
Sekai: A Video Dataset towards World Exploration

Zhen Li^{1,2,4*}[§] Chuanhao Li^{1**†}, Xiaofeng Mao¹, Shaoheng Lin¹, Ming Li¹,
Shitian Zhao¹, Zhaopan Xu¹, Xinyue Li¹, Yukang Feng³, Jianwen Sun³,
Zizhen Li³, Fanrui Zhang³, Jiaxin Ai³, Zhixiang Wang⁵, Yuwei Wu^{2,4†},
Tong He¹, Jiangmiao Pang¹, Yu Qiao¹, Yunde Jia⁴, Kaipeng Zhang^{1,3†‡}

¹Shanghai AI Laboratory ²Beijing Institute of Technology

³Shanghai Innovation Institute ⁴Shenzhen MSU-BIT University

⁵The University of Tokyo

<https://lixsp11.github.io/sekai-project/>

Abstract

Video generation techniques have made remarkable progress, promising to be the foundation of interactive world exploration. However, existing video generation datasets are not well-suited for world exploration training as they suffer from some limitations: limited locations, short duration, static scenes, and a lack of annotations about exploration and the world. In this paper, we introduce Sekai (meaning “world” in Japanese), a high-quality first-person view worldwide video dataset with rich annotations for world exploration. It consists of over 5,000 hours of walking or drone view (FPV and UVA) videos from over 100 countries and regions across 750 cities. We develop an efficient and effective toolbox to collect, pre-process and annotate videos with location, scene, weather, crowd density, captions, and camera trajectories. Comprehensive analyses and experiments demonstrate the dataset’s scale, diversity, annotation quality, and effectiveness for training video generation models. We believe Sekai will benefit the area of video generation and world exploration, and motivate valuable applications.

1 Introduction

Explore. Dream. Discover. — Mark Twain

World exploration and interaction form the foundation of humankind’s odyssey, which are practical scenarios for world generation models [1]. These models aim to adhere to the world laws (real world or games) while facilitating unrestricted exploration and interaction within environments. In this paper, we focus on the first act of world generation—world exploration, which aims to use image, text, or video to construct a dynamic and realistic world for interactive and unrestricted exploration.

Recent advancements in video generation [2, 3, 4, 5, 6] have been remarkable, making it a promising approach for world generation through video generation. Meanwhile, camera-controlled video generation [7, 8, 9] is a suitable way for world exploration, since camera trajectories can be converted by keyboard and mouse inputs. However, generating *long* and *realistic* videos with *precise* camera control remains a significant challenge. A major bottleneck lies in the data itself. Existing video

[§]This work was done during the internship at Shanghai AI Laboratory.

^{*}Equal contribution.

[†]Corresponding authors: wuyuwei@bit.edu.cn; lichuanhao@pjlab.org.cn; zhangkaipeng@pjlab.org.cn

[‡]Project leader.

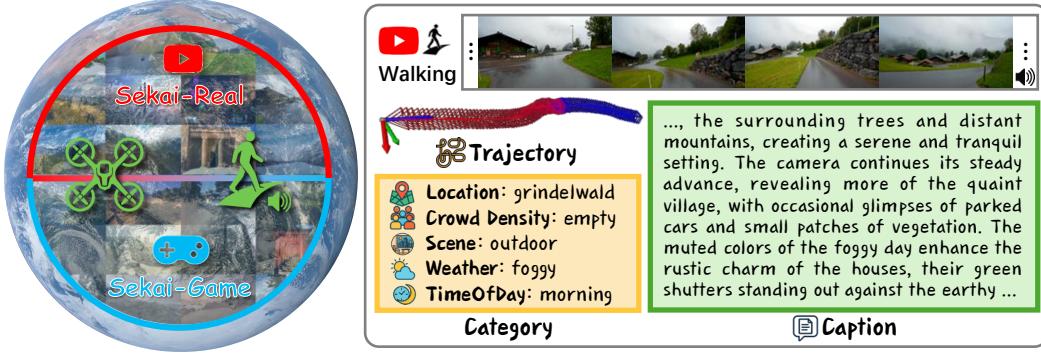


Figure 1: Sekai is collected from YouTube and a video game. It consists of walking and drone-view egocentric videos with recorded audio. We provide rich annotations of camera trajectories, location, crowd density, scene, weather, time of day, and captions.

generation datasets [10, 11, 12] are not well-suited for world exploration as they suffer from limitations: limited locations, short duration, static scenes, and a lack of annotations about exploration (*e.g.*, camera trajectories) and world annotations (*e.g.*, location, weather and scene).

In this paper, we introduce Sekai (せかい, meaning “world” in Japanese), a high-quality egocentric worldwide video dataset for world exploration (see Figure 1 and Figure 2). Most videos contain audio for an immersive world generation. It also benefits other applications, such as video understanding, navigation, and video-audio co-generation. Sekai-Real comprises over 5000 hours of videos collected from YouTube with high-quality annotations. Sekai-Game comprises videos from a realistic video game, Lushfoil Photography Sim, with ground-truth annotations. It has five distinct features: (1) **High-quality and diverse video**. All videos are recorded in 720p at 30 FPS, featuring diverse weather conditions, various times, and dynamic scenes. (2) **Worldwide location**. Videos are captured across 101 countries and regions, featuring over 750 cities with diverse cultures, activities, architectures, and landscapes. (3) **Walking and drone view**. Beyond the walking videos (*e.g.*, citywalk and hiking), Sekai contains drone view (FPV and UAV) videos for unrestricted world exploration. (4) **Long duration**. All walking videos are at least 60 seconds long, ensuring real-world, long-term world exploration. (5) **Rich annotations**. All videos are annotated with location, scene, weather, crowd density, captions, and camera trajectories. YouTube videos’ annotations are of high quality, while annotations from the game are considered ground truth.

To construct the Sekai dataset, we develop a curation pipeline (see Section 3) for Sekai-Real (YouTube videos) and Sekai-Game (video game videos). (1) For Sekai-Real, we first manually search and download high-quality walking and drone videos. Then we introduce a pre-processing pipeline to obtain video clips by shot detection, video transcoding, and quality evaluation. After that, we develop an annotation framework to annotate location, scene type, weather, crowd density, captions, and camera trajectories. Considering the large amount of data and practical usage, we further introduce a video sampling module to sample the top-tier videos according to the computational resources for training the video generation model. (2) For the Sekai-Game, we first play Lushfoil Photography Sim and record videos. Then we use the same pre-processing pipeline to obtain video clips. For the annotation, we develop a toolbox to record ground-truth annotations while playing.

We conduct statistical analyses to characterize the scale and diversity of the dataset and independently validate the accuracy of YouTube annotations. We then fine-tune a video generation foundation model on the top-tier part of Sekai-Real for text-to-video and image-to-video, yielding consistent gains in world-exploration scenarios, especially in video dynamics and visual quality. In addition, leveraging Sekai’s per-frame camera pose annotations, we train for camera-controlled video generation, where the input includes a prescribed camera trajectory and the model is required to generate video consistent with that motion. Across Sekai-Real and Sekai-Game, this training substantially improves camera control, significantly reducing the error between the trajectories of the generated video and the target.

To summarize, our contributions are threefold:

- We introduce Sekai, a large-scale, high-quality long-form video dataset for worldwide exploration via walking and drone footage, with rich annotations.



Figure 2: An overview of the Sekai dataset. Sekai-Real is collected from YouTube with high-quality annotations, while Sekai-Game is collected from a game with ground-truth annotations.

- We develop a curation pipeline that efficiently collects, filters, and annotates videos from the web and from video games.
- We validate the quality and effectiveness of the dataset through comprehensive analyses, annotation verification, and experiments on various video generation tasks.

2 Related Work

2.1 World Generation Model

Recent years have seen a growing interest in video generation [2, 6, 5, 13, 14, 15, 16], 3D scene generation [17, 18, 19, 20, 21, 22], and 4D generation [23, 24, 25, 26, 27], with significant advancements opening up new possibilities in the development of world generation models [28, 29, 30, 31, 32]. In the realm of video generation, text-to-video generation [13, 14] has played a pivotal role, achieving high-fidelity results, while image-to-video generation [15, 16, 33] has also seen notable advancements. Sora [28] further underscores the significance of video generation in the context of world generation models. Among 3D scene generation methods, techniques [19, 20, 21, 17] utilize depth estimation models [34, 35, 36] to extend 2D scenes into 3D representations. 4D scene generation [23, 24, 25] further introduces dynamics, focusing on the evolution of objects or scenes over time [26] and dynamic interactions [27]. This paper primarily focuses on interactive video generation for world exploration, aiming to construct a dynamic and realistic world using image, text, or video for unrestricted exploration.

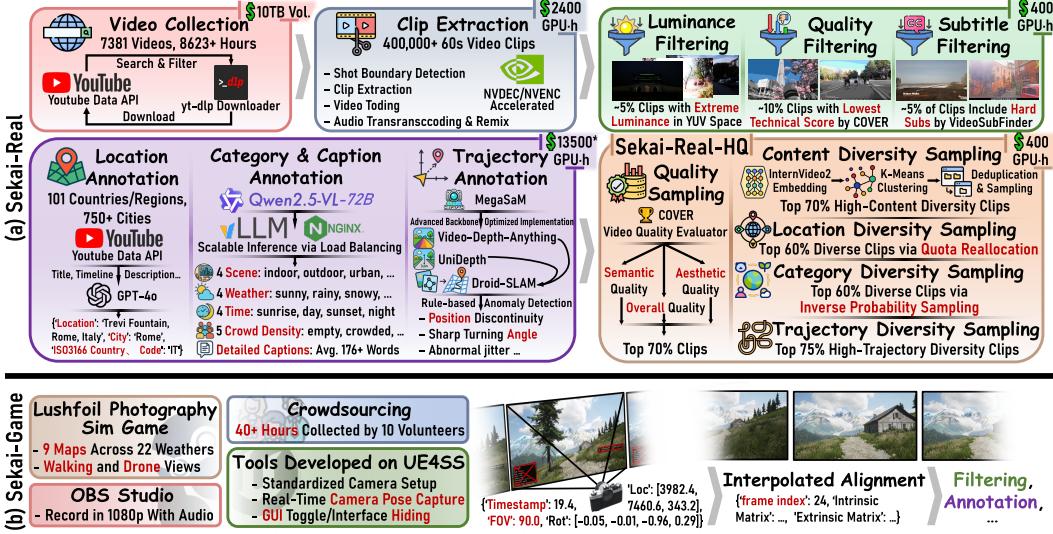


Figure 3: The dataset curation pipeline. *indicates that the statistics were derived from a subset of trajectory annotations.

2.2 Video Generation Dataset

The continuous development of annotated datasets has played a pivotal role in shaping the landscape of artificial intelligence-generated content, offering both insights and challenges for accurate model assessment. Existing video generation datasets can be categorized as specific-scenario and open-scenario. Typical specific-scenario datasets including UCF-101 [37], Taichi-HD [38], Sky-Timelapse [39], FaceForensics++ [40], ChronoMagic [41] and CelebV-HQ [42]. These datasets have limited amount of data (with a total duration of less than 800 hours), limited individual video duration (with an average length of less than 20 seconds), and generally lack annotation information (only a few datasets, such as ChronoMagic, provide caption annotations). Open-scenario datasets [43, 44, 45, 46] have somewhat alleviated issues with data scale and annotation information. For example, OpenSoraPlan-V1.0 [45] includes videos with a total duration of 274 hours, each accompanied by detailed captions. Similarly, the recently introduced OpenVid-1M dataset [10] comprises videos totaling 2100 hours, with long captions provided for each video. However, the average duration of individual videos still does not exceed 25 seconds, and they only provide caption annotations. MiraData [12] consists of longer videos with an average length of 72.1 seconds. It is still not long enough for the world exploration, and exploration annotations (*e.g.*, camera poses or keyboard and mouse inputs) and world annotations (*e.g.*, location, time and weather) are missing. By contrast, the proposed Sekai dataset focuses on egocentric world exploration, which covers walking and drone view videos across diverse locations and scenes with long video duration (1 to 39 minutes, average is 2 minutes) and rich exploratory and world annotation.

3 Dataset Curation

The overall process of curating the Sekai dataset includes four major parts: video collection, pre-processing, annotation, and sampling, seeing Figure 3 for an illustration.

3.1 Video Collection

In the collection stage, we collect over 8623 hours of YouTube videos and over 40 hours of game videos from Lushfoil Photography Sim.

YouTuber. We manually collect high-quality video URLs from popular YouTubers and extend them by searching additional videos using related keywords (*e.g.*, walk, drone, HDR, and 4K). In total, we collect 10471 hours of walking videos (with stereo audio) and 628 hours of drone (FPV or UAV) videos. All videos were released over the past three years, with a 30-minute to 12-hour duration.

They are at least 1080P with 30 to 60 FPS. We download the 1080P version with the highest Mbps for further video processing and annotation. Due to network issues and some videos are broken, there are 8409 hours of walking videos and 214 hours of drone videos after downloading.

Video Game. Beyond real-world data, we collect additional data from the video game since its ground-truth annotations are accessible (*e.g.*, location, weather, and camera trajectory). Lushfoil Photography Sim is a video game that allows walking or using a first-person drone to explore real-world landscapes. It is built by Unreal Engine 5 and showcases the game’s locations in stunning visual fidelity, making it an excellent source for collecting realistic synthetic data. We use OBS Studio to record 40 hours videos at 1080P 30FPS (8 to 12 Mbps) with diverse locations and weather. Scaling the amount of data is low-cost.

3.2 Video Pre-processing

For YouTube videos, we trim two minutes from the start and end of each original video to remove the opening and ending. Then we do the following steps and obtain 6620 hours (Sekai-Real) and 60 hours (Sekai-Game) of video clips for YouTube and the game, respectively.

Shot Boundary Detection. YouTube videos are often cut and stitched, and video games commonly feature teleportation points—both of which contribute to discontinuous shot segments in one video. Thus, following Cosmos [29], we employ TransNetV2 [47] with a threshold of 0.4 for shot boundary detection. However, the original implementation runs slowly. We refactored the codebase for GPU acceleration, which is five times faster than the original version. In particular, we use the PyNVideoCodec library for video decoding and employ the CVCUDA library to offload frame operations such as color space conversion and histogram computation to the GPU. We trim five seconds from the start and end of each shot. After shot detection, the duration of video clips is from 1 to 5.88 hours.

Clip Extraction and Transcoding. Considering practical processing, we split each shot into multiple one-minute clips (shorter than one minute will be discarded). In model training, we can stitch contiguous clips according to the computation resources. We re-encode each video clip using the PyNVideoCodec library to standardize the diverse codec configurations in the raw videos, targeting 720p at 30fps in H.265 MP4 format with a bitrate of 4 Mbps. Evaluation of the transcoded video clips across diverse scenes yields PSNR values above 35, indicating no perceptible visual degradation. We think the world exploration should contain realistic sound. Thus, we keep the audio of walking videos. We trim the audio tracks based on the timestamps of the video clips, re-encode them into AAC format using FFmpeg at 48kHz, and mux each audio clip with its corresponding video clip.

Luminance Filtering. Overly dark or bright videos are not suitable for model training. We apply a simple filter based on the luma channel in YUV color space, and remove video clips with more than 15 consecutive frames of extremely high or low average brightness. Especially, this step is necessary for video game data, as the engine often employs simplified lighting and camera systems. In this step, we filter out 300 hours of videos.

Quality Filtering. We use COVER [48], a comprehensive video quality evaluator to filter low-quality video clips according to the technical quality metric. Technical quality evaluates issues such as image clarity, transmission distortion, and transcoding artifacts. The lowest-scoring 10% of video clips are removed after filtering.

Subtitle Filtering. Some videos contain hardcoded subtitles, which are artificial texts embedded in the video frames. These subtitles compromise the video’s fidelity to the real world and may introduce misleading patterns during model training. To mitigate this, we apply VideoSubFinder to detect hardcoded subtitles on the bottom one-third of the video frames. A clip is flagged if it contains any subtitle that remains visible for more than 0.75 seconds, in order to reduce false positives. All flagged clips are removed, resulting in the exclusion of approximately 5% of the video clips.

Camera Trajectory Filtering. For Sekai-Real, we employ a state-of-the-art structure from motion (SfM) model to extract camera trajectories. However, some trajectories exhibit implausible or counter-intuitive motions, so we heuristically filter out abnormal cases using the following rules. Specifically, we exclude video clips if they satisfy either of the following: (1) Multiple abrupt trajectory reversals (*i.e.*, directional changes exceeding 150 degrees) within a 10-second window. (2) A camera viewpoint shift greater than 60 degrees between two consecutive frames. (3) A camera position displacement

greater than 5 times the average displacement of the 30 consecutive frames containing these two frames. This filtering phase is performed on partially selected data annotated with trajectories.

3.3 Video Annotation of Sekai-Real

We annotate the video data from multiple perspectives, including geographic locations, content category and caption, and per-frame camera trajectories.

Location. Utilizing the Google YouTube Data API, we fetch the title and description of each video. Since most videos contain multiple chapters filmed at different locations with timeline-based descriptions, we employ GPT-4o [49] to extract a formatted location for each chapter with the ISO 3166 country/region code attached for subsequent processing. We use the interval tree to efficiently match each video clip to its corresponding chapter based on the timestamp, thereby retrieving the location information. Video clips that cannot be uniquely matched to a chapter are discarded, which accounts for approximately 8% of the total clips.

Category and Caption. We adopt a two-stage strategy to annotate each video with category and caption. In the first stage, the video is classified along four orthogonal dimensions: scene type, weather, time of day, and crowd density, each with mutually exclusive labels. The model selects the most suitable label for each and abstains when uncertain. In the second stage, we carefully design prompts that incorporate the predicted category labels, location information, and video frames to generate detailed, time-ordered descriptions of actions and scenes for each video clip. Practically, we extract one frame every two seconds from each video clip and use 72B version of Qwen2.5-VL [50] to annotate them. We deploy vLLM [51] inference services with Nginx [52] for load balance. The final caption length averages over 176 words per video clip.

Camera Trajectories. We experiment with various camera trajectory annotation methods of different types, including the visual odometry method DPVO [53], the deep visual SLAM framework MegaSaM [34], and a carefully designed 3D transformer VGGT [54] that outputs 3D quantities. Through empirical experiments and comparisons, we choose MegaSaM as the baseline annotation method and made adjustments to optimize annotation accuracy and efficiency. Additionally, we replace the monocular depth estimation model Depth Anything [55] used in MegaSaM with Video Depth Anything [35], which performs better in terms of temporal consistency. We also optimize the official implementation of MegaSaM to support cross-machine, multi-GPU parallel inference, significantly improving annotation efficiency.

3.4 Video Annotation of Sekai-Game

We developed a concise yet comprehensive toolchain based on the open-source tools RE-UE4SS and OBS Studio to capture ground-truth annotations from video games. RE-UE4SS is a powerful script system for Unreal Engine, enabling access and modification of the UE object system with minimal overhead at runtime. Based on its Lua Scripting API, we develop practical tools for video collection and annotation, including the standardization of camera system configuration, real-time camera pose capture, GUI hiding, ensuring the collection of clean data with aligned annotations.

The location and category are obtained from the description of the game map, and the prompt used for captioning is tightly modified to better suit the video game context. For camera trajectories, the captured camera poses are further calibrated to compensate for delays and interpolated to synchronize with the video frames.

3.5 Video Sampling

Given the prohibitive cost of training on the full Sekai-Real, we propose a strategy to sample the top-tier clips with the highest quality and diversity. The number is related to the computational budget for further video generation model training. In this paper, we sample 400 hours of the videos as Sekai-Real-HQ.

3.5.1 Quality Sampling

We sample the highest-quality clips according to two aspects: aesthetic quality and semantic quality. Aesthetic quality reflects the visual harmony among different elements in the video. Semantic quality

assesses the semantic completeness and consistency of the content. We use COVER [48] to obtain two quality scores and sum them for each video clip. We sample a $\alpha_{quality} = 0.7$ proportion of video clips with the highest scores.

3.5.2 Diversity Sampling

We balance the videos using the following modules one by one. And for Sekai-Real-HQ, the sampling ratio $\alpha_{content}$, α_{loc} , α_{cate} , α_{camera} are equal to 70%, 60%, 60%, and 75%, respectively.

Content Diversity. Given the vast volume of video clips, the presence of similar video clips is inevitable. We use InternVideo2 [56] to extract embeddings for each video clip, and apply mini batch K-Means [57] to cluster the embeddings of each country/region. Subsequently, in each cluster, we use the scores in quality sampling to rank the samples. Then we iteratively sample a video clip and remove its most similar one until $1 - \alpha_{content}$ proportion of video clips have been removed.

Location Diversity. We denote the number of cities as N_c . For each city, we count the number of video clips as N . Given a sampling ratio α_{loc} , we sort the cities in ascending order based on their N . For each city in this order, we sample approximately $N \cdot \alpha_{loc}/N$ videos from each city. If it is larger than the corresponding N , we sample all video clips for this city and redistribute the shortfall proportionally across the remaining cities by updating α_{loc} .

Category Diversity. To ensure broad coverage across semantic categories, we perform inverse-probability weighted sampling based on four independent categories: weather, scene, time of day, and crowd density. For each category, we compute the frequency of each label and assign sampling probabilities inversely proportional to their frequencies. Assuming independence among categories, the sampling probability for a video is initialized as the product of its label probabilities across the four categories. These probabilities are then normalized to sum to 1. We perform non-replacement sampling according to these probabilities until α_{cate} proportion of video clips have been sampled.

Camera Trajectory Diversity. We perform trajectory-aware sampling by the following steps. First, for the remaining videos, we calculate a direction vector (from the start to end of the trajectory) and the overall jitter, defined as the Euclidean norm of positional variance computed every 30 frames. Next, direction vectors are discretized into bins mapped onto a sphere, and jitter values are also discretized into bins. Then, a joint grouping is formed based on the direction and jitter bins. Finally, we do average sampling in each joint group according to the sampling ratio α_{camera} .

4 Dataset Statistics

Figure 4 summarizes the statistics of Sekai-Real, which covers 101 countries and regions with a clear long-tail distribution in video duration. The top eight countries (e.g., Japan, the United States, and the United Kingdom) account for about 60% of the total duration. The dataset is categorized by four weather types, four scene types, four time-of-day categories, and five crowd-density levels from various perspectives. Specifically, most videos are outdoor scenes, primarily under sunny or cloudy conditions, while rain and snow further enrich diversity. Daytime footage dominates, followed by nighttime scenes, providing a range of lighting conditions for model learning. Crowd density is evenly distributed, from sparse rural areas to densely populated city streets, supporting tasks such as curriculum learning and evaluation under varying crowd levels. For the Sekai-Game collection, data balance was considered during gameplay.

The statistics of Sekai-Real and Sekai-Real-HQ across multiple dimensions are shown in Figure 5. Sekai-Real-HQ, a top-tier subset of Sekai-Real, features a more balanced data distribution. Seeing Figure 5 (a), Sekai-Real demonstrates strong overall video quality scores, with more than half of

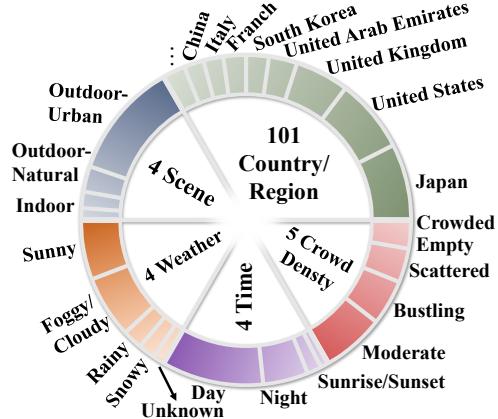


Figure 4: Statistical information on five dimensions of the Sekai-Real dataset.

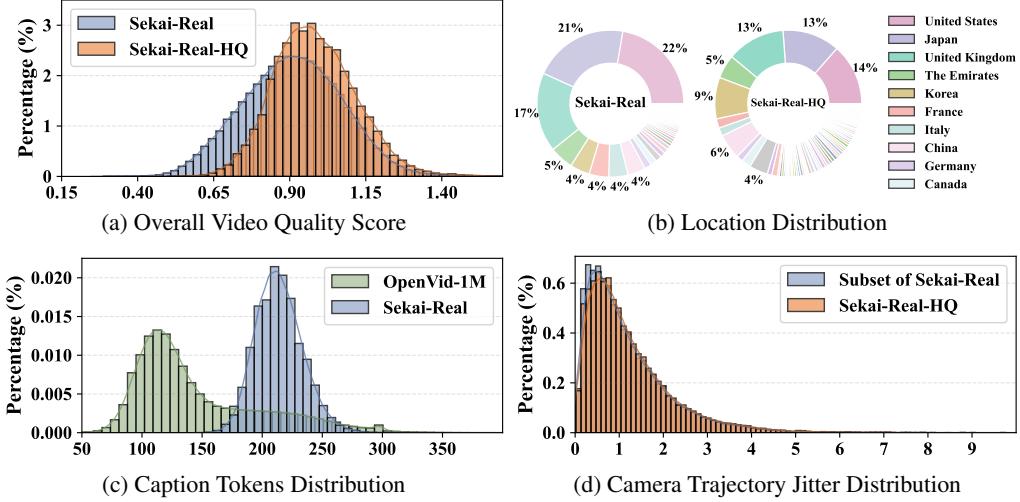


Figure 5: Statistics of the proposed Sekai-Real and Sekai-Real-HQ dataset.

the videos scoring above 0.9, while Sekai-Real-HQ exhibits a higher mean video quality score and a lower variance to address the long-tail distribution issue. Figure 5 (b) shows the distribution of Sekai-Real’s locations. Both Sekai-Real and Sekai-Real-HQ cover a wide range of countries globally. Sekai-Real-HQ demonstrates a more balanced distribution, which is more effective in mitigating potential bias during model training. In terms of captions, Figure 5(c) shows that Sekai-Real exhibits a higher average token count compared to OpenVid-1M [10], providing richer textual supervision. Figure 5 (d) shows the distribution of camera trajectory jitter before and after applying camera trajectory sampling. We can observe that the distribution for Sekai-Real-HQ is smoother than that of partially selected Sekai-Real data. This indicates that Sekai-Real-HQ achieves better diversity and a more uniform distribution.

5 Experiments

In this section, we first validate the quality of the annotation in Sekai. Then we use the top-tier subset Sekai-Real-HQ to fine-tune a video generation foundation model for text-to-video generation and image-to-video generation to validate the effectiveness of the data. Additionally, we explore camera-controlled video generation with the camera trajectories annotated in Sekai.

5.1 Evaluation of Annotation Quality

We evaluate the quality of the annotated location, camera trajectory, and category.

Location Quality. For videos in Sekai-Real, formatted locations were standardized using GPT-4o [49] based on original YouTube titles and descriptions. To evaluate their quality, we randomly sampled 500 videos and asked co-authors to verify each location using online maps, checking for three possible issues: (1) Omission – missing or incorrectly merged segments; (2) Temporal mismatch – misalignment between the timestamp and location; (3) Location hallucination – inferred rather than explicitly stated locations. Since the title and description provide rich information for GPT-4o, the evaluation revealed that such issues were rare (<5%), indicating that the overall location quality produced by GPT-4o was remarkably high.

Camera Trajectory Quality. We use two representative methods of two categories in the field of Structure from Motion, cascaded and end-to-end, namely, MegaSAM [34] and VGGT [54], to annotate 100 walking video clips and 100 drone-view video clips to evaluate their accuracy of camera trajectory prediction. Our validation experiments show that: (1) MegaSAM produces smoother camera trajectories than VGGT, as it has a global optimization module. (2) VGGT offers the advantage of faster inference speed but lower annotation quality. Since data quality is our priority and smoother camera trajectories are more beneficial for model training, we opted for MegaSAM to annotate camera trajectories.

Table 1: Evaluation across training steps for text-to-video generation and image-to-video generation. Higher is better for all metrics.

Task	Step	I2V Subject	I2V Background	Subject Consistency	Background Consistency	Motion Smoothness	Dynamic Degree	Aesthetic Quality	Imaging Quality	Overall Score
T2V	5000	–	–	91.93%	92.41%	98.40%	90.67%	48.38%	57.04%	4.26
	10000	–	–	91.33%	91.78%	97.72%	94.67%	48.42%	60.68%	4.28
	15000	–	–	93.14%	93.02%	97.66%	89.33%	49.36%	60.46%	4.30
	20000	–	–	96.02%	93.58%	98.29%	78.66%	52.09%	60.90%	4.34
I2V	5000	93.74%	93.85%	87.18%	90.26%	97.04%	100.00%	48.76%	64.84%	6.10
	10000	96.11%	95.83%	90.39%	90.79%	97.63%	98.67%	49.94%	68.54%	6.26
	17500	97.27%	96.65%	92.68%	91.86%	98.70%	85.00%	50.46%	66.54%	6.29

Category Quality. We randomly sample 500 examples and ask co-authors to label them for evaluating category annotation quality. The sampling strategy follows the category diversity sampling to ensure label variety. The results show that the overall agreement between Qwen2.5-VL and human annotations exceeds 90%. For weather, most discrepancies occur between cloudy/foggy and rainy labels. The difficulty lies in that rain is often imperceptible in a single frame and becomes evident only across consecutive frames, indicating that large vision-language models still struggle with temporal visual reasoning. We plan to leverage dedicated weather prediction datasets to fine-tune video understanding models [56] for more accurate weather annotations. Notably, we exclude indoor scenes from the analysis, as indoor lighting often affects the accuracy of both weather and time-of-day predictions for models and human annotators.

5.2 Video Generation

We fine-tune the SkyReels-V2-14B-540P video generation foundation model on the Sekai-Real-HQ dataset for text-to-video and image-to-video tasks to validate the effectiveness of the dataset.

5.2.1 Settings

Implementation Details. We keep the same model architecture and training configurations as those of SkyReels-V2-T2V-14B-540P and SkyReels-V2-I2V-14B-540P for text-to-video and image-to-video generation, respectively. All models are trained with video resolutions of 544×960×49, an FPS of 16, a batch size of 1, and a learning rate of 1e-5. Training was conducted on 8 NVIDIA H100 GPUs for a total of 20,000 iterations. The Adam optimizer is used across all training stages. During inference, we adopt the same resolution and frame rate, with an inference step count of 50.

Evaluation Dataset. For a fair evaluation, Sekai-Real-HQ is randomly divided into ten folds, with the last two folds used as the candidate test set and excluded from the training set. Subsequently, independent annotators are invited to manually select 50 clips from the candidate test set, with an emphasis on maintaining diversity during the selection process.

Evaluation Metrics. We adopt the VBench [58] evaluation metrics to comprehensively assess the model’s performance at different training steps. Specifically, *Subject Consistency* measures whether the subject’s appearance remains consistent. *Background Consistency* evaluates the temporal stability of background scenes. *Motion Smoothness* assesses whether motion is smooth and physically plausible. *Dynamic Degree* quantifies the extent of motion to avoid static videos. *Aesthetic Quality* reflects the perceived artistic and visual appeal. Finally, *Imaging Quality* evaluates distortions such as over-exposure, noise, and blur. For the image-to-video generation task, we further adopt the VBench++ [59] metrics *I2V Subject* and *I2V Background* to better evaluate the alignment between the prompt image and the generated video.

5.2.2 Quantitative Results

Table 1 presents the results of fine-tuning video generation foundation models in different tasks on the Sekai-Real-HQ. We observed that (1) on both text-to-image generation and image-to-video generation tasks, the overall generation quality improves with training, with consistent gains across most metrics and a steady rise in the *Overall Score*. (2) For image-to-video generation, the *I2V Subject* and *I2V Background* metrics improve markedly, imaging quality increases steadily through training, and the *Overall Score* keeps rising. (3) *Dynamic Degree* decreases after early peaks. This is

Table 2: Evaluation on camera-controlled video generation trained on the drone-view portion of Sekai-Real. Lower is better for *TransErr* and *RotErr*; higher is better for the others.

Method	TransErr (↓)	RotErr (↓)	Subject Consistency	Background Consistency	Motion Smoothness	Dynamic Degree	Aesthetic Quality	Imaging Quality
baseline	28.32	27.2	97.61%	94.85%	99.22%	10.67%	58.25%	74.73%
fine-tuned	17.19	19.89	97.34%	95.56%	99.11%	10.92%	59.18%	75.83%

a rebalancing where the model shifts from initially exaggerating motion to focusing more on sharper details and cleaner frames, so motion becomes more moderate while overall quality keeps improving.

5.3 Camera-Controlled Video Generation

Camera-controlled video generation requires the model to take a camera trajectory, an initial image, and a text prompt as inputs to generate a video that follows the defined camera motion. We fine-tune the Wan2.1-Fun-V1.1-1.3B-Control-Camera [5] model with camera trajectories annotated in Sekai-Real and Sekai-Game.

5.3.1 Settings

The baseline model uses a rule-based approach to convert discrete camera control action inputs into camera parameter matrices, from which it computes Plücker embeddings [60] for each frame and injects them into the model. In contrast, we directly use the per-frame camera parameter matrices annotated in Sekai as inputs for fine-tuning. We fine-tune the baseline model for two epochs on the drone-view portion of Sekai-Real and the entire Sekai-Game, respectively. For evaluation, we sample 50 test videos using the same procedure described in the previous section. In addition to the VBench metrics, we adopt two metrics from CameraCtrl [7]: *TransErr* and *RotErr*, which quantitatively evaluate camera control by measuring the translation and rotation discrepancies between the input trajectory and the trajectory extracted from the generated videos using Mega-SAM.

5.3.2 Quantitative Results

Table 2 shows the results of the baseline and the fine-tuned models trained on the drone-view portion of Sekai-Real. The fine-tuned model shows a clear improvement in camera control accuracy, achieving $\Delta 11.13$ reduction in *TransErr* and $\Delta 7.31$ reduction in *RotErr*. Meanwhile, other metrics also show consistent improvements. These results indicate that fine-tuning on Sekai not only enhances camera control but also improves overall video generation quality in a balanced and comprehensive manner.

We also fine-tune the baseline model on Sekai-Game, as illustrated in Table 3. The fine-tuned model demonstrates consistent improvements in camera control, with the error rates reduced by more than 30% on average.

Table 3: Evaluation on camera-controlled video generation trained on Sekai-Game. Lower is better.

Method	TransErr (↓)	RotErr (↓)
baseline	7.64	8.36
fine-tuned	4.22	6.22

6 Conclusion

In this paper, we have introduced a new video dataset, Sekai, for video generation-based world exploration. It consists of over 5,000 hours of walking or drone view (FPV and UVA) videos collected from 101 countries and more than 750 cities. We have developed an efficient and effective pipeline to process, filter and annotate the videos. For each video, we annotate location, scene type, weather, crowd density, captions, and camera trajectories. In addition, we present a video sampling module that selects top-tier videos according to the model training budget. Our comprehensive analyses and experiments validate the dataset’s scale, diversity, annotation quality, and effectiveness in supporting world exploration video generation model training. We believe that Sekai will benefit the field of video world generation and inspire valuable future applications.

Acknowledgments This work was supported by the National Key R&D Program of China No.2022ZD0160101, Natural Science Foundation of China (NSFC) under No. 62172041 and No. 62176021, Shenzhen Science and Technology Program under Grant No. JCYJ20241202130548062, and Natural Science Foundation of Shenzhen under Grant No. JCYJ20230807142703006.

References

- [1] Haoyi Duan, Hong-Xing Yu, Sirui Chen, Li Fei-Fei, and Jiajun Wu. Worldscore: A unified evaluation benchmark for world generation. *arXiv preprint arXiv:2504.00983*, 2025.
- [2] Lvmin Zhang and Maneesh Agrawala. Packing input frame context in next-frame prediction models for video generation. *arXiv preprint arXiv:2504.12626*, 2025.
- [3] Zhuoyi Yang, Jiayan Teng, Wendi Zheng, Ming Ding, Shiyu Huang, Jiazheng Xu, Yuanming Yang, Wenyi Hong, Xiaohan Zhang, Guanyu Feng, et al. Cogvideox: Text-to-video diffusion models with an expert transformer. In *The Thirteenth International Conference on Learning Representations*, 2025.
- [4] Xiangyu Peng, Zangwei Zheng, Chenhui Shen, Tom Young, Xinying Guo, Binluo Wang, Hang Xu, Hongxin Liu, Mingyan Jiang, Wenjun Li, Yuhui Wang, Anbang Ye, Gang Ren, Qianran Ma, Wanying Liang, Xiang Lian, Xiwen Wu, Yuting Zhong, Zhuangyan Li, Chaoyu Gong, Guojun Lei, Leijun Cheng, Limin Zhang, Minghao Li, Ruijie Zhang, Silan Hu, Shijie Huang, Xiaokang Wang, Yuanheng Zhao, Yuqi Wang, Ziang Wei, and Yang You. Open-sora 2.0: Training a commercial-level video generation model in \$200k. *arXiv preprint arXiv:2503.09642*, 2025.
- [5] Team Wan, Ang Wang, Baole Ai, Bin Wen, Chaojie Mao, Chen-Wei Xie, Di Chen, Feiwu Yu, Haiming Zhao, Jianxiao Yang, et al. Wan: Open and advanced large-scale video generative models. *arXiv preprint arXiv:2503.20314*, 2025.
- [6] Weijie Kong, Qi Tian, Zijian Zhang, Rox Min, Zuozhuo Dai, Jin Zhou, Jiangfeng Xiong, Xin Li, Bo Wu, Jianwei Zhang, et al. Hunyuanvideo: A systematic framework for large video generative models. *arXiv preprint arXiv:2412.03603*, 2024.
- [7] Hao He, Yinghao Xu, Yuwei Guo, Gordon Wetzstein, Bo Dai, Hongsheng Li, and Ceyuan Yang. Cameractrl: Enabling camera control for video diffusion models. In *The Thirteenth International Conference on Learning Representations*, 2025.
- [8] Koichi Namekata, Sherwin Bahmani, Ziyi Wu, Yash Kant, Igor Gilitschenski, and David B. Lindell. Sg-i2v: Self-guided trajectory control in image-to-video generation. In *The Thirteenth International Conference on Learning Representations*, 2025.
- [9] Chen Hou, Guoqiang Wei, Yan Zeng, and Zhibo Chen. Training-free camera control for video generation. In *The Thirteenth International Conference on Learning Representations*, 2025.
- [10] Kepan Nan, Rui Xie, Penghao Zhou, Tiehan Fan, Zhenheng Yang, Zhijie Chen, Xiang Li, Jian Yang, and Ying Tai. Openvid-1m: A large-scale high-quality dataset for text-to-video generation. In *The Thirteenth International Conference on Learning Representations*, 2025.
- [11] Tsai-Shien Chen, Aliaksandr Siarohin, Willi Menapace, Ekaterina Deyneka, Hsiang-wei Chao, Byung Eun Jeon, Yuwei Fang, Hsin-Ying Lee, Jian Ren, Ming-Hsuan Yang, et al. Panda-70m: Captioning 70m videos with multiple cross-modality teachers. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 13320–13331, 2024.
- [12] Xuan Ju, Yiming Gao, Zhaoyang Zhang, Ziyang Yuan, Xintao Wang, Ailing Zeng, Yu Xiong, Qiang Xu, and Ying Shan. Miradata: A large-scale video dataset with long durations and structured captions. *Advances in Neural Information Processing Systems*, 37:48955–48970, 2024.
- [13] Haoxin Chen, Yong Zhang, Xiaodong Cun, Menghan Xia, Xintao Wang, Chao Weng, and Ying Shan. Videocrafter2: Overcoming data limitations for high-quality video diffusion models. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 7310–7320, 2024.
- [14] Jiachen Li, Weixi Feng, Tsu-Jui Fu, Xinyi Wang, Sugato Basu, Wenhu Chen, and William Yang Wang. T2v-turbo: Breaking the quality bottleneck of video consistency model with mixed reward feedback. *Advances in neural information processing systems*, 37:75692–75726, 2024.
- [15] Jinbo Xing, Menghan Xia, Yong Zhang, Haoxin Chen, Wangbo Yu, Hanyuan Liu, Gongye Liu, Xintao Wang, Ying Shan, and Tien-Tsin Wong. Dynamicrafter: Animