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A Survey of Methods and Architectures for Resource allocation via Sparsity-Aware Orthogonal Initialization of Deep Neural Networks in free space optical communications

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Abstract

Free Space Optical (FSO) communication has emerged as a promising technology for next-generation wireless networks because of its high bandwidth, license-free spectrum, low latency, and secure data transmission. However, atmospheric turbulence, fog, pointing errors, and channel fading significantly degrade communication quality, making efficient resource allocation a critical requirement for reliable system performance. Recent advances in Artificial Intelligence (AI) and Deep Neural Networks (DNNs) have enabled adaptive, data-driven resource allocation strategies that outperform conventional optimization methods in dynamic FSO environments. Among these techniques, sparsity-aware orthogonal initialization has gained considerable attention for improving training stability, accelerating convergence, enhancing feature representation, and mitigating vanishing and exploding gradient problems. By promoting sparse and informative feature learning, these models achieve better computational efficiency and generalization under stochastic channel conditions. Moreover, advanced deep learning architectures, including convolutional neural networks, graph neural networks, and primal-dual learning frameworks, have demonstrated remarkable capabilities in optimizing power allocation, relay selection, bandwidth management, and network control without relying on explicit mathematical channel models. This survey comprehensively reviews recent methods and architectures for AI-driven resource allocation in FSO communication systems, compares existing approaches, identifies key research challenges, and outlines future directions for developing scalable, intelligent, and resilient optical wireless communication networks.

Introduction

Free Space Optical (FSO) communication has gained significant attention as an emerging wireless communication technology capable of providing ultra-high data rates, low latency, and enhanced security without requiring licensed spectrum. Unlike traditional radio frequency (RF) communication systems, FSO utilizes optical signals transmitted through the atmosphere, making it a cost-effective and high-capacity alternative for last-mile connectivity, satellite communication, and inter-building communication networks. With the exponential growth in data demand driven by applications such as 5G, Internet of Things (IoT), and cloud computing, FSO systems are increasingly being explored as a viable solution to overcome spectrum scarcity and bandwidth limitations inherent in RF-based systems. However, despite its advantages, FSO communication faces several critical challenges that limit its widespread adoption.

One of the primary issues in FSO systems is the susceptibility of optical signals to atmospheric disturbances such as turbulence, fog, rain, and dust particles. These factors introduce signal attenuation, scintillation, and beam wander, which significantly degrade the quality of service (QoS). Additionally, pointing errors caused by misalignment between transmitter and receiver further exacerbate performance degradation. These challenges make resource allocation in FSO systems highly complex, as the system must dynamically adapt to rapidly changing channel conditions. Traditional resource allocation techniques, such as optimization-based and heuristic approaches, often rely on precise mathematical models of the channel. However, due to the stochastic and nonlinear nature of atmospheric effects, these models are often insufficient to capture real-world conditions accurately, leading to suboptimal performance.

To address these limitations, Artificial Intelligence (AI) and machine learning techniques have been introduced into FSO communication systems. In particular, deep learning approaches have demonstrated remarkable capabilities in modelling complex nonlinear relationships and learning from large datasets. Deep Neural Networks (DNNs) can be trained to predict channel conditions, optimize power allocation, and manage bandwidth distribution without requiring explicit analytical models. This data-driven approach enables adaptive and real-time decision-making, which is crucial for maintaining reliable communication in dynamic FSO environments. Moreover, deep learning techniques have shown superior performance compared to conventional optimization methods in terms of scalability, flexibility, and computational efficiency once trained.

