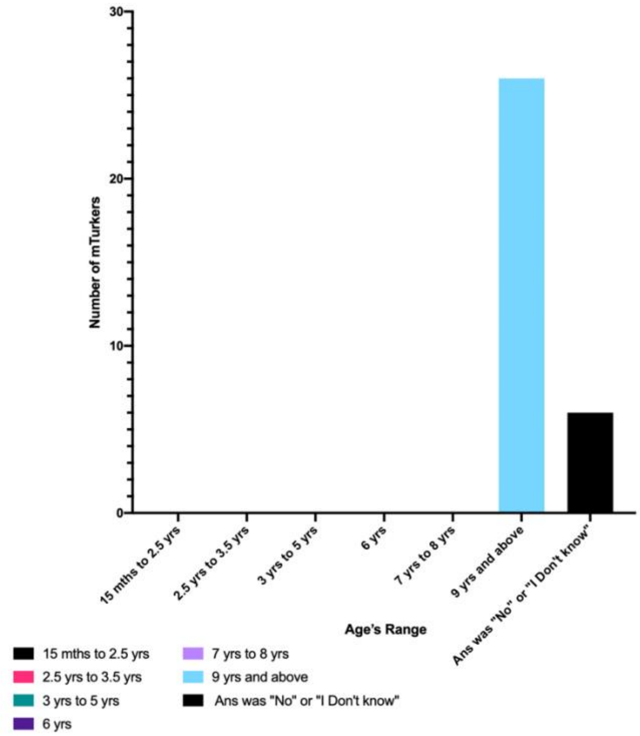

Figure. 7 Histogram of the Number of mTurkers versus the Perceived Age Range.

4. Analysis

From Figure. 2, we make "0" represents "Incorrect" digit whereas "1" represents "Correct" digit. We observed that the digits ranging from 0 to 3 has a mean value of 0, which means that the majority of the mTurkers did not recognize the digits generated correctly. However, the digits ranging from 4 to 9 has a mean value of 1, except for the digit 7 that we classify as an outlier in the range, which means that the majority of the mTurkers recognized the digits in this range correctly. In another figure, which is Figure. 3, we see that the differences between the actual digits and the digits that mTurkers recognized are the largest between the digits ranging from 0 to 3 with particularly large standard deviations for digits ranging from 1 to 3 and particularly large mean for the digit 0. Additionally, in Figure. 4 and Figure. 5, we see that there are much more variability in the perceived digits before the digit 4, which means that the Generative Adversarial Network is still learning to generate more recognizable digits at the beginning phases, and thus our humans do not have a consensus on the perceived digits.

The last question that we asked mTurkers was "Are the digits written by humans?". About 81.25% of the mTurkers answered "yes", which might suggest that humans do correlate to the handwritings generated by the Generative Adversarial Network to a certain extent. Only 3.125% of the study participants, which is 1 out of 32 participants indicated "No", whereas a mere 15.625%, which is 5 out of 32 participants indicated "I don't know". Further, we provided the study participants with a few sets of age range and asked them to choose an age range that they think the handwriting belongs to if they think that the handwritten digits were from a human. We chose the age range based on the researched state of maturity of the handwritings of the general children populations at different age range (Puranik et. al. 2014, Puranik et. al. 2018, Ritchson 2006). 81.25% of the mTurkers indicated that the handwritten digits belong to children who are 9 years and above while the remaining 18.75% answered "No" or "I don't know" to the question that asked whether they think those digits are written by humans, which gives a slight indication that the handwritten digits generated by the Generative Adversarial Network were matured enough to be indistinguishable from the handwritten digits of those from the 9 year old children.

