

Interdisciplinary Research (IDR) Origination Awards

Cover Page

Project Title

Title: Brain-inspired Analog Circuits for Low-energy Machine Learning

Principal Investigator(s) (full-time faculty)

Name (PI listed first)	Department	College
Nancy Fulda	Computer Science	CPMS
Jordan Yorgason	Cell Biology and Physiology	Life Sciences
Wood Chiang	Electrical & Computer Engr.	Engineering
Karl Warnick	Electrical & Computer Engr.	Engineering

Track

Track two

Abstract

Existing machine learning methods use orders of magnitude more energy than biological learning in the brain. Our project combines recent understanding of brain neuron chemistry and behavior with innovations in analog and mixed signal circuit design to create a new hardware platform that can run large-scale machine learning algorithms at a fraction of the cost of existing digital methods. This vision relies on two critical innovations: (1) a machine learning algorithm that leverages biologically inspired principles to learn complex pattern-matching behavior without the use of backpropagation or a gradient calculation chain, (2) a physical computer chip that has been custom designed to implement this learning algorithm in analog hardware. Using existing external partnerships, we will manufacture a prototype of the proposed computer chip for testing, validation, and proof-of-concept.

Summary of Plans for External Funding

The National Science Foundation has several programs that support work in neuromorphic circuits for machine learning: Integrative Strategies for Understanding Neural and Cognitive Systems (NCS), Brain-Inspired Dynamics for Engineering Energy-Efficient Circuits and Artificial Intelligence (BRAID), and Bioinspired Design Collaborations to Accelerate the Discovery-Translation Process (BioDesign). A preliminary proposal was submitted to the NSF BRAID program last year and received two ratings of "Very Good" with comments including "The integration of theoretical neuroscience and engineering is very strong" and "This is a well written proposal about a project striking a well thought out balance of theoretical neuroscience and circuit design and analysis", but "the properties of the spiking neurons are not clear" and "It would be better to show the scalability of the proposed CMOS design". Based on this feedback, we feel confident that the work will soon be mature enough to garner external support.

We have begun organizing a multi-university collaboration in neuromorphic learning circuits for a proposal to the National Science Foundation Computer and Information Science and Engineering: Core Programs, Large Projects (CISE Large) program. The work described here will play a key role in that proposal.

Project Narrative

1 Introduction

Emerging AI technologies like DALL-E, ChatGPT, diffusion networks and Bing’s new AI search offer enormous potential benefits to society, but they also have a high computational cost, requiring billions of transistors clocked at GHz rates to calculate the flow of signals through a single neural network. Every generated image, chat response, language translation, or text rephrasing produced by any of the internet’s 5.6 billion users has a concrete financial and environmental cost. As an example, Strubell, Ganesh, and McCallum estimate the carbon emissions produced during the design and training of a single large-scale transformer network to be roughly five times that produced by an average car over its entire lifespan [1]. The financial cost for the same model was estimated at \$942,973–\$3,201,722.

As intimidating as those numbers are, they describe only the first phase of a neural network’s lifespan. Once a machine learning model has been trained, it may be called upon at will to generate images, create chat responses, power search engines, or revise user-generated text. As of this writing, the popular image generation network DALL-E 2 has over 1.5 million users generating an estimated 2 million images per day [2]. GitHub Co-pilot is used by an estimated 1.2 million developers as part of their daily work [3], and ChatGPT has more than 100 million users and 13 million daily visitors [4]. In short, our society is investing billions of dollars per day into AI infrastructure, with corresponding energy and environmental impacts, and the trend is strongly upward. As an inevitable corollary, this also means that many of the most impressive AI technologies of the modern age will remain available only to the financially privileged, leaving much of the world’s populace in digital ghettos.

Our research seeks to address this problem by designing a new kind of hardware that is custom-manufactured to support machine learning at scale, but with only a fraction of the energy requirements. Rather than using digital hardware, in which signals are propagated as 0’s and 1’s, our proposed design will use custom designed *analog* hardware. In this paradigm, the mathematical operations needed to power a neural network are built directly onto a computer chip in the form of registers, wires, and capacitors, an approach that requires orders of magnitude less energy than the digital neural networks currently being deployed.

Prior researchers have demonstrated both the energy efficiency of analog circuits as compared to digital ones, as well as their suitedness for a machine learning variants known as *spiking neural networks* [5–8], but there is a catch: The backpropagation update algorithm – which is widely relied upon for machine learning architectures and forms the computational backbone of AI models like GPT-3, ChatGPT, DALL-E and DALL-E-2 – is too computationally intensive for implementation on a physical analog chip. Backpropagation requires a precise record of every calculation performed during a neural network’s forward pass so that the weight parameters can be properly adjusted during the backward pass []. This is easily accomplished on digital hardware, which relies on CPUs, GPUs, and memory registers to store intermediate loss gradients. Analog hardware, in contrast, relies on mathematical operations that are built directly onto the physical. The intermediate loss gradients required by the backpropagation algorithm are prohibitively complicated to be constructed this way. In other words, the analog chip does not have enough space to store a record of past calculations.

We therefore propose to design a new kind of learning algorithm: one that is able to update its weight parameters without requiring an unbroken gradient chain. We know that such a learning algorithm is possible, because the human brain accomplishes comparable feats with far fewer operations and orders of magnitude less energy than current computing infrastructure, and the brain’s neurons do not keep a record of past computations. Prior work by our research group has demonstrated that biological brain behaviors mediated by modulatory neurotransmitters can be integrated into a spiking neural network architecture and is implementable on a physical chip [9]. Building on this work, we will leverage additional insights from recent neurobiological discoveries in order to facilitate low-energy consumption chips that are custom-designed

for machine learning. The resulting analog chip will differ from Intel’s Loihi 2 [10], BrainChip’s Akida processor [11], and other recent advances in neuromorphic computing in that we use an analog rather than digital hardware platform and we abandon the concept of backpropagation rather than seeking clever approximations of it. The concrete deliverables of this project will be:

1. A novel spiking neural network architecture inspired by mechanisms and modalities in biological brains
2. A unique weight update rule compatible with our architecture which does not rely on a traditional loss gradient chain, thus making it suitable for deployment in analog computation environments
3. A physical analog chip that will be custom manufactured with our neural network circuitry
4. Empirical results from a small-scale proof-of-concept evaluation demonstrating the chip’s ability to learn meaningful tasks with low power consumption

2 Research Team

This work is based on synergies between the fields of neuroscience (Yorgason), machine learning (Fulda), circuit design (Chiang), and numerical modeling and applications (Warnick).