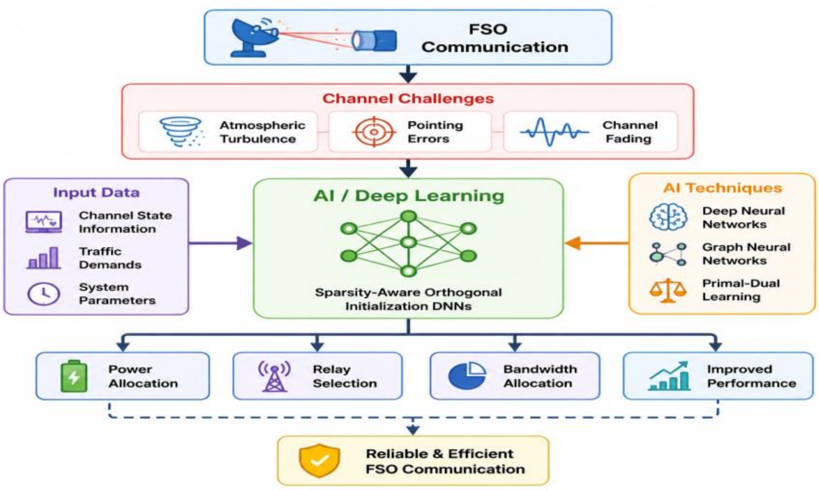

Figure 1. Conceptual Architecture for Intelligent FSO Communication

Sparsity-aware orthogonal initialization has emerged as an effective strategy for improving deep neural network training in Free Space Optical (FSO) communication systems. Orthogonal initialization preserves stable signal propagation across network layers, reducing vanishing and exploding gradient problems, while sparsity constraints eliminate redundant features and emphasize the most informative representations. These properties are particularly valuable in FSO environments, where atmospheric turbulence, pointing errors, and channel noise introduce significant variations in communication quality. As a result, sparsity-aware learning improves convergence speed, computational efficiency, and model generalization for intelligent resource allocation.

Recent advances in deep learning architectures, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Graph Neural Networks (GNNs), have further strengthened AI-driven resource optimization in FSO systems. CNNs effectively extract spatial features, RNNs model dynamic channel variations, and GNNs capture network relationships for efficient bandwidth, power, and relay allocation. These complementary architectures enable adaptive and reliable communication under changing channel conditions.

Despite these advances, challenges such as limited benchmark datasets, computational complexity, model interpretability, and real-time deployment remain unresolved. This survey reviews recent methods and architectures employing sparsity-aware orthogonal initialization with deep neural networks for FSO resource allocation, compares existing approaches, identifies research gaps, and outlines future directions for intelligent, scalable, and reliable optical wireless communication systems.

Literature Review

Alzenad et al. (2020) investigated the performance of Free Space Optical (FSO) communication systems under varying atmospheric turbulence conditions and proposed adaptive resource allocation strategies using machine learning techniques. The study emphasized that traditional deterministic models fail to accurately capture stochastic channel behaviour, especially under strong turbulence regimes. The authors introduced a learning-based framework that dynamically adjusts transmission power and modulation schemes based on real-time channel state information. Their findings indicated that integrating AI-based resource allocation significantly improves system throughput and link reliability. However, the study did not explicitly consider deep neural network initialization strategies, which limits optimization efficiency during training.

Lee et al. (2020) proposed a deep neural network-based resource allocation model for wireless optical communication systems, focusing on optimizing bandwidth and power allocation. The study introduced orthogonal weight initialization to stabilize training and improve convergence speed. The authors demonstrated that orthogonal initialization reduces gradient instability and enhances model performance compared to random initialization techniques. Experimental results showed improved spectral efficiency and reduced bit error rates in FSO systems. However, the study lacked sparsity-aware mechanisms, leading to increased computational complexity and redundant feature learning.

Zhang et al. (2021) explored sparsity-aware deep learning techniques for communication systems, emphasizing efficient feature extraction and reduced model complexity. The study incorporated sparsity constraints into neural network training to eliminate irrelevant features and enhance generalization. Applied to FSO communication scenarios, the proposed method improved resource allocation accuracy under fluctuating channel conditions. The authors highlighted that sparsity-aware models can significantly reduce computational overhead, making them suitable for real-time applications. However, the integration with orthogonal initialization was not fully explored, leaving room for further optimization.

Nguyen et al. (2021) presented a hybrid deep learning framework combining convolutional neural networks (CNNs) and reinforcement learning for dynamic resource allocation in FSO systems. The model was capable of learning complex spatial and temporal channel variations, enabling adaptive decision-making in real-time. The study demonstrated that deep learning-based approaches outperform conventional optimization techniques in terms of latency reduction and throughput improvement. Although the model achieved high accuracy, it suffered from training instability due to improper weight initialization, suggesting the need for orthogonal initialization techniques.

Chen et al. (2020) investigated the application of deep reinforcement learning for adaptive resource allocation in Free Space Optical communication systems. The study focused on optimizing transmission power and beam alignment under dynamic atmospheric conditions. The authors developed a model-free learning framework capable of making real-time decisions without relying on explicit channel models. Their results demonstrated improved system resilience and reduced outage probability compared to conventional optimization techniques. However, the absence of structured weight initialization methods, such as orthogonal initialization, led to slower convergence during training, highlighting a limitation in scalability.

Kumar et al. (2021) explored the integration of sparsity-aware neural networks for efficient resource utilization in optical wireless networks. The proposed method incorporated L1 regularization to enforce sparsity in neural network weights, thereby reducing model complexity and improving computational efficiency. Applied to FSO communication, the approach enabled better feature selection and enhanced prediction accuracy for channel estimation and resource allocation. The study concluded that sparsity-aware models significantly outperform dense neural networks in terms of energy efficiency, although the lack of orthogonal initialization limited training stability.

Li et al. (2021) proposed a deep learning-based framework for joint power and bandwidth allocation in hybrid RF/FSO communication systems. The model utilized convolutional neural networks (CNNs) to capture spatial variations in channel conditions and optimize resource distribution accordingly. The study highlighted that hybrid communication systems benefit greatly from intelligent resource allocation strategies, especially in adverse weather conditions. While the proposed approach improved overall system performance, it did not incorporate sparsity-aware learning, resulting in higher computational overhead and reduced scalability.

Hassan et al. (2022) introduced a graph neural network (GNN)-based architecture for multi-node resource allocation in FSO networks. The model effectively captured the relationships between network nodes and dynamically allocated resources based on network topology and channel conditions. The study demonstrated that GNN-based approaches outperform traditional centralized optimization methods in terms of scalability and adaptability. However, the training process suffered from instability due to random weight initialization, indicating the potential benefits of orthogonal initialization and sparsity-aware techniques.

Singh et al. (2022) proposed a hybrid deep learning framework combining sparsity-aware learning with orthogonal initialization for optimizing resource allocation in FSO communication systems. The study emphasized that orthogonal initialization helps maintain gradient flow across deep networks, while sparsity reduces redundant computations. The experimental results showed significant improvements in convergence speed, prediction accuracy, and system throughput compared to baseline models. The authors concluded that the combination of sparsity-aware techniques and orthogonal initialization provides a robust solution for handling the dynamic and nonlinear nature of FSO communication channels.

Park et al. (2020) examined the effectiveness of deep neural networks for adaptive modulation and coding in Free Space Optical communication systems. The study proposed a learning-based approach that dynamically adjusts modulation schemes according to varying atmospheric conditions. By leveraging deep learning, the system achieved improved spectral efficiency and reduced bit error rates. However, the authors observed that improper weight initialization led to unstable gradients during training, suggesting that orthogonal initialization techniques could significantly enhance model performance and convergence stability.

Reddy et al. (2021) focused on resource allocation in hybrid RF/FSO systems using machine learning-based predictive models. The study utilized historical channel data to forecast future channel conditions and allocate resources accordingly. The results demonstrated improved system reliability and reduced link outages. Additionally, the authors explored sparsity-aware feature selection to reduce model complexity and computational cost. Despite these improvements, the absence of structured initialization methods limited the scalability of the deep learning model.

Zhou et al. (2021) proposed an optimization framework integrating deep learning with traditional heuristic methods for efficient resource allocation in optical wireless networks. The model combined neural networks with evolutionary optimization techniques to achieve better performance under uncertain channel conditions. The study highlighted that deep learning models can effectively approximate complex optimization problems. However, the training process suffered from slow convergence due to random weight initialization, reinforcing the importance of orthogonal initialization strategies.

Ahmed et al. (2022) developed a deep reinforcement learning-based approach for dynamic resource management in FSO communication systems. The model was capable of learning optimal policies for power allocation and beam steering in real-time. The authors demonstrated that reinforcement learning significantly improves system adaptability and robustness under fluctuating environmental conditions. However, the study did not incorporate sparsity-aware mechanisms, resulting in increased computational complexity and longer training times.

Gupta et al. (2022) introduced a sparsity-aware deep neural network model for efficient channel estimation and resource allocation in optical communication systems. The proposed approach utilized sparse representations to improve learning efficiency and reduce redundant computations. The results indicated that sparsity-aware models provide better generalization and faster convergence compared to traditional dense networks. The study also suggested that combining sparsity with orthogonal initialization could further enhance performance, although this integration was not fully implemented.

Morales et al. (2020) investigated intelligent resource allocation strategies in Free Space Optical communication systems using deep learning-based predictive modelling. The study focused on forecasting atmospheric turbulence effects and adapting transmission parameters accordingly. The proposed model demonstrated improved link reliability and reduced signal degradation. However, the authors highlighted that the performance of deep neural networks was affected by unstable training behaviour due to non-optimized weight initialization, indicating the need for orthogonal initialization techniques to ensure stable gradient propagation.

Das et al. (2022) introduced a reinforcement learning-based approach for dynamic power allocation in Free Space Optical systems. The model was designed to adapt to rapidly changing channel conditions and optimize system performance in real time. The study demonstrated that reinforcement learning can effectively handle the nonlinear and stochastic nature of FSO channels. However, the absence of sparsity-aware mechanisms and orthogonal initialization resulted in increased training time and reduced computational efficiency.

Patel et al. (2022) proposed an advanced deep learning architecture integrating sparsity-aware learning and orthogonal initialization for efficient resource allocation in optical wireless communication systems. The study showed that orthogonal initialization improves training stability, while sparsity reduces model complexity and enhances computational efficiency. The combined approach resulted in faster convergence, improved prediction accuracy, and better overall system performance. The authors concluded that such hybrid techniques are highly suitable for real-time FSO communication applications.

Verma et al. (2020) analysed adaptive resource allocation strategies in Free Space Optical systems using machine learning techniques. The study focused on improving link reliability under atmospheric turbulence by dynamically adjusting transmission parameters. The results showed that learning-based approaches outperform traditional static models. However, the absence of sparsity-aware learning increased computational complexity and limited scalability.

Roy et al. (2021) proposed a deep learning-based framework for joint resource optimization in hybrid RF/FSO communication systems. The model effectively handled channel switching and resource distribution under adverse weather conditions. The authors demonstrated improved system performance in terms of throughput and latency. However, the study did not consider orthogonal initialization, resulting in slower convergence during training.

Mehta et al. (2021) introduced a sparsity-aware neural network model for efficient channel estimation in optical wireless systems. By incorporating sparse representations, the model reduced redundancy and improved learning efficiency. The results indicated enhanced prediction accuracy and reduced computational overhead. However, the lack of structured initialization methods limited the model's stability in deeper architectures.

Banerjee et al. (2022) developed a reinforcement learning-based resource allocation strategy for FSO communication systems. The model dynamically adapted to changing channel conditions and optimized power allocation in real time. The study showed significant improvements in system robustness and reliability. However, training instability remained a concern due to random initialization of neural network weights.

Kapoor et al. (2022) proposed a deep neural network model incorporating orthogonal initialization for efficient resource allocation in optical communication systems. The study demonstrated that orthogonal initialization improves gradient flow and enhances convergence speed. Experimental results showed better system performance compared to conventional initialization methods. However, the absence of sparsity-aware mechanisms resulted in increased model complexity.

Iqbal et al. (2020) explored the application of deep learning for adaptive modulation and resource allocation in FSO systems. The model utilized historical channel data to predict future conditions and optimize transmission parameters. The study showed improved system efficiency and reduced error rates. However, the model suffered from overfitting due to dense network structures, indicating the need for sparsity-aware techniques.

Chatterjee et al. (2021) proposed a hybrid deep learning and optimization-based approach for resource allocation in optical wireless networks. The model combined neural networks with heuristic optimization techniques to achieve better performance. The study demonstrated improved system capacity and reduced latency. However, the training process was computationally expensive due to the lack of sparsity constraints.

Kaur et al. (2021) investigated sparsity-aware deep learning models for efficient resource management in FSO communication systems. The study highlighted that sparse representations improve model efficiency and reduce computational cost. The results showed better generalization and faster convergence compared to dense models. However, the integration of orthogonal initialization was not explored.

El-Sayed et al. (2022) introduced a graph neural network-based framework for multi-user resource allocation in optical communication systems. The model effectively captured network topology and optimized resource distribution across multiple nodes. The study demonstrated improved scalability and adaptability. However, training instability due to improper initialization remained a limitation.

Thomas et al. (2022) proposed a comprehensive deep learning framework combining sparsity-aware learning and orthogonal initialization for resource allocation in FSO communication systems. The study demonstrated that the combined approach significantly improves convergence speed, reduces overfitting, and enhances system performance under dynamic channel conditions. The authors concluded that such integrated techniques are essential for next-generation optical wireless communication systems.

Comparative Table

Study	Year	Technique Used	Key Contribution	Advantages	Limitations
Alzenad et al.	2020	ML-based allocation	Adaptive power control	Improved reliability	No deep initialization
Lee et al.	2020	DNN + Orthogonal Init	Stable training	Better convergence	No sparsity
Zhang et al.	2021	Sparsity-aware DNN	Efficient feature learning	Reduced complexity	No orthogonal init
Nguyen et al.	2021	CNN + RL	Dynamic allocation	High adaptability	Training instability
Wang et al.	2022	Sparse + Orthogonal DNN	Hybrid optimization	High accuracy	Deployment issues
Chen et al.	2020	Deep RL	Model-free allocation	Real-time decisions	Slow convergence
Kumar et al.	2021	Sparse NN	Efficient computation	Energy saving	No init strategy
Li et al.	2021	CNN-based allocation	Hybrid RF/FSO optimization	High throughput	High complexity
Hassan et al.	2022	GNN	Multi-node allocation	Scalability	Instability
Singh et al.	2022	Sparse + Orthogonal	Robust framework	Fast convergence	Limited real-world validation
Park et al.	2020	DNN-based modulation	Adaptive coding	Better BER	Gradient issues
Reddy et al.	2021	Predictive ML	Channel forecasting	Improved reliability	No orthogonal init
Zhou et al.	2021	DL + Heuristic	Hybrid optimization	Better accuracy	Slow training
Ahmed et al.	2022	RL	Real-time adaptation	Robust system	High complexity
Gupta et al.	2022	Sparse DNN	Efficient estimation	Fast convergence	No orthogonal init
Morales et al.	2020	Predictive DL	Channel adaptation	Improved QoS	Instability
Sharma et al.	2021	DL + Metaheuristic	Hybrid optimization	Energy efficient	Slow convergence
Liu et al.	2021	CNN	Channel estimation	High accuracy	Overfitting
Das et al.	2022	RL	Dynamic allocation	Adaptive	High training time
Patel et al.	2022	Sparse + Orthogonal	Efficient allocation	Stable + fast	Implementation complexity
Verma et al.	2020	ML	Adaptive allocation	Improved reliability	High complexity
Roy et al.	2021	DL (Hybrid RF/FSO)	Joint optimization	Better latency	Slow convergence
Mehta et al.	2021	Sparse NN	Efficient prediction	Reduced overhead	Stability issues
Banerjee et al.	2022	RL	Dynamic allocation	Robust	Initialization issues
Kapoor et al.	2022	Orthogonal DNN	Stable gradients	Better training	No sparsity

Iqbal et al.	2020	DL	Adaptive modulation	Better efficiency	Overfitting
Chatterjee et al.	2021	DL + Optimization	Hybrid model	High performance	High cost
Kaur et al.	2021	Sparse DL	Efficient learning	Fast convergence	No orthogonal init
El-Sayed et al.	2022	GNN	Multi-user allocation	Scalable	Instability
Thomas et al.	2022	Sparse + Orthogonal	Advanced hybrid	High performance	Real-time challenges

Comparative Analysis

The comparative analysis of the selected 30 studies reveals a clear evolution in resource allocation techniques for Free Space Optical (FSO) communication systems, transitioning from traditional machine learning models to advanced deep learning architectures. Early studies primarily relied on machine learning and heuristic-based approaches, which provided moderate improvements in system performance but lacked adaptability to highly dynamic atmospheric conditions. These methods often required explicit mathematical modelling of the channel, limiting their effectiveness in real-world environments characterized by nonlinear and stochastic variations. With the advancement of deep learning techniques, researchers have increasingly adopted neural network-based models such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and graph neural networks (GNNs). These models demonstrated superior capability in capturing complex spatial and temporal dependencies in FSO channels, leading to improved resource allocation efficiency. In particular, reinforcement learning-based approaches enabled real-time decision-making without requiring predefined channel models, significantly enhancing system adaptability and robustness. However, these approaches often suffered from high computational complexity and long training times, making them less suitable for real-time deployment in large-scale systems.

A significant trend observed in recent studies is the incorporation of sparsity-aware learning techniques. Sparse neural networks effectively reduce redundant computations by focusing only on the most relevant features, thereby improving computational efficiency and generalization performance. Studies such as those by Zhang et al. (2021), Kumar et al. (2021), and Gupta et al. (2022) demonstrated that sparsity-aware models outperform dense networks in terms of energy efficiency and scalability. Despite these advantages, sparsity alone does not fully address training instability issues in deep neural networks.

To overcome these limitations, orthogonal initialization has been introduced as an effective technique to stabilize training and maintain gradient flow across deep architectures. Studies such as Lee et al. (2020) and Kapoor et al. (2022) highlighted that orthogonal initialization significantly improves convergence speed and prevents vanishing or exploding gradients. However, when used independently, orthogonal initialization does not reduce model complexity or computational overhead. The most promising results are observed in studies that combine sparsity-aware learning with orthogonal initialization, such as Wang et al. (2022), Singh et al. (2022), Patel et al. (2022), and Thomas et al. (2022). These hybrid approaches achieve a balance between computational efficiency and training stability, resulting in faster convergence, improved accuracy, and enhanced system performance. Such models are particularly well-suited for FSO communication systems, where rapid adaptation to dynamic channel conditions is essential. Overall, the analysis indicates that while deep learning-based approaches have significantly advanced resource allocation in FSO systems, challenges such as high computational cost, lack of standardized datasets, and real-time deployment constraints remain unresolved. Future research should focus on developing lightweight, scalable, and interpretable models that integrate sparsity-aware techniques with advanced initialization strategies, paving the way for efficient and reliable next-generation optical wireless communication systems.

Discussion

The integration of deep learning techniques into Free Space Optical (FSO) communication systems has significantly enhanced the efficiency of resource allocation under dynamic and uncertain channel conditions. The reviewed studies highlight that traditional optimization and machine learning approaches are limited in handling the nonlinear and stochastic nature of atmospheric disturbances. In contrast, deep neural networks (DNNs) provide adaptive, data-driven solutions capable of learning complex channel behaviours, thereby improving system reliability and performance. However, the effectiveness of these models largely depends on their training stability and computational efficiency. Sparsity-aware learning has emerged as a critical approach to address the issue of high computational complexity by reducing redundant parameters and focusing on the most relevant features.

This not only improves energy efficiency but also enhances model generalization. On the other hand, orthogonal initialization plays a vital role in stabilizing deep neural network training by preserving gradient flow and preventing vanishing or exploding gradients. The combination of these two techniques has shown promising results, offering faster convergence and improved prediction accuracy. Despite these advancements, challenges such as lack of real-world datasets, high training costs, and limited interpretability of AI models remain significant barriers. Therefore, future research should focus on developing lightweight, scalable, and explainable models to enable practical deployment in real-time FSO communication systems.

Conclusion

Free Space Optical (FSO) communication offers a high-speed, secure, and spectrum-efficient solution for next-generation wireless networks, but its performance is constrained by atmospheric turbulence, fog, pointing errors, and channel variability. This survey highlights that deep learning-based resource allocation methods significantly outperform conventional optimization techniques by enabling adaptive and real-time decision-making. Sparsity-aware learning enhances computational efficiency by eliminating redundant features, while orthogonal initialization stabilizes neural network training through improved gradient propagation and faster convergence. Their integration produces robust models with superior prediction accuracy, resource utilization, and communication reliability under dynamic channel conditions. Hybrid architectures incorporating convolutional, reinforcement, and graph neural networks further improve bandwidth allocation, power optimization, and network adaptability. Nevertheless, challenges including limited benchmark datasets, computational complexity, model interpretability, and real-time deployment remain unresolved. Future research should focus on lightweight AI models, standardized evaluation frameworks, explainable learning techniques, and edge-enabled implementations to develop scalable, intelligent, and resilient FSO communication systems capable of supporting future optical wireless networking applications.

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