Anthony Chen, Shiwen Mao *Department of Electrical and Computer Engineering, Auburn University, Auburn, AL*
Zhu Li *Department of Computer Science & Electrical Engineering, University of Missouri-Kansas City, MO*

Editor: Shiwen Mao

Emerging Standards for Gaussian Splatting in 3D Content Representation: An Overview

As Gaussian Splatting (GS) is increasingly integrated into products and production pipelines across industry, organizations and researchers have begun developing standardization practices to formally accommodate this emerging technology. Originally regarded primarily as a 3D rendering technique for novel view synthesis, 3DGS can be applied more broadly to represent a wide range of 3D computer graphics content. However, as GS is a relatively recent technology, much of its development remains at an experimental stage, resulting in a sparse standardization landscape. As 3D modeling becomes increasingly comprehensive and the applications and implementations of GS rapidly diversify, many organizations have recognized the need for standardization, introducing new formats such as SPZ or adapting GS to existing 3D asset standards like glTF. In this article, we review the initial standardization efforts led by organizations such as Metaverse Standards Forum, Niantic, Khronos, and MPEG, which aim to unify baseline testing conditions, performance metrics, and development practices for GS. We begin by outlining the implementation and evolution of GS, highlighting how it advances beyond previous 3D scene representation approaches. We then provide an overview of emerging splatting standards. Finally, we conclude by discussing future research directions for GS and examining its current and potential applications.

In this era, digital technologies increasingly and progressively seek to capture and render the physical world at all scales, from small consumer products [1] to expansive environments such as entire cities [2]. As companies pursue the reconstruction of real-world environments and the digital replication of physical objects through 3D scene reconstruction, a broad range of industries has come to recognize the versatility and potential of novel view synthesis (NVS). As the primary new NVS technology, Gaussian Splatting (GS) is being rapidly adopted in many industries, exemplified by Tesla's scene reconstruction with their Electric Vehicles (EVs) [3], Meta's Virtual Reality/Augmented Reality (VR/AR) [2] headset ecosystems, and even Google Maps with their street views [2]. For organizations seeking to render 3D graphics efficiently and at scale, integrating GS into their pipelines represents a significant advancement.

As an advanced novel view synthesis technique, GS can generate a detailed 3D scene from a handful of images or even a single video sequence. Owing to its strong capabilities, Gaussian Splatting (GS) enables both scene training and rendering with relatively low computational requirements compared to previous approaches, achieving high frame rates on mobile devices across a wide range of applications and even in web-based deployments [4]. GS aims to deliver photorealistic scene reconstructions, a streamlined pipeline from image acquisition to splat representation, user-friendly deployment, and low computational overhead. Building on its advantages over prior NVS approaches, GS has gained increasing traction as a scalable solution for high-fidelity scene rendering and representation across a diverse range of applications. As researchers work to further streamline GS through compression (like the case of its predecessor, NeRF [7]), splatting files remain extremely large due to the numerous attributes associated with each Gaussian (e.g., up to 192 bytes for color alone) and Gaussian counts that can reach the millions. Consequently, compression and scalability have emerged as key challenges for GS, motivating the development of baseline standards to address these issues.

As GS has emerged only in recent years, its standardization efforts are still in their early stages. Over the past year, organizations such as MPEG, Niantic, and Metaverse Standards Forum have spearheaded initial standardization initiatives [2, 5], aiming to normalize testing methodologies, tooling, and feedback mechanisms for GS-related work. Establishing such standards enables consistent evaluation of different implementations and supports the rapid maturation of GS technology. As a rendering technique, GS is particularly sensitive to variations in splat quality and performance, making standardization essential for reliable and comparable results. In virtual and augmented reality (VR/AR) scenarios, GS directly impacts users' Quality of Experience (QoE) [6], as performance variations across different stages of the splatting pipeline can significantly influence the quality of the resulting Gaussian representations. At the same time, companies seeking to integrate GS into their products often wish to benchmark different GS implementations under common test conditions or using standardized quality metrics, such as those proposed by the MPEG working group [5]. While many stakeholders advocate for rapid standardization of GS, others (including Metaverse Standards Forum) have questioned whether the technology has reached sufficient maturity for formal tandardization, noting that GS may still be too nascent [2].