Nancy Fulda (PI) specializes in deep learning, knowledge representation, neural network architectures, and generative neural models. Fulda’s group will oversee the integration of traditional machine learning methods with biologically motivated insights during the development of the proposed learning algorithm. In particular, Fulda’s group will simulate and evaluate the performance of bio-inspired learning algorithms prior to chip manufacture; explore novel network architectures, activation functions, and recurrence patterns in the context of analog computing; and will design the machine learning evaluation framework that will be used to validate the completed chip.

Shiuh-hua Wood Chiang (Co-PI) has extensive experience in CMOS circuit design with particular emphasis on analog/mixed-signal circuits for low-power, high-performance applications. His group has expertise in designing custom chips for communications, sensors, and scientific instrumentations. Chiang’s group will be responsible for the CMOS implementation of the bio-inspired AI chip including schematic design, circuit simulations, layout, chip measurement, and PCB design.

Jordan Yorgason (Co-PI) has background training in circuit function and ionotropic and metabotropic receptor pharmacology, with methodological expertise in performing and interpreting physiology, electrochemistry and microscopy experiments. Dr. Yorgason’s research has an emphasis in mesolimbic dopamine circuitry, pharmacology of drugs of abuse and behavioral neuroscience, with over 37 peer reviewed publications in these topics. The Yorgason lab will provide this research group with insight into biological learning and transmission modalities at the cellular and sub-cellular level.

Karl F. Warnick (Co-PI) has expertise in numerical simulation methods for circuits and systems, which is critical to bridging the gap between traditional ML algorithms and analog circuit design. Warnick’s group will hybridize time-domain circuit solvers with ML training to design and train analog circuit networks with the desired functionality, and will oversee the validation of the manufactured chip.

3 Methodology

The purpose of our research is to enable energy-efficient computing for deep spiking neural networks that can be deployed at scale in commercial settings. In pursuit of this goal, we are exploring a radical shift in the hardware used for network learning and neural network inference. The proposed research requires a novel machine learning algorithm paired with analog hardware that has been custom manufactured to implement it. Past work from our research group demonstrates that we have the requisite skills to achieve this objective.

Preliminary work has been completed on both the learning algorithm and the hardware implementation, as described below.

3.1 The Learning Algorithm

Prior work by this research group was based on the biological discovery of modulatory neurotransmitters and the application of similar principles in machine learning contexts [9]. That research shows that the biological principle of neuromodulatory activities can be used as a machine learning mechanism and that is implementable on low-energy consumption chips. However, the research also exposed issues faced by modern-day neuromorphic hardware, including its dependency on the backpropagation algorithm and an unbroken gradient chain. The current project tackles this limitation head-on, seeking to replace the back-propagation algorithm with a biologically inspired alternative.

Neurotransmitters such as dopamine, glutamate, serotonin, histamine, norepinephrine and many others have unique modulatory effects on neuron behavior [12–14]. Because there are many possible neurotransmitters, biological neurons utilize different types of signals to mediate information flow [15]. In particular, Retrograde Signals (RS) [16] involve the release from the postsynaptic neuron of a neurotransmitter which diffuses to the presynaptic bouton, thus impacting the transmission behavior of future incoming signals. As a thought experiment, and an introduction to our proposed learning algorithm, let us call signals that calculate the mathematical behavior of a neural network “forward signals” (FS). In biological brains, there is a known type of RS which travels explicitly along with traces left by forward signals, allowing the RS to precisely update the synaptic weight of neurons which participated in decision-making *without* knowing the precise sequence of calculations performed during the decision-making process. Moreover, depending on the type of RS, retrograde and forward signals can overwrite each other when they meet along biological neural pathways [15]. Critically, the simultaneous transmission of both RS and FS through a given neuron does not increase the neuron’s firing frequency beyond that which would have been achieved via the forward signal alone. Thus, the existence of a retrograde signal does not explicitly increase the energy consumption of network activities.

We model our proposed learning algorithm on the biological principle of mixed signal learning with both RS and FS. In our algorithm, forward signals are given to input layers, and retrograde signals are given to output layers. The former propagates in the direction of the output layer while the latter propagates to the direction to input layers. Each neuron utilizes a set of rules to determine its state upon receiving FS or RS. When FS and RS met in a single neuron, the state of the neuron changes, triggering a synaptic adjustment event. A neuron in the FS state can only fire FS signals, and one in the RS state can only fire RS signals. We use the Leaky-integration-and-fire (LIF) [17] neuron model because it closely resembles biological neurons and has an established theoretical relationship to the commonly-used RELU activation function in artificial neural networks [18]. To implement RS we add a binary value to each neuron which tracks traces left by FS; a binary value indicating the state of the neuron; and a continuous value to track RS signals. The neuron behaves as follows:

$$O_{i_t} = H(v_{i_t}) * I \quad (1)$$

$$H(v_{i_t}) = \begin{cases} 1, & \text{if } (v_t \geq \theta) \& G(i_t) \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

$$v_{i_t} = \left(\sum_{j=0}^n O_{j_t} * w_{ij} \right) + d * v_{i_{t-1}} * (1 - H(v_{i_{t-1}})) \quad (3)$$

where v_{i_t} is the voltage (membrane potential) of the neuron i at time t . O_{j_t} is the output of neuron j through Heaviside Step function H . I represents the existence of output current. θ is the activation threshold

of neurons. w_{ij} is the synaptic weight between two neurons. d is the ratio of voltage remaining from the previous time step $t - 1$. $G()$ is a gating function that prevents negative RS signals from traveling through neurons without traces of FS. $G()$ can be denoted as:

$$G(i_t) = \begin{cases} 1, & \text{if } (f_{i_t} \& r_{i_t} < 0) \text{ or } r_{i_t} > 0 \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

$$f_{i_t} = \begin{cases} 1, & \text{if } i \text{ received FS since last firing} \\ 0, & \text{otherwise} \end{cases} \quad (5)$$

f_{i_t} is a binary value indicating that neuron i received the FS signal since last firing. Using f_{i_t} ensures that gating function G will allow negative accumulated RS r_{i_t} only when an FS trace was detected. The state of neuron j at any given time t can be calculated as:

$$s_{j_t} = \begin{cases} 1, & \text{if } (r_{i_t} > 0 \ \& \ f_{i_t} == 0) \text{ or } (r_{i_t}) < 0 \\ s_{j_{t-1}}, & \text{if no signal was received on } t - 1 \\ 0, & \text{otherwise} \end{cases} \quad (6)$$