5. Conclusions

In essence, our research presents an analysis of the perceived digits at each phase by the mTurkers and correlates to that of the actual digit generated by Generative Adversarial Network via NVIDIA DIGITS to examine the outputs of Generative Adversarial Network as they are perceived by humans. We then examine the perceptions and interpretations of humans on the sequence of handwritten digits generated by Generative Adversarial Network through NVIDIA DIGITS. The goal of this analysis is to spur discussions among researchers researching in the intersection of human intelligence and artificial intelligence to go deeper in investigating the correlation of the outputs from artificial intelligence and human intelligence. Our explorative analysis on leveraging humans' intelligence to examine the maturity of the outputs of the Generative Adversarial Network is hoped to bring a new way of thinking to the community that does human-artificial intelligence research. It would be interesting to see the levels of expertise in humans that are needed to generate the same quality of outputs that are generated by different neural networks in the future.

References

Creswell, Antonia, and Anil Anthony Bharath. 2016. Inverting The Generator Of A Generative Adversarial Network. *Neural Information Processing Systems Workshop on Adversarial Training.* Web.

Eghbal-zadeh, Hamid, and Gerhard Widmer. 2017. Probabilistic Generative Adversarial Networks. *Neural Information Processing Systems*. Web.

Gan, Zhe, Liqun Chen, Weiyao Wang, Yunchen Pu, Yizhe Zhang, Hao Liu, Chunyuan Li, and Lawrence Carin. 2017. Triangle Generative Adversarial Networks. *Neural Information Processing Systems.* Web.

Ge, Jianqiao, Shihui Han, and Jan Lauwereyns. 2008. Distinctive Neurocognitive Strategies for Comprehensions of Human and Artificial Intelligence (Human/Artificial Intelligence). *PLoS ONE* 3.7: E2797. Web.

Goodfellow, Ian J. et al. 2014. Generative Adversarial Networks. *Neural Information Processing Systems Proceedings*: 2672-2680.

Liu, Ming-Yu, and Oncel Tuzel. 2016. Coupled Generative Adversarial Networks. *Neural Information Processing Systems*. Web.

NVIDIA Corporations. Image Creation using Generative Adversarial Networks with Tensorflow and DIGITS. *NVIDIA Courses*. Web.

Puranik, Cynthia S., and Christopher J. Lonigan. Emergent Writing in Preschoolers: Preliminary Evidence for a Theoretical Framework. *Reading Research Quarterly* 49.4 (2014): 453-67. Web.

Puranik, Phillips, Lonigan, and Gibson. 2018. Home Literacy Practices and Preschool Children's Emergent Writing Skills: An Initial Investigation. *Early Childhood Research Quarterly* 42 (2018): 228-38. Web.

Reder, Stephen M., and J. M. Bynner. 2009. Tracking Adult Literacy and Numeracy Skills: Findings from Longitudinal Research. *1st ed. New York: Routledge*. Print. Routledge Research in Education.

Ritchson, Amy Delacova. 2006. The Relation of Classroom Environment to Preschool Children's Emergent Writing Behaviors. Print.

Servick, Kelly. 2018. Brain Scientists Dive into Deep Neural Networks: Increasingly Skilled Artificial Intelligence Could Hold Clues to Human Sensory Systems. *Science* 361.6408 (2018): 1177. Web.

Ullman, Shimon. 2019. Using Neuroscience to Develop Artificial Intelligence: Combining Deep Learning with Brain-like Innate Structures May Guide Network Models toward Human-like Learning. *Science* 363.6428 (2019): 692-693. Web.

Wagman, Morton. 1997. Cognitive Science and the Symbolic Operations of Human and Artificial Intelligence: Theory and Research into the Intellective Processes. *Westport, Conn,:Praeger*. Print.

Wang, Yaxing, Lichao Zhang, and Joost Van De Weijer. 2016. Ensembles of Generative Adversarial Networks. *Neural Information Processing Systems Workshop on Adversarial Training*. Web.

Biographies

Jia Lin Cheoh is a Senior Undergraduate Student in Computer Science at Purdue University, West Lafayette, Indiana, USA. She is a researcher in the field of human-computer interaction and artificial intelligence where she has been invited to present in over 10 international and national conference. She is a recipient of a National Fellowship Award of USD 300,000, the Purdue Research Scholar Award, and the Grasshopper Research Scholar Award by the Computing Research Association.

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