Currently, GS is being categorized as static GS, dynamic GS, and generative GS with a majority of research being done in the static GS domain. Since the original authors of GS developed splatting as a means of rendering still 3D scenes, researchers and developers are still experimenting on including time as a domain in their GS execution. Thusly, GS "videos" are still in development, where all current standardization of GS is on the static GS category.

In the remainder of this article, we first introduce GS and its origins in the next section. "Emerging Splatting Standards" provides an overview of current standard-

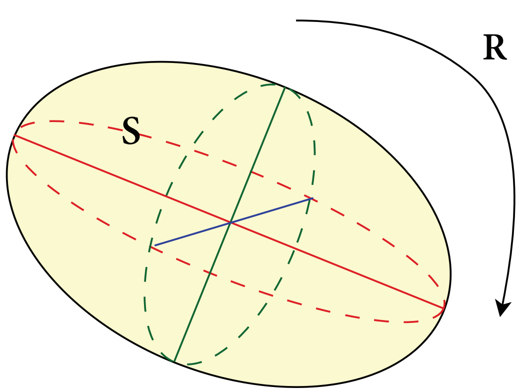

FIGURE 1. Representation of a Gaussian in the 3D space.

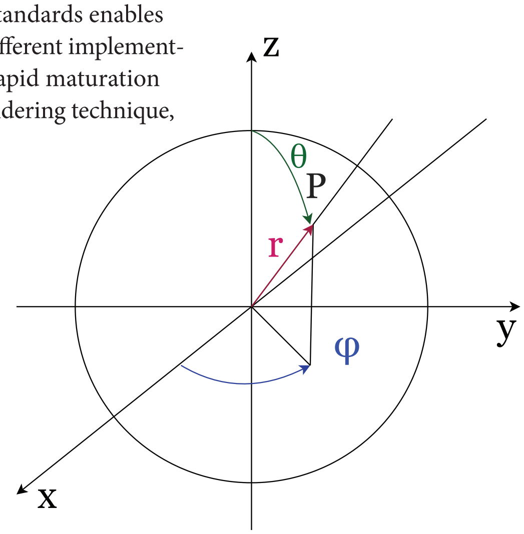

FIGURE 2. Illustrating the spherical harmonic function inputs.

