NDSEG personal statement: **Answer the following: What are your short and long-term professional goals? How did these goals develop? How have you already begun to lay the foundation for these goals? How does this fellowship fit into these goals? Keep in mind this is your introduction to the Reviewer. Additionally, this year we ask that you DO NOT reference, YOUR NAME, SCHOOL NAME, ADVISOR NAME, or anything that denotes who you are and what school you attend.**

My life is defined through intersections. Growing up in a military and an academic family, the union of these two environments presented an appreciation for inquiry and investigation, yet also a sense of duty and service to the community, a blending of curiosity and purpose. I similarly found my interests in school piqued by the confluence of physics and optimization, an exciting interdisciplinary field holding potential to advance understanding and impact in currently intractable problems, an intersection of theory and application. I aim to continue this path of integration and believe the NDSEG fellowship and a DoD career are precisely aligned to help me grow in this endeavor.

I had always specialized in physics prior to college, but was amazed by my first introduction to Operations Research (OR), which presented a new perspective and optimization-oriented approach to framing the same topics I first learned in physics. I subsequently pivoted to a compelling realm of problem-solving, blending physics with the power of modern computation. This choice has led me through a diverse range of research and education in many defense-oriented applications of STEM and exposed me to the direct impacts proper theory and application can have in our society. This solidified my short-term goal to attain a PhD in this realm—an intersection of physics and OR, of fundamental inquiry and public relevance.

My current PhD progress towards this aim has confirmed my long-term plan to expand my education in collaborative and impactful research in these topics in a government setting. My capability in this endeavor is corroborated by my diverse research accomplishments and leadership experiences (detailed in my CV). This background provides me a unique exposure to the intersections of DoD-relevant fields and a perspective that bridges the gaps between specialized communities, enabling effective communication between theorists, analysts, and administrators alike, promoting intrinsic motivation to explore where others require close supervision. I thrive in this integration, and know this program is exceptionally suited to my skills and interests.

Physics and OR have long been tied to the DoD, as OR originated from investigating how to maximize the effects of wartime actions, whose operational technologies were informed by physics. The DoD represents the intersection of these two fields I find fascinating, and I am certain the opportunity to work alongside the NDSEG Mentors in this intersection will be both stimulating and rewarding. The DoD's mission to support our country aligns with my objective-oriented approach to STEM and service-oriented mindset, and I seek the chance to collaborate among a team of likeminded peers. The professional experience and mentorship NDSEG provides offers a multidisciplinary preparation for the challenges of academic and government careers; from translating objectives to checkpoints that are tackled with careful theory and practice, to explaining and teaching results to individuals with diverse academic or cultural backgrounds. I welcome these challenges and want to become a multi-faceted leader and communicator in my field, and know your program is both aligned with my background and a crucial opportunity to achieve my goals.

Research Proposal: "AI Designers" of Photonic Metamaterials

Research Goal Summary: This project aims to develop artificial intelligence (AI) models to investigate data-driven and complementary forms of designing multi-component photonic metamaterials for defense, in order to expand current capabilities in metamaterial design and seed early-stage research into how complex hierarchical geometries influence photonic properties to further inform defense applications.

Background/Motivation: The advent of contemporary fabrication methods has spurred a renaissance of *metamaterials*, referring to devices and components engineered from the ground-up for a desirable set of properties, i.e., "designer" materials whose structural form is driven by their preferred function. *Photonic* metamaterials are structures which are optimized for functions related to interactions with light or electromagnetic radiation. Their optimized structures control the flow of light in non-intuitive and custom-picked ways, such as passive directing, filtering, or scattering at different wavelengths, which can improve electromagnetic shielding or camouflage for satellites or vehicles, or offer a means to more efficient photovoltaic cells for increased power capabilities in a field setting, among other applications.

Photonic metamaterials represent an innovative paradigm shift in design-thinking by proposing materials created solely for their intended functions (instead of using known materials to achieve a composite with desired properties) and herald a groundbreaking revolution in sensor and other defense technologies compared to current capabilities because of their potential to reduce costs (smaller multi-functional devices) and improve performance. However, progress in this subfield has been limited to date by limitations in additive manufacturing technologies (i.e., the resolution necessary to fabricate at wavelength or sub-wavelength scales, since device features must be on similar length scales to the radiation the material interacts with). Photonic metamaterials have only been realized and implemented for the first time in the past few years[1,2] due to advancements in computational power and nanofabrication technologies, which has led to a renewed interest in these materials and how to design them.

Due to the power of modern computation, photonic metamaterial designs have evolved from simpler heuristic-based geometries to complex optimization-based geometries that can encode multiple custom-picked functionalities into a single volume[2]. With computing power continuing to increase by the year, **we are thus faced with the question of what will define the next advancement of present capabilities in metamaterial design**. Most state-of-the-art photonic metamaterials design methods are limited to 3D *voxel-based topology optimization*, a direct gradient-based method for iteratively choosing the refractive index at every sublocation (voxel) in the output volume[1-3]. Current photonics research and results employing these methods share a common set of features, namely:

- *Binary*: The studies use a single material in their designs (each voxel is material or free space), which requires additional continuity constraints in the optimization (no free-floating material).
- *Complexity*: The optimized structures are often complex; disordered or even "organic" in appearance (Fig. 1). This in itself is not bad (restricting to *only* periodic options neglects many higher-performing geometries), but very irregular designs can create additional difficulty in device fabrication, which already requires sub-wavelength resolution/accuracy in printing.
- *Scaling*: The number of optimizable parameters grows with both total design size and design resolution (the number of voxels). This is tractable for designs on the order of a few hundred wavelengths (miniaturized sensors, etc.), but is intractable for large systems (centimeters-scale, like LIDAR-blocking tiles for military aircraft, etc.) that are not microscopically periodic (reduced complexity).

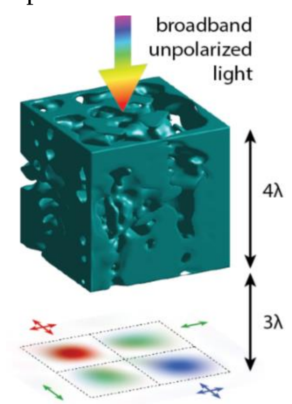

Figure 1: Directly-optimized device for polarization and color splitting. Directly optimized designs tend to be complex and irregular in appearance. (from Camayd-Muñoz *et al.*, 2020)[1]

These models offer advantages in functionality through their complexity capabilities, but also shun the full potential of an unconstrained parameter space with multiple material types, do not offer the same capabilities at large scale, and are sensitive to starting conditions. Furthermore, the current complexity precludes further analytical or human learning of how particular structures influence photonic properties—that is, that we can design optimized structures for given functionalities, but have no way of relating the resulting designs to the property space, or mapping between particular microstructures and a given photonic property. **We could benefit from complementary methods of generation/analysis that preserve complexity, permit further investigation/utilization of complex structures, and are scalable to a wider array of applications with less constraints. Can we extend and employ current results to a robust, widespread, and scalable architecture for photonic metamaterial generation that enhances US Defense capabilities?**

Artificial Intelligence (AI) offers many different resolutions to this question, forming the basis of this proposal and offering a chance to employ successful tools from several disciplines for defense. For instance, *Generative Adversarial Networks* (GANs) were invented in 2014 and consist of two competing neural networks that learn a *probabilistic distribution* over supplied training data, and then can generate more samples from this distribution[4]. GANs have outpaced other models in creating realistic pictures and paintings that can fool humans, and can even be trained to have "creative capabilities"; i.e., generating novel samples that humans cannot, samples that match the data distribution but are ambiguous with respect to predefined types of training data[5]. GANs have also shown success for complex regular and irregular texture generation/analysis for computer graphics and fashion research[6], suggesting their capabilities in geometry generation for metamaterials are already robust. GANs could thus be trained to generate (even "creatively") complex microstructures that humans could not for photonic metamaterials, and the resulting learned probability distribution could offer an investigative means to furthermore *relate* and analyze microstructures against their resulting properties for the first time.

Additionally, biomechanics research has found recent success in generating voxel-based robotic geometries via Compositional Pattern Producing Networks (CPPNs), whose *network structures* are iteratively tuned via genetic algorithms to optimize a given target objective (CPPN-NEAT)[7]. These networks incorporate non-standard activation functions that smoothly "pattern" the output space of the network as the output of composed functions. This approach dramatically reduces the dimensionality of the system to *only* the parameters of the network (i.e. not the resolution of the resulting structure) and results in infinite scalability, as voxels are determined by discretizing the functional output of the network at any desirable resolution. CPPNs can handle multiple material types and result in arbitrarily complex but regular patterns that can be optimized for multifunctional purposes[8] (Fig. 2). The features of this model thus suggest a scalable, non-binary architecture by which to generate metamaterial structures optimized for a given target property that preserve output complexity, but in a more-regular manner that is more conducive to fabrication under modern printing and lithography capabilities. Furthermore, unlike standard direct-optimization approaches where intermediate results during the optimization are often unrealistic or limited in function, the intermediate models during the training of CPPNs also offer viable structures to analyze.

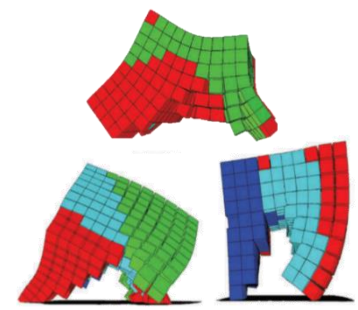

Figure 2: Soft robot designs by CPPNs. Notice the regularity of these multi-material designs (more conducive to fabrication), compared to those by direct optimization. (From Cheney *et al*., 2014)[7]

Given the success of these models in similar problems, it stands to reason that GANs and CPPNs should be explored for photonic metamaterial design and further understanding the fundamental structure-properties relations at different scales. Specifically, **a CPPN architecture is proposed as a means to produce multi-component optimized designs, and a GAN architecture is additionally proposed as a means to learn about microstructures from both current optimized designs and those generated by the CPPN as well as a means to generate data-driven metamaterial designs.**

Innovation and Relevance: Such a project offers investigation into AI-enabled and data-driven design of complex photonic metamaterials, as a next-generation approach to high-performance material design and a means to identify foundational connections between hierarchical microstructural forms and final photonic properties where such learning has been absent to date, in direct relevance to BAA targets. The innovation comes in merging nascent successes in metamaterial capabilities with proven methodologies from non-photonic disciplines, and thus serves to advance both in-field and cross-field knowledge through the extension of known techniques in a new way. The relevance to defense is ample, as many defense technologies rely on photonic components that could be miniaturized or improved via a robust

architecture for metamaterial design—such a means for encoding objective- or mission-specific properties into compact devices would reduce costs and material requirements as well as augment performance.
Benefits and Applications: The ramifications for successful scalable photonic metamaterials are staggering across myriad disciplines in addition to defense, as any functionality dependent on the flow control of electromagnetic radiation becomes feasible, from sensitive single-substance mid-IR chemical sensors in chemistry and medicine, to large-aperture optics, high-efficiency photovoltaic cells, radiation protection equipment, miniaturized sensors, and passive robust satellite instrumentation. With these wide-spread applications in reach, I would also expect a long-term increase of interest in the fields of metamaterials and optimization among a new generation of scientists. Near-term, the models could be modularized to create an amateur-friendly and widely applicable tool in AI-generated/analyzed geometries utilizable for knowledge creation in fields even beyond metamaterials, such as computer graphics or robotics, which could even be distributed open-source to encourage further innovation.
Aims/Methods/Measures: The goal of this proposal is to develop "AI Designers" of photonic metamaterials—efficient tools to expand functionalities and augment current approaches in generating novel optimal structures, as well as investigate relationships between structures and overall function. The development of these models as well as their benchmarking lend themselves well to a three-year timeline:
- *Aim 1: GAN for Data-Driven design/investigation (1.5 yr):* Existing optimized structures from contemporary research or structures generated from current methods offer training data for a GAN to learn the distribution of structures for a given photonic functionality and generate novel (i.e. "creative") geometries from this distribution. GAN architectures for 3D metamaterials would be developed to be trained on existing structural data *(0.5 yr)*. Sampling from the resulting distributions is low-cost and would provide a first-time statistical inference for relating complex geometrical forms to photonic function by comparing the frequencies of different hierarchical structures in a distribution against those from different learned distributions given a set of different photonic functionalities *(0.5 yr)*. Samples from a specific functionality (e.g., spectrum-splitting solar cells) would also be computationally assessed and fabricated/evaluated as a direct measure of GAN capability against current methods *(0.5 yr)*.
-*Aim 2: CPPN-NEAT for optimal design/fabrication (1.5 yr):* A CPPN architecture would be developed that evolves to optimize structures for the chosen photonic property, with the expanded capabilities of handling multiple material types and scaling to arbitrary structural sizes with significantly smaller model dimensionality, as well as preserving complexity but in a manner more conducive to fabrication *(0.5 yr)*. Network dimensionality and training time would then be benchmarked against current optimization techniques, as well as ease-of-fabrication and performance of the subsequent geometries *(0.5 yr)*. These designs and their intermediate forms can also be fed back to the GAN as additional training data, to deliver further learning on how structural form influences photonic properties through additional frequency analysis, completing the full cycle of structure design and analysis *(0.5 yr)*.
Feasibility and Resources: The success of GANs and CPPNs in their respective fields already offers promise to their extension into geometry creation for metamaterials, but even more so stems from the present doctoral research of the author which offers promising results for the capability of GANs to learn, generate, and interpret 2D metastructures relative to their *mechanical* properties (Fig. 3), since swapping from mechanical to optical evaluation merely requires changing the post-processing physics code, independent from the GAN and structural generation itself. The author is well-versed in optimization and GANs, and the models to evaluate properties as well as the evaluation and fabrication hardware are either already used by the author or already exist at the author's institution under the sponsorship of the author's advisers, offering an investigation with ample experience, little overhead, and large ramifications.

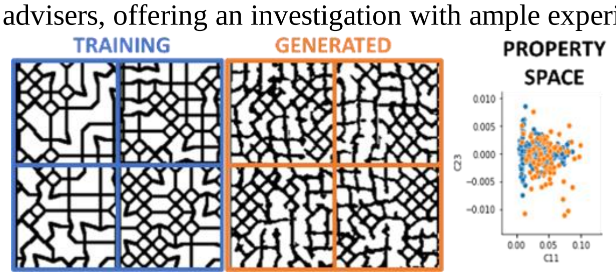

Figure 3: The author's ongoing GAN work. A GAN can be trained to generate new 2D structures from training data that have similar, but not identical, mechanical properties to those of the training set, suggesting potential in their ability to learn about optimized structures for a given *photonic* functionality, and then generate new structures with similar or improved performance in property space. Likewise, comparison of many generated samples and the frequency of particular structural features within them could be used to inform a relationship between microstructure and the resulting properties of the material.