A value of $s_{j_t} = 1$ indicates a retrograde (RS) state. A value of 1 indicates the FS state. The change of the synaptic weight is computed as:

$$\Delta w = \begin{cases} -1 * c, & \text{if } s_{j_t} \neq s_{j_{t-1}} \ \& \ r_{i_t} < 0 \\ c, & \text{if } s_{j_t} \neq s_{j_{t-1}} \ \& \ r_{i_t} > 0 \\ 0, & \text{otherwise} \end{cases} \quad (7)$$

The synaptic weight change happens only when the neuron state s_{j_t} changes. The direction of change depends on the accumulated value of r_{i_t} . Therefore, the RS value determines how the weight is updated.

3.2 The Physical Chip

This research group has experience designing and fabricating analog spiking neurons. We previously published work on a novel analog spiking neuron that implemented a brain-dopamine-inspired learning algorithm [9]. That neuron design consumed an average of around 1.4pJ of energy per computation, which is many orders of magnitude smaller than today’s power-hungry backpropagation-based neurons.

Within the past few months, our group has designed a second version of this neuron. This updated design includes more advanced features including time-domain computing, more weight storage, and a more area efficient synapse circuit. This design went beyond a single neuron, and includes a 3x4 neuron array to show that we can perform basic learning tasks on our hardware. It achieves a best-case power consumption only 153fJ of energy per computation. The full chip layout is shown in figure 1. In April, we will receive the completed chip from our chip manufacturing partner TSMC, and will begin testing. Because of the limited number of neurons on our chip, we will be learning tasks with only few internal features such as the XOR task. Once we prove our algorithm and hardware work, we will design a larger, more computationally powerful chip.

Building on the success of these neuron designs, we will add new features to make our next chip fully compatible with the novel learning algorithm proposed in section 3.1. Digital memory and logic, which will augment the core analog design of the chip, can easily remember which neurons fired during a network’s forward pass and whether a neuron has received a FS since its last firing. We will modify the synapse to receive signals in both the forward and reverse direction.

The remaining elements of the learning algorithm can be realized with a modular computing block between each neuron. Since the learning algorithm updates the synapse weights based on very localized

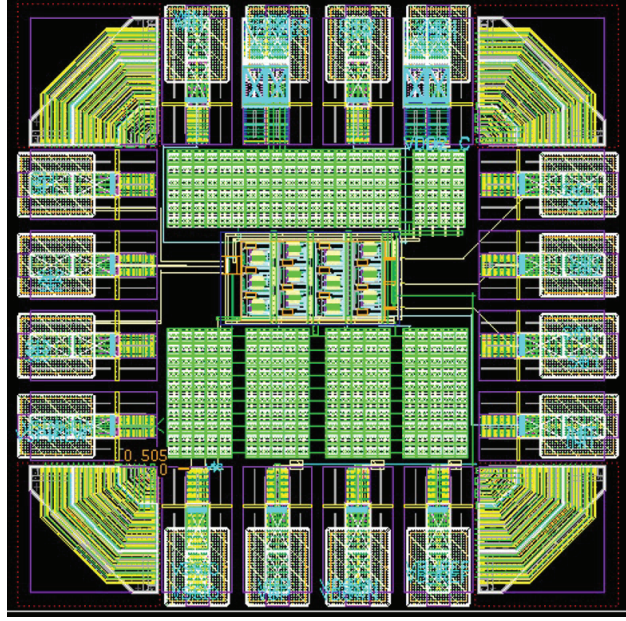


Figure 1: Layout of time-domain neural network chip. The full chip occupies only 561 x 561 microns.

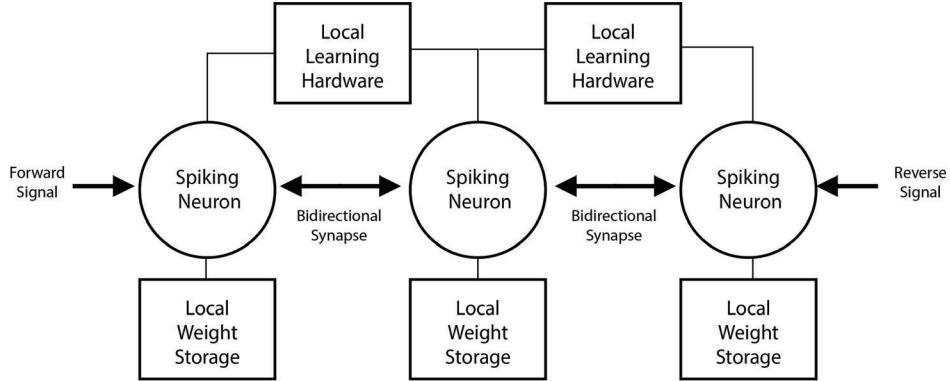


Figure 2: Block diagram of the proposed hardware design implementing the novel learning algorithm presented in this proposal.

parameters, there is no need for complex signal routing hardware. Furthermore, all the computing circuitry can be physically located near the neurons, greatly reducing signal wire length and therefore power consumption and area. This approach to on-chip learning is a big improvement on existing architectures, which completely separate the neuron circuitry from the digital learning circuitry and require complicated signal routing hardware and algorithms. A block diagram of the proposed chip is shown in figure 2.

After the chip has been manufactured, we will evaluate its performance in the context of audio signal processing, and will compare not only energy consumption, but also sample complexity, convergence rate, and final performance accuracy between our manufactured chip and a comparable machine learning architecture implemented on traditional hardware. We hope that the results will provide a valuable proof of concept and a springboard toward external funding from agencies such as NSF, DOE, and other entities.

Budget and Budget Narrative

Year 1:

Student salaries: \$15,000

Supplies and fabrication: \$5,000

Total: \$20,000

Year 2:

Student salaries: \$15,000

Supplies and fabrication: \$5,000

Total: \$20,000

Budget narrative

We are requesting funding for 1 graduate student working at 50% capacity over two years (\$15,000 per year). The funds will support research assistance with algorithm design, circuit layout, and testing and validation. Additionally, we are requesting \$5000 per year in supplies and fabrication cost to support the manufacturing of multiple chip prototypes.

References

- [1] E. Strubell, A. Ganesh, and A. McCallum, “Energy and policy considerations for deep learning in nlp,” in *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*. Florence, Italy: Association for Computational Linguistics, 2019, pp. 3645–3650. [Online]. Available: <https://aclanthology.org/P19-1355>
- [2] “The definitive guide to use dall-e-2, the best ai image generator.” [Online]. Available: <https://www.zmo.ai/the-definitive-guide-to-use-dall-e-2-the-best-ai-image-generator/>
- [3] “Github copilot makes developers 1.55x more productive.” [Online]. Available: https://www.linkedin.com/pulse/github-copilot-makes-developers-155x-more-productive-michael-spencer?trk=pulse-article_more-articles_related-content-card
- [4] “Chatgpt statistics for 2023: Comprehensive facts and data.” [Online]. Available: <https://www.demandsage.com/chatgpt-statistics/>
- [5] A. L. Hodgkin and A. F. Huxley, “A quantitative description of membrane current and its application to conduction and excitation in nerve,” *The Journal of physiology*, vol. 117, no. 4, pp. 500–544, 1952.
- [6] J. Xin and M. Embrechts, “Supervised learning with spiking neural networks,” in *IJCNN’01. International Joint Conference on Neural Networks. Proceedings (Cat. No.01CH37222)*, vol. 3, 2001, pp. 1772–1777 vol.3.
- [7] S. Ghosh-Dastidar and H. Adeli, “Spiking neural networks,” *International journal of neural systems*, vol. 19, no. 04, pp. 295–308, 2009.
- [8] G. Indiveri, B. Linares-odoarranco, T. J. Hamilton, A. Van Schaik, R. Etienne-Cummings, T. Delbruck, S.-C. Liu, P. Dudek, P. Häfliger, and S. Renaud, “Neuromorphic silicon neuron circuits,” *Frontiers in neuroscience*, vol. 5, p. 73, 2011.
- [9] T. Barton, H. Yu, K. Rogers, N. Fulda, S.-h. W. Chiang, J. Yorgason, and K. F. Warnick, “Towards low-power machine learning architectures inspired by brain neuromodulatory signalling,” *Journal of Low Power Electronics and Applications*, vol. 12, no. 4, 2022. [Online]. Available: <https://www.mdpi.com/2079-9268/12/4/59>
- [10] “Taking neuromorphic computing to the next level with loihi 2, technology brief.” [Online]. Available: <https://download.intel.com/newsroom/2021/new-technologies/neuromorphic-computing-loihi-2-brief.pdf>
- [11] “akida akd1000.” [Online]. Available: <https://brainchip.com/akida-neural-processor-soc/>
- [12] M. Kutlu, J. Zachry, P. Melugin, S. Cajigas, M. Chevee, S. Kelly, B. Kutlu, L. Tian, C. Siciliano, and E. Calipari, “Dopamine release in the nucleus accumbens core signals perceived saliency,” *Current Biology*, vol. 31, no. 21, pp. 4748–4761.e8, 2021, cited By 1. [Online]. Available: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85117251656&doi=10.1016%2fj.cub.2021.08.052&partnerID=40&md5=e70954421765fc839559cf66a7d957ef>
- [13] S. Flagel, J. Clark, T. Robinson, L. Mayo, A. Czuj, I. Willuhn, C. Akers, S. Clinton, P. Phillips, and H. Akil, “A selective role for dopamine in stimulus-reward learning,” *Nature*, vol. 469, no. 7328, pp. 53–59, 2011, cited By 601. [Online]. Available: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-78650971061&doi=10.1038%2fnature09588&partnerID=40&md5=1437586cde1bc8ba77afb2068c279219>

- [14] M. Solanto, “Neuropsychopharmacological mechanisms of stimulant drug action in attention-deficit hyperactivity disorder: A review and integration,” *Behavioural Brain Research*, vol. 94, no. 1, pp. 127–152, 1998, cited By 573. [Online]. Available: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-0032127304&doi=10.1016%2fS0166-4328%2897%2900175-7&partnerID=40&md5=7ba9fa18bb216330e8ece0ef2ad00e06>
- [15] H. Li, M. Pratelli, S. Godavarthi, S. Zambetti, and N. Spitzer, “Decoding neurotransmitter switching: The road forward,” *The Journal of Neuroscience*, vol. 40, pp. 4078–4089, 05 2020.
- [16] W. G. Regehr, M. R. Carey, and A. R. Best, “Activity-dependent regulation of synapses by retrograde messengers,” *Neuron*, vol. 63, no. 2, pp. 154–170, 2009. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0896627309005078>
- [17] “Abbott Lf. lapicque’s introduction of the integrate-and-fire model neuron (1907),” vol. (50)5-6, pp. 303–4.
- [18] S. Lu and F. Xu, “Linear leaky-integrate-and-fire neuron model based spiking neural networks and its mapping relationship to deep neural networks,” *Frontiers in neuroscience*, p. 1368, 2022.

4 Plans for external funding

Our work fits well with these programs, for which we will prepare proposals and apply during the next year of the project period:

Grant Program	Description	Amount	Deadline
NSF NCS Integrative Strategies for Understanding Neural and Cognitive Systems	Seeks integrative, boundary-crossing proposals that advance understanding of neuroengineering and neuroscience. Funds high-risk, high-payoff methods.	\$500,000	TBD Dec. 2023/Feb. 2024
NSF EFRI-BRAID Brain-Inspired Dynamics for Engineering Energy-Efficient Circuits and Artificial Intelligence	Invites proposals from diverse teams of engineering-led researchers that will enable the broad yet ethical deployment of novel engineered learning systems. The inclusion of theoretical neuroscience expertise on each team is mandatory.	\$2,000,000 across 4 years	TBD Oct. 2023/Feb. 2024
NSF BioDesign Bioinspired Design Collaborations to Accelerate the Discovery-Translation Process	Successful proposals will couple strong grounding in biology and engineering design with a plan for how the foundational and use-inspired research can be extended toward prototype development which, in the longer term, aims to solve a specific societal or economic challenge.	Not yet disclosed	TBD
NSF CISE Computer and Information Science and Engineering: Core Programs, Large Projects (CISE Medium and Large)	Invites proposals on bold new ideas tackling ambitious and fundamental research problems. Large projects must be comprehensive and well-integrated, tackling ambitious computer and information science and engineering problems that are well suited to a large-scale, integrated, collaborative project.	\$1,200,000 - \$5,000,000 over 4-5 years	Sept 30, 2024

The last of the above proposals is already underway. We have begun organizing a multi-university collaboration in neuromorphic learning circuits with the intent to submit a proposal to the National Science Foundation Computer and Information Science and Engineering: Core Programs, Large Projects (CISE Large) program. However, without substantive initial results and a demonstrable track record in the field, the funding effort is less likely to be successful.

NSF BIOGRAPHICAL SKETCH

Provide the following information for the Senior personnel.
Follow this format for each person. **DO NOT EXCEED 3 PAGES.**

IDENTIFYING INFORMATION:

NAME: Fulda, Nancy

POSITION TITLE: Assistant Professor

ORGANIZATION AND LOCATION: Brigham Young University

Professional Preparation:

ORGANIZATION AND LOCATION	DEGREE (if applicable)	DATE RECEIVED	FIELD OF STUDY
Brigham Young University, Provo, UT	PHD	2019	Computer Science
Brigham Young University, Provo, UT	MS	2004	Computer Science
Brigham Young University, Provo, UT	BS	2002	Computer Science

Appointments and Positions

2020 - present Assistant Professor, Brigham Young University
 2019 - 2020 Visiting Professor, Brigham Young University
 2018 - 2018 Team Lead, Amazon Alexa Prize, BYU Perception Control and Cognition Laboratory
 2016 - 2019 Graduate Researcher, BYU Perception Control and Cognition Laboratory
 2016 - 2016 Adjunct Instructor, Brigham Young University
 2009 - 2016 Software Developer, PV Elektrotechnik, GmbH, Edeweicht, Germany

Products**Products Most Closely Related to the Proposed Project**

1. Zachary Brown, Nathaniel Robinson, David Wingate, Nancy Fulda. Towards Neural Programming Interfaces. Proceedings of the Thirty-Fourth Conference on Neural Information Processing Systems (NeurIPS); 2020; c2020.
2. Fulda Nancy, Tibbets Nathan, Brown Zachary, Wingate David. Harnessing Common-Sense Navigational Knowledge for Robotics from Uncurated Text Corpora. Proceedings of the 1st Conference on Robot Learning (CoRL); 2017; c2017.
3. Fulda Nancy, Ricks Daniel, Murdoch Ben, Wingate David. What Can You do with a Rock? Affordance Extraction via Word Embeddings. International Joint Conference on Artificial Intelligence (IJCAI); 2017; c2017.
4. Peterson Todd S, Owens Nancy E, Carroll James L. Towards automatic shaping in robot navigation. Proceedings of the IEEE International Conference on Robotics and Automation (ICRA); 2001; c2001.
5. Barton T, Yu H, Rogers K, Fulda N, Chiang S, Yorgason J, Warnick K. Towards Low-Power Machine Learning Architectures Inspired by Brain Neuromodulatory Signalling. Journal of Low

Other Significant Products, Whether or Not Related to the Proposed Project

1. Andrus Berkeley R, Nasiri Yeganeh, Cui Shilong, Cullen Benjamin, Fulda Nancy. Enhanced story comprehension for large language models through dynamic document-based knowledge graphs. Proceedings of the AAAI Conference on Artificial Intelligence; 2022; c2022.
2. Myers Will, Etchart Tyler, Fulda Nancy. Conversational Scaffolding: An Analogy-Based Approach to Response Prioritization in Open-Domain Dialogs. Proceedings of the 12th International Conference on Agents and Artificial Intelligence (ICAART); 2020; c2020.
3. Andrus Berkeley, Fulda Nancy. Immersive Gameplay via Improved Natural Language Understanding. Foundations of Digital Games Conference (FDG); 2020; c2020.
4. Nancy Fulda, Ben Murdoch Daniel Ricks, David Wingate. Informing Action Primitives Through Free-Form Text. NeurIPS Workshop on Visually Grounded Interaction and Language; 2017; c2017.
5. Fulda Nancy, Ventura Dan. Predicting and Preventing Coordination Problems in Cooperative Q-learning Systems. Proceedings of the International Joint Conference on Artificial Intelligence; ; c2007.

Synergistic Activities

1. National Science Foundation (NSF): Ad hoc reviewer for Small Business Innovation Research (SBIR), 2020; Honorable Mention, Graduate Research Fellowship, 2016.
2. Amazon Alexa Prize: Team Lead, BYU-EVE project, 2018. This project involved the design, implementation, and texting of a massively parallel, fully-integrated AI system for Amazon Alexa, including load balancing, natural language understanding, intent detection, response generation, and the ability to maintain hundreds of real-time conversations in a commercial setting.
3. Academic Conferences: Invited Speaker, NeurIPS Workshop on Reinforcement and Language Learning in Text-Based Games, 2019; Program Committee Member, International Conference on Computational Linguistics, 2020; Program Committee Member, Doctoral Consortium at the Conference on Artificial Intelligence and Interactive Digital Entertainment (AIIDE), 2019. Program Committee Member, AAAI Workshop on Knowledge Extraction from Games, 2018.
4. Education and Teaching: Guest Lecturer, Graduate course on Interactive Fiction and Text Generation, University of Pennsylvania, 2020; Invited Speaker, Computer Science for Lawyers, 2020; Invited Speaker, BYU College of Physical and Mathematical Sciences Volunteer Leadership Council, 2017; Guest Lecturer, CS 404-Computer Ethics, “Women in Computer Science”, 2016.
5. Advising: Committee Chair for 2 Doctor of Philosophy (Ph.D.) and 2 Master of Science (M.S.) students; on Committee for 6 Ph.D. and 9 M.S. students (2019–present).

Certification:

When the individual signs the certification on behalf of themselves, they are certifying that the information is current, accurate, and complete. This includes, but is not limited to, information related to domestic and foreign appointments and positions. Misrepresentations and/or omissions may be

NAME: Karl Foster Warnick

POSITION TITLE & INSTITUTION: Professor, Brigham Young University

A. PROFESSIONAL PREPARATION - (see [PAPPG Chapter II.C.2.f.\(i\)\(a\)](#))

INSTITUTION	LOCATION	MAJOR/AREA OF STUDY	DEGREE (if applicable)	YEAR (YYYY)
Brigham Young University	Provo, UT	Electrical & Computer Engineering	BS	1993
Brigham Young University	Provo, UT	Electrical & Computer Engineering	PhD	1997
University of Illinois at Urbana-Champaign	Urbana, IL	Computational Electromagnetics	Postdoc	1998-2000

B. APPOINTMENTS - (see [PAPPG Chapter II.C.2.f.\(i\)\(b\)](#))

From - To	Position Title, Organization and Location
2011-present	Professor, Brigham Young University, Department of Electrical and Computer Engineering
2006-2011	Associate Professor, Brigham Young University, Department of Electrical and Computer Engineering
2000-2006	Assistant Professor, Brigham Young University, Department of Electrical and Computer Engineering
July-Aug. 2005 and Sep.-Dec. 2007	Visiting Professor, Technische Universität München, Germany
Jun. 1998 – Aug 2000	Visiting Assistant Professor, University of Illinois at Urbana-Champaign

C. PRODUCTS - (see [PAPPG Chapter II.C.2.f.\(i\)\(c\)](#)) Products Most Closely Related to the Proposed Project

1. P. DeFranco, J. Mackie, M. Morin, and K. F. Warnick, "Bio-inspired electromagnetic orientation for UAVs in a GPS-denied environment using MIMO channel sounding," IEEE Transactions on Antennas and Propagation, Vol. 62, No. 10, pp. 5250-5259, 2014.
2. K. F. Warnick, Numerical Methods for Engineering with MATLAB and Computational Electromagnetics Examples Second Edition, IET Press, 2020.
3. L. R. Sahawneh, J. K. Wickle, A. K. Roberts, J. C. Spencer, R. W. Beard, T. W. McLain, K. F. Warnick, "A ground-based sense-and-avoid system for small unmanned aircraft," Journal of Aerospace Information Systems, Vol. 15, No. 8, 2018.
4. L. Sahawneh, J. Mackie, J. Spencer, R. W. Beard, and K. F. Warnick, "Airborne radar-based collision detection and risk estimation for small unmanned aircraft systems," Journal of Aerospace Information Systems, doi: 10.2514/1.I010284, 11 pages, 2015.
5. K. F. Warnick, S. J. Francom, Paul H. Humble, R. T. Kelly, A. T. Woolley, M. L. Lee, and H. D. Tolley, "Field gradient electrophoresis," Electrophoresis, Vol. 26, No. 2, pp. 405-414, Jan. 2005.

NAME: Yorgason, Jordan Thomas

POSITION TITLE & INSTITUTION: Assistant Professor, Brigham Young University

A. PROFESSIONAL PREPARATION - (see [PAPPG Chapter II.C.2.f.\(i\)\(a\)](#))

INSTITUTION	LOCATION	MAJOR/AREA OF STUDY	DEGREE (if applicable)	YEAR (YYYY)
Utah Valley University	Orem, UT	General	AS	2004
Brigham Young University	Provo, UT	Neuroscience	BS	2008
Wake Forest School of Medicine	Winston-Salem, NC	Neuroscience	PhD	2013

B. APPOINTMENTS - (see [PAPPG Chapter II.C.2.f.\(i\)\(b\)](#))

From - To	Position Title, Organization and Location
2018-Present	Assistant Professor, Department of Cellular Biology and Physiology, Neuroscience Center, Brigham Young University, Provo UT
2016-2018	Postdoctoral Fellow, Department of Psychology and Neuroscience Center, Brigham Young University, Provo UT
2013-2016	Postdoctoral Fellow, Vollum Institute of Advanced Biomedical Research, Oregon Health and Sciences University, Portland OR

C. PRODUCTS - (see [PAPPG Chapter II.C.2.f.\(i\)\(c\)](#)) Products Most Closely Related to the Proposed Project

1. Everett AC, Graul BE, Ronström JW, Robinson JK, Watts DB, España RA, Siciliano CA, Yorgason JT (2022). Effectiveness and Relationship between Biased and Unbiased Measures of Dopamine Release and Clearance. *ACS Chemical Neurosci.* 13(10):1534-1548.
2. Yorgason JT, Schilaty ND, Hedges DM, Jang EY, Murdock E, Wadsworth HA, Anderson EJ, Wallner M, Steffensen SC (2022). Modulation of dopamine release by ethanol is mediated by atypical GABAA receptors on cholinergic interneurons in the Nucleus Accumbens. *Addiction Biology.* 27(1):e13108.
3. Brundage JN, Finuf CS, Mason CP, Nelson JJ, Wadsworth HA, Ronstroem J, Steffensen SC, Yorgason JT (2022). Regional and sex differences in spontaneous striatal dopamine transmission. *J Neurochem.* 160(6):598-612.
4. Yorgason JT, Hedges DM, O Bray JD, Jang EY, Bills KB, Woodbury W, Williams B, Parsons MJ, Andres MA, Steffensen SC (2020). Methamphetamine increases dopamine release in the nucleus accumbens through calcium-dependent processes. *Psychopharmacology.* 237(5):1317-1330.
5. Yorgason JT, Zeppenfeld DM, Williams JT (2017). Cholinergic interneurons underlie spontaneous dopamine release in nucleus accumbens. *J Neurosci* 37:2086-2096.

NAME:

POSITION TITLE & INSTITUTION:

A. PROFESSIONAL PREPARATION - (see [PAPPG Chapter II.C.2.f.\(i\)\(a\)](#))

INSTITUTION	LOCATION	MAJOR/AREA OF STUDY	DEGREE (if applicable)	YEAR (YYYY)

B. APPOINTMENTS - (see [PAPPG Chapter II.C.2.f.\(i\)\(b\)](#))

From - To	Position Title, Organization and Location

C. PRODUCTS - (see [PAPPG Chapter II.C.2.f.\(i\)\(c\)](#)) Products Most Closely Related to the Proposed Project

PI/co-PI/Senior Personnel: Fulda, Nancy

PROJECT/PROPOSAL CURRENT SUPPORT

1. Project/Proposal Title: MRI: Acquisition of the LanguageLens for Large-Scale Language Modeling

Proposal/Award Number (if available): 2214708

Source of Support: NSF MRI

Primary Place of Performance: Brigham Young University

Project/Proposal Support Start Date (if available): 08/2022

Project/Proposal Support End Date (if available): 07/2025

Total Award Amount (including Indirect Costs): \$1,014,815

Person-Month(s) (or Partial Person-Months) Per Year Committed to the Project:

Year	Person-months per year committed
2022	0.1
2023	0.1
2024	0.1
2025	0.1

Overall Objectives: This proposal seeks to acquire a high-performance instrument designed to support next-gen NLP research, including training and analyzing large-scale language models. Among other objectives, this instrument will directly support interdisciplinary research that leverages language models to address pressing social problems such as racism, and will have significant national impact by making high-quality language models freely available to all.

Statement of Potential Overlap: None

2. Project/Proposal Title: EAGER: Harnessing Accurate Bias in Large-Scale Language Models

Proposal/Award Number (if available): 2141680

Source of Support: NSF

Primary Place of Performance: BYU

Project/Proposal Support Start Date (if available): 09/2021

Project/Proposal Support End Date (if available): 02/2023

Total Award Amount (including Indirect Costs): \$278,914

Person-Month(s) (or Partial Person-Months) Per Year Committed to the Project:

Year	Person-months per year committed
2022	0.25
2023	0.25

Overall Objectives: This project asks if researchers can harness the bias embedded in large scale language models (LSLMs) to advance our understanding of the social beliefs, political attitudes, and behavior of individuals. We explore the potential of LSLMs to serve as surrogates for human populations, act as a triage mechanism for survey questions and experimental interventions, test social science theories, and generate unexpected insights about human cognition and behavior.

Statement of Potential Overlap: N/A

PROJECT/PROPOSAL PENDING SUPPORT

1. Project/Proposal Title: Brain-inspired Analog Circuits for Low-energy Machine Learning

Proposal/Award Number (if available):

Source of Support: Brigham Young University

Primary Place of Performance: Brigham Young University

Project/Proposal Support Start Date (if available): 09/2023

Project/Proposal Support End Date (if available): 09/2024

Total Award Amount (including Indirect Costs): \$20,000

Person-Month(s) (or Partial Person-Months) Per Year Committed to the Project:

Year	Person-months per year committed
2023	0.5
2024	0.5

Overall Objectives: Existing machine learning uses orders of magnitude more energy than biological learning in the brain. Our collaborating is combining recent understanding of brain neuron chemistry and behavior with innovations in analog and mixed signal circuit design and new architectures for neural networks to create new brain-inspired learning circuits that power

robotics and mobile systems with machine learning at much lower energy requirement than existing technologies.

Statement of Potential Overlap: N/A

2. Project/Proposal Title: NAIRI: Theme 2: Advancing the Neurocognitive Foundations of AI through Human Centered Creative AI

Proposal/Award Number (if available):

Source of Support: UNCC/NSF NAIRI

Primary Place of Performance: BYU

Project/Proposal Support Start Date (if available): 06/2023

Project/Proposal Support End Date (if available): 05/2028

Total Award Amount (including Indirect Costs): \$2,569,942

Person-Month(s) (or Partial Person-Months) Per Year Committed to the Project:

Year	Person-months per year committed
2023	1
2024	1
2025	1
2026	1
2027	1

Overall Objectives: The CreativeAI Institute seeks to revolutionize the neurocognitive foundations of artificial intelligence by embracing understudied hallmarks of human intelligence, which we broadly term "creativity".

Statement of Potential Overlap: None

*PI/co-PI/Senior Personnel Name:

***Required fields**

Note: NSF has provided 15 project/proposal and 10 in-kind contribution entries for users to populate. Please leave any unused entries blank.

Project/Proposal Section:

Current and Pending Support includes all resources made available to an individual in support of and/or related to all of his/her research efforts, regardless of whether or not they have monetary value.^[1] Information must be provided about all current and pending support, including this project, for ongoing projects, and for any proposals currently under consideration from whatever source, irrespective of whether such support is provided through the proposing organization or is provided directly to the individual. This includes, for example, Federal, State, local, foreign, public or private foundations, non-profit organizations, industrial or other commercial organizations, or internal funds allocated toward specific projects. Concurrent submission of a proposal to other organizations will not prejudice its review by NSF, if disclosed.^[2]

^[1] If the time commitment or dollar value is not readily ascertainable, reasonable estimates should be provided.

^[2] The Biological Sciences Directorate exception to this policy is delineated in PAPPG Chapter II.D.2.

Projects/Proposals

1.*Project/Proposal Title :

*Status of Support : Current Pending Submission Planned Transfer of Support

Proposal/Award Number (if available):

*Source of Support:

*Primary Place of Performance :

Project/Proposal Start Date (MM/YYYY) (if available) :

Project/Proposal End Date (MM/YYYY) (if available) :

*Total Award Amount (including Indirect Costs): \$

*Person-Month(s) (or Partial Person-Months) Per Year Committed to the Project

*Year (YYYY)	*Person Months (##.##)	Year (YYYY)	Person Months (##.##)
1.		4.	
2.		5.	
3.			

*Overall Objectives :

*Statement of
Potential Overlap :

Projects/Proposals

2.*Project/Proposal Title :

*Status of Support : Current Pending Submission Planned Transfer of Support

Proposal/Award Number (if available):

*Source of Support:

*Primary Place of Performance :

Project/Proposal Start Date (MM/YYYY) (if available) :

Project/Proposal End Date (MM/YYYY) (if available) :

*Total Award Amount (including Indirect Costs): \$

*Person-Month(s) (or Partial Person-Months) Per Year Committed to the Project

*Year (YYYY)	*Person Months (##.##)	Year (YYYY)	Person Months (##.##)
1.		4.	
2.		5.	
3.			

*Overall Objectives :

*Statement of
Potential Overlap :

Projects/Proposals

3.*Project/Proposal Title :

*Status of Support : Current Pending Submission Planned Transfer of Support

Proposal/Award Number (if available):

*Source of Support:

*Primary Place of Performance :

Project/Proposal Start Date (MM/YYYY) (if available) :

Project/Proposal End Date (MM/YYYY) (if available) :

*Total Award Amount (including Indirect Costs): \$

*Person-Month(s) (or Partial Person-Months) Per Year Committed to the Project

*Year (YYYY)	*Person Months (##.##)	Year (YYYY)	Person Months (##.##)
1.		4.	
2.		5.	
3.			

*Overall Objectives :

*Statement of
Potential Overlap :

Projects/Proposals

4.*Project/Proposal Title :

*Status of Support : Current Pending Submission Planned Transfer of Support

Proposal/Award Number (if available):

*Source of Support:

*Primary Place of Performance :

Project/Proposal Start Date (MM/YYYY) (if available) :

Project/Proposal End Date (MM/YYYY) (if available) :

*Total Award Amount (including Indirect Costs): \$

*Person-Month(s) (or Partial Person-Months) Per Year Committed to the Project

*Year (YYYY)	*Person Months (##.##)	Year (YYYY)	Person Months (##.##)
1.		4.	
2.		5.	
3.			

*Overall Objectives :

*Statement of
Potential Overlap :

Projects/Proposals

5.*Project/Proposal Title :

*Status of Support : Current Pending Submission Planned Transfer of Support

Proposal/Award Number (if available):

*Source of Support:

*Primary Place of Performance :

Project/Proposal Start Date (MM/YYYY) (if available) :

Project/Proposal End Date (MM/YYYY) (if available) :

*Total Award Amount (including Indirect Costs): \$

*Person-Month(s) (or Partial Person-Months) Per Year Committed to the Project

*Year (YYYY)	*Person Months (##.##)	Year (YYYY)	Person Months (##.##)
1.		4.	
2.		5.	
3.			

*Overall Objectives :

*Statement of
Potential Overlap :

Current and Pending Support

Karl F. Warnick

Current

“ALPACA: Advanced Cryogenic L-band Phased Array Camera for the Arecibo Radio Telescope,” National Science Foundation, Co-PI, 6/2018 to 5/2023, \$5,820,529. Calendar: 0.1

“Collaborative Research: SWIFT: LARGE: Spectrum Sharing Via Interference-resilient Passive Receivers and Passive-aware Active Services,” National Science Foundation, Co-PI, 8/2020 to 8/2023, \$333,267. Calendar: 0.06

“Steerable, Directional Antennas to Increase Small Mobile Platform Communication Range,” Office of Naval Research ImSAR LLC STTR Phase I Subcontract, PI, 6/2022 to 7/2023, \$56,000. Calendar: 0.06.

Pending

“Modeling, Detection and Mitigation of Adverse Weather affecting Urban Air Flight,” NASA ULI, Co-PI, 6/2023 to 5/2026, \$601,512, Calendar: 0.1.

*PI/co-PI/Senior Personnel Name: Jordan Thomas Yorgason

***Required fields**

Note: NSF has provided 15 project/proposal and 10 in-kind contribution entries for users to populate. Please leave any unused entries blank.

Project/Proposal Section:

Current and Pending Support includes all resources made available to an individual in support of and/or related to all of his/her research efforts, regardless of whether or not they have monetary value.^[1] Information must be provided about all current and pending support, including this project, for ongoing projects, and for any proposals currently under consideration from whatever source, irrespective of whether such support is provided through the proposing organization or is provided directly to the individual. This includes, for example, Federal, State, local, foreign, public or private foundations, non-profit organizations, industrial or other commercial organizations, or internal funds allocated toward specific projects. Concurrent submission of a proposal to other organizations will not prejudice its review by NSF, if disclosed.^[2]

^[1] If the time commitment or dollar value is not readily ascertainable, reasonable estimates should be provided.

^[2] The Biological Sciences Directorate exception to this policy is delineated in PAPPG Chapter II.D.2.

Projects/Proposals

1.*Project/Proposal Title : : Neuroimmune mechanisms of alcohol reward

*Status of Support : ☐ Current ☒ Pending ☐ Submission Planned ☐ Transfer of Support

Proposal/Award Number (if available):

*Source of Support: NIAAA

*Primary Place of Performance : Brigham Young University

Project/Proposal Start Date (MM/YYYY) (if available) : 06/2023

Project/Proposal End Date (MM/YYYY) (if available) : 05/2028

*Total Award Amount (including Indirect Costs): \$ 1,861,873

*Person-Month(s) (or Partial Person-Months) Per Year Committed to the Project

*Year (YYYY)	*Person Months (##.##)	Year (YYYY)	Person Months (##.##)
1. 2023	1.00	4. 2026	1.00
2. 2024	1.00	5. 2027	1.00
3. 2025	1.00		

*Overall Objectives : Examine the interactions between the peripheral immune system and mesolimbic circuitry.

*Statement of Potential Overlap : None

Projects/Proposals

2.*Project/Proposal Title : Collaborative research between NOORDA College of Medicine and Brigham Young University

*Status of Support : ☒ Current ☐ Pending ☐ Submission Planned ☐ Transfer of Support

Proposal/Award Number (if available):

*Source of Support: Noorda College of Medicine

*Primary Place of Performance : Brigham Young University

Project/Proposal Start Date (MM/YYYY) (if available) : 06/2023

Project/Proposal End Date (MM/YYYY) (if available) : 05/2025

*Total Award Amount (including Indirect Costs): \$ 108,000

*Person-Month(s) (or Partial Person-Months) Per Year Committed to the Project

*Year (YYYY)	*Person Months (##.##)	Year (YYYY)	Person Months (##.##)
1. 2023	0.25	4.	
2. 2024	0.25	5.	
3. 2025	0.25		

*Overall Objectives : This funding is for maintaining laboratory animal research in connection with existing and future research projects alongside Noorda College of Medicine located near BYU. Current projects are investigating effects of opioids and alcohol on anxiety related neural circuitry.

*Statement of Potential Overlap : None