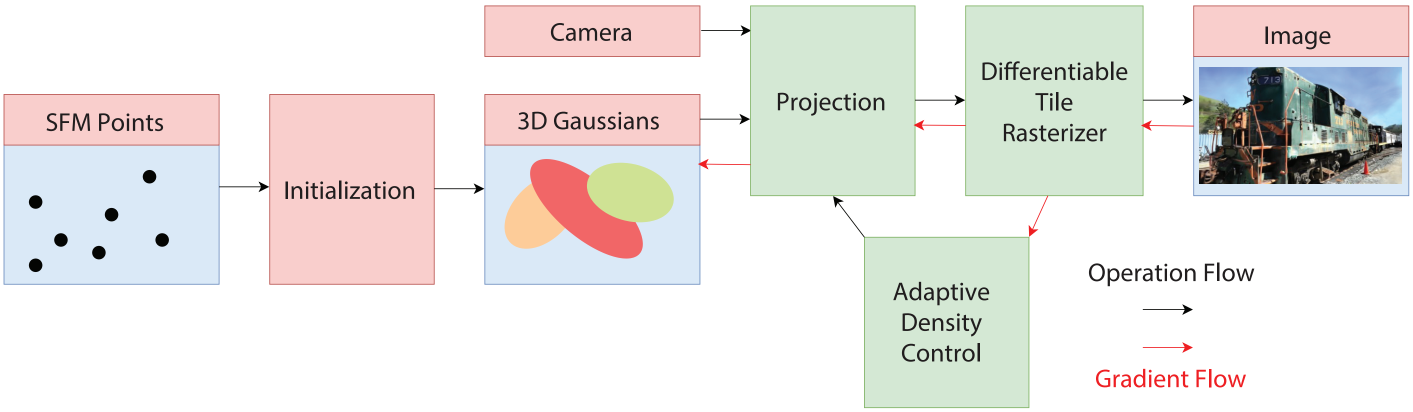

FIGURE 3. The Gaussian Splatting process.

TABLE 1. Gaussian Attribute Sizes

Attribute	Size (Bytes)
3D Positions	12
Quaternions (Rotation)	16
3D Scales	12
Opacities	4
Spherical Harmonics (3rd degree)	192 (48 coefficients, 4 bytes per coefficient)

ization efforts and the general direction of GS standardization. Finally, we conclude by examining GS applications and discussing ongoing research and development toward the future of the technology.

THE BASELINE GS PROCESS

Before discussing GS standards, it is important to understand the structure of typical Gaussian splats and how they are generated and optimized. Like their predecessors, such as point clouds [8] and NeRFs [7], splats consist of collections of objects represented in 3D space. In point clouds, these objects are individual points; in NeRFs, they are volumetric radiance fields; and in Gaussian splats, they are commonly referred to as *Gaussians*. Although the term Gaussian may suggest a probabilistic interpretation, these functions are in fact deterministic and are used primarily to represent ellipsoids. Gaussian functions are particularly suitable because they naturally encode the orientation and shape of ellipsoids in 3D space.

As can be seen in Figure 1, a Gaussian's spatial aspects can be portrayed by its center point, a scale matrix **S**, and a rotational matrix **R**. The scale matrix is a 3×3 matrix that represents the information on the length, height, and width of the ellipse, while the rotational matrix is a 3×3 matrix that represents the rotation of the ellipse originally in quaternion form. A combination of these two matrices gives the covariance of the Gaussian function: $\mathbf{\Sigma} = \mathbf{R}\mathbf{S}\mathbf{S}^{\mathrm{T}}\mathbf{R}^{\mathrm{T}}$. In addition to the **R** and **S** matrices, the final spatial attribute of Gaussians is the point μ, which contains x, y, and z values and indicates the center point of the ellipse. This center point is considered the mean of the Gaussian, making it a Gaussian function with attributes (μ, $\mathbf{\Sigma}$).

In addition to spatial attributes, Gaussians in splats also have other feature attributes in the form of color and opacity. While the opacity of Gaussians can be represented in terms of a singular value, the color of each Gaussian needs to be represented more delicately. These colors are depicted through the combination of spherical harmonics (SH) as in NeRFs. Like NeRFs that are neural radiance fields, splats are radiance field without the "neural" portion. As such, their colors are depicted such that each point inside Gaussians have different colors. Spherical harmonics can be imagined as spheres that output different colors depending on the point within the sphere and the coefficients of the spherical harmonic function. Each sphere can be singular in color, or even a collage of different colors throughout the entire spectrum. By adding together, the corresponding coefficients representing different color spheres, the output will be a singular color sphere with the colors that a Gaussian aims to display.

These SHs are a function that takes inputs as shown in Figure 2, where the distance from the center is shown by r, the polar angle is shown by θ, and the azimuthal angle is shown by φ to generate the output value P on the surface of the sphere. A function of all of these inputs generates the SHs. The combination of each of these attributes results in a single Gaussian, where each overall Gaussian splat contains up to millions of these Gaussians with these attributes to make a ".ply" file in the baseline GS standard [2]. As such, the total number of attributes contained within a single splat file is usually enormous. The size of each Gaussian within a file is summarized in Table I, where each attribute's size is shown. As can be seen from the table, a majority of the Gaussian's size comes from its color attribute, where depending on the degree of SH, the size of the file increases quadratically. To combat such large sizes, a large amount of research and standardization is aimed towards testing the limits of compression on GS.

After discussing the basic primitives of splats, we now transition to introduce the general splatting process. An overview of the GS process is shown in Figure 3 [9]. The process begins with producing Structure From Motion (SFM) points. This is the pre-processing, where a special point cloud including camera angles is generated from a collection of images or a video sequence. This is commonly accomplished through the use of an SFM software such as COLMAP, finding the common points and initial camera angles utilized for the images uploaded. This yields a collection of points which are initialized by adding initial attributes like covariances, colors, and opacities, resulting in a collection of initial points like Figure 4, for each of which a 3D Gaussian is initialized. These 3D Gaussians then take in the camera angles from the SFM point cloud for projection to 2D. These projections are then optimized through tile-based rasterization with frustrum culling [9] as well as Stochastic Gradient Descent based on a combination L_1 and Data Structural Similarity Index Measure (D-SSIM) losses to adjust splats incorrectly positioned through projection. These splats then undergo adaptive density control where Gaussians undergo splitting or cloning based on whether an area is under-represented or over-represented, as shown in Figure 5. At fixed iteration intervals, Gaussians below a specified transparency/opacity threshold are pruned since transparent Gaussians consume computing resources without contributing much to the overall image. To control the number of Gaussians, Gaussian opacities are set to 0 at large intervals, where Gaussians then have their opacities increased as needed or culled. After all the optimization steps are accomplished, the final output consists of the final Gaussian splats, each with different colors and opacities as shown in Figure 6. The final image displayed to the user, shown in Figure 7, is rendered through the usage of a popular computer graphics technique called alpha blending [10], which consists of "adding" all the overlapping Gaussians seen from the user's viewpoint. This process is the baseline for GS standardization, which generates a ".PLY" file with Gaussians of the five given attributes, as other works seek to either improve upon certain attributes of the splats themselves or adjust the technique to match their needs [2, 11, 12].

EMERGING SPLATTING STANDARDS

Many organizations have taken an interest in standardizing GS, with Metaverse Standards Forum, MPEG, The Khronos Group, and Niantic in particular, leading the standardization efforts. A brief overview of the timeline of GS standardization initiatives is shown in Figure 8, displaying dates of major updates to the GS standards currently being developed. As GS was recently developed in 2023, many companies only began working on standardization in late 2024 to mid 2025. The first of these companies to work on expanding the GS standard is Niantic, which developed the SPZ file format for Gaussian splats. Compared to the original PLY file format which consisted of 236 bytes per gaussian, the newly developed SPZ file format only required 64 bytes per Gaussian with up to 87.5% size reductions in certain gaussian attributes. This format applied a combination of quantization and scaling to reduce most of the PLY float values to 8-bit integer values [12]. This SPZ format is intended to be a universal splat format, compressed and optimized towards the compression/quality tradeoff of the original PLY format. While SPZ was originally released in 2023, open source development on improving this format is rapidly evolving, driven by ongoing efforts to reduce overhead and improve performance of GS. Niantic's goal with this format is improving the accessibility of GS.

In conjunction with the development of SPZ, Niantic has also been porting GS to mobile devices with their app Scaniverse, allowing these splats to be deployed quickly with minimal computing resources. These products have also been presented as part of the Metaverse Standards Forum's GS Town Halls [11]. While Metaverse Standards Forum began standardization work on GS a little bit later than Niantic, they have heavily pushed the standardization scene of GS with series of workshops on standards. Many of these town halls seek to solve the size limitations of Gaussian splats through the likes of either compaction or compression of Gaussians. Whereas compression seeks to shrink Gaussians, compaction seeks to reduce the number of Gaussians through the likes of pruning or merging. In addition to discussions on the current standards of GS, the Metaverse Standards Forum is also pushing new standards and extensions of GS through expansion on Niantic's SPZ and introducing GS into the existing 3D asset standard of glTF belonging to the Khronos Group. While most standardization practices have been aimed at the optimization of Gaussian splats, the glTF standard is oriented towards the delivery of 3D assets [13].

Although the Metaverse Standards Forum is seeking to create standards for GS, they seek to stay flexible in standardization practices to adapt to the rapidly changing ecosystem of GS development.

The final large group that works on GS standardization development is the MPEG working group, which began their standardization the latest among the other organizations. By providing common test conditions, use cases, and coding

FIGURE 4. Initial splat points, generated from the open-source dataset Tanks and Temples' Train scene [9].

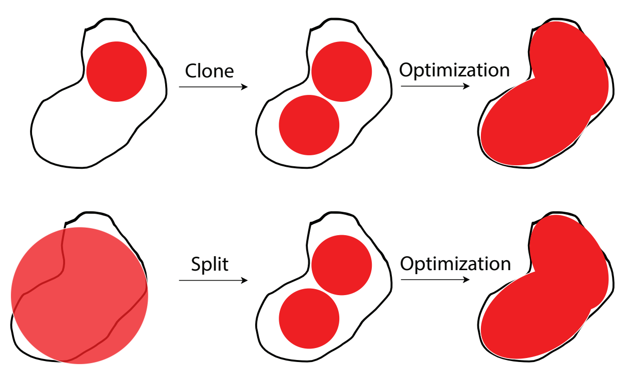

FIGURE 5. Adaptive density optimization of Gaussians.

FIGURE 6. Splat output after optimization, generated from the open-source dataset Tanks and Temples' Train scene [9].

FIGURE 7. The fully rendered scene, generated from the open-source dataset Tanks and Temples' Train scene [9].

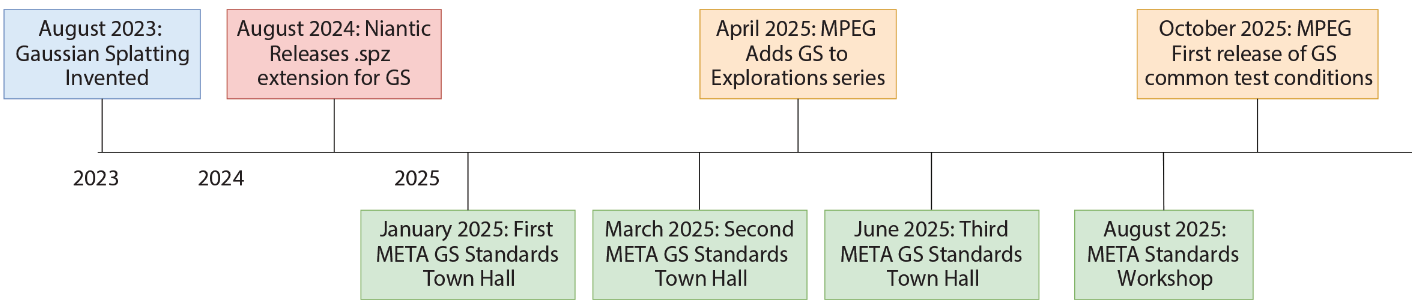

FIGURE 8. Standardization timeline of GS.

requirements, they have created a common testbed for GS research comparisons. While no official standard has been released under the MPEG working group yet, MPEG has classified GS into static (1F for single frame) and dynamic (NF) categories, preparing future standards for both traditional GS and GS video, like the MPEG point cloud standards [5]. Despite the novelty of GS, many organizations are seeking to create standards for easy GS deployment and development. From generating formats to optimizing the splatting process, different companies are seeking ways to unify the base threshold of GS, solving urgent "pain points" in GS development [11].

APPLICATIONS AND FUTURE TRENDS

As a brand-new technology rapidly being adopted by the industry, research on GS has rapidly advanced the foundations, scalability, and optimization of this rendering technique. With many organizations developing applications to expand splatting into new domains and others working on improving GS itself, GS is trending toward rapid development. Although no GS standards have yet been formally ratified by standards organizations, the rapid advancement of the field suggests that an initial official standard is likely to emerge in the near future [2].

As major industry stakeholders continue to invest in splatting technologies, GS is poised for rapid advancement and accelerated standardization in the near future

A. Recent/Future Developments

As discussed in the previous sections, a majority of the standardization in GS is currently aimed at improving either the GS process or expanding the capacities of GS. Many recent works have adopted the usage of neural networks and anchors to predict attributes of splats, while others have tried adding video codes to compress Gaussian features [14]. Some works have aimed to expand GS into video [14] or generative splatting, producing new scenes from trained images [15]. Although traditionally GS takes advantage of its direct representation to improve computation speed, recent developments are leaning towards using implicit representations of Gaussians to achieve much higher compression rates for small computational overhead or quality tradeoffs [14]. By compressing parameters or restructuring the GS architecture, many works aim to increase the efficiency of splatting such that deployment no longer suffers from huge memory footprints, large computations, or short dynamic scenes [16].

B. Applications

With Gaussian Splatting quickly becoming the go-to 3D scene representation technology, many companies are making the switch from old photogrammetry techniques and point clouds to splats that render faster than real-time [2, 3]. As Gaussian splats are supported by various gaming engines like Unreal Engine and Unity, GS has become the center of modern-day content creation with stakes in games, animation, and VR/AR. Even outside of the entertainment sphere, GS has made a sizeable impact on everyday life due to its scene reconstruction capabilities, being included in products like Google Maps or Tesla's scene re-creation capabilities. The introduction of expanded GS standards can possibly push this technology into even more markets like those of movie backgrounds or military use.

CONCLUSION

In this article, we have examined the emergence of GS standards, as major organizations such as the Metaverse Standards Forum, Niantic, and MPEG have initiated early standardization efforts through presentations, as well as the development of new formats and extensions. We discussed the evolution of GS from its original PLY-based representations with unwieldy file sizes to more recent implementations that incorporate compression and data compaction. As major industry stakeholders continue to invest in splatting technologies, GS is poised for rapid advancement and accelerated standardization in the near future. ■

Acknowledgment

This work was supported in part by the NSF under grants CNS-2148382 and CNS-2107190.

Anthony Chen received his MS degree in electrical and computer engineering from Clemson University, Clemson, SC in 2022. Currently, he is pursuing a PhD degree in the Department of Electrical and Computer Engineering at Auburn University, Auburn, AL. His research interests include wireless communications, deep learning, and optimization.

Shiwen Mao received his PhD in electrical and computer engineering from Polytechnic University, Brooklyn, NY in 2004. Currently, he is Samuel Ginn Endowed Professor and Director of Wireless Engineering Research and Education Center at Auburn University, Auburn, AL. His research interests include wireless networks, multimedia communications, and smart grid. He is a Fellow of the IEEE and a Life Member of the ACM.

Zhu Li received his PhD degree in electrical and computer engineering from Northwestern University in 2004. From 2012 to 2015, he was the senior staff researcher/senior manager with Samsung Research America's Multimedia Standards Research. He is currently a professor with the Department of Computer Science and Electrical Engineering, University of Missouri, and the Director of the NSF I/UCRC Center for Big Learning, UMKC. His research interests include point cloud and light field compression, graph signal processing, and deep learning.

REFERENCES

[1] M. Attaran and B. G. Celik. 2023. Digital twin: Benefits, use cases, challenges, and opportunities. *Decision Analytics Journal*, vol. 6, 100165.

[2] P. Cozzi and A. Medvedev. Jan. 2025. Gaussian splatting: Ready for standardization? *Industry Town Hall/Metaverse Standards Forum,* [online] https://metaverse-standards.org/event/gaussian-splats-ready-for-standardization/

[3] A. Masood. Gaussian primitive-based scene representations for real-time neural rendering. *Medium*, [online] https://medium.com/@adnanmasood/gaussian-primitive-based-scene-representations-for-real-time-neural-rendering-a1c9cbe01ca0

[4] Niantic Scaniverse. Feb. 2025. Creating splats with your phone: Which app should you choose? *Scaniverse*. [online] https://scaniverse.com/news/creating-splats-which-app-to-choose.

[5] ISO. Oct. 2025. Common test conditions for Gaussian splat coding. Document ISO/IEC JTC 1/SC 29/WG 04, N0751, *Explorations*.

[6] P. Martin, A. Rodrigues, J. Ascenso and M. P. Queluz. Sept./Oct. 2025. GS-QA: Comprehensive quality assessment benchmark for Gaussian Splatting view synthesis. *Proceedings of the 17th International Conference on Quality of Multimedia Experience (QoMEX)*, Madrid, Spain, 1-7.

[7] B. Mildenhall, P. P. Srinivasan, M. Tancik, J. T. Barron, R. Ramamoorthi, and R. Ng. Dec. 2021. Nerf: Representing scenes as neural radiance fields for view synthesis. *Communications of the ACM*, vol. 65, no. 1, 99-106.

[8] S. Schwarz et al. March 2019. Emerging MPEG standards for point cloud compression. *IEEE Journal on Emerging and Selected Topics in Circuits and Systems*, vol. 9, no. 1, 133-148.

[9] B. Kerbl, G. Kopanas, T. Leimkühler, and G. Drettakis. July 2023. 3D Gaussian Splatting for real-time radiance field rendering. *ACM Transactions on Graphics*, vol. 42, no. 4, Article No.: 139.

[10] J. F. Blinn. Sept. 1994. Compositing. 1. Theory. *IEEE Computer Graphics and Applications*, vol. 14, no. 5, 83-87.

[11] C. Lassner, Z. Wang, W. Morgenstern, P. Bandyopadhyay, and J. Sobotka. June 2025. Gaussian Splats town hall: Part 3 research insights and interoperability. *Metaverse Standards Forum* [online]. https://metaverse-standards.org/event/gaussian-splats-town-hall-part-3/.

[12] Niantic Scaniverse. Oct. 2024. Open-sourcing .SPZ: It's .JPG for 3D Gaussian Splats. *Scaniverse*. [online] https://scaniverse.com/news/spz-gaussian-splat-open-source-file-format.

[13] T. Belayneh, K. Weznel, A. Morgan, A. Morris, and A. Balabanian. Aug. 2025. Khronos, OGC, and geospatial leaders add 3D Gaussian Splats to the glTF asset standard. *The Khronos Group*. [online]. https://www.khronos.org/blog/khronos-ogc-and-geospatial-leaders-add-3d-gaussian-splats-to-the-gltf-asset-standard.

[14] G. Wu, T. Yi, J. Fang, L. Xie, X. Zhang, W. Wei, W. Liu, Q. Tian, and X. Wang. July 2024. 4D Gaussian Splatting for real-time dynamic scene rendering. *arXiv:2310.08528* [online] https://arxiv.org/abs/2310.08528.

[15] J. Tang, J. Ren, H. Zhou, Z. Liu, and G. Zeng. March 2024. Dreamgaussian: Generative Gaussian Splatting for efficient 3D content creation. *arXiv:2309.16653* [online]. https://arxiv.org/abs/2309.16653.

[16] S. Youn, S. Lee, G. Kim, W. Kwon, S.-H. Bae, and J. Oh. Dec. 2025. Success-GS: Survey of compactness and compression for efficient static and dynamic Gaussian Splatting. *arXiv:2512.07197* [online] https://www.arxiv.org/abs/2512.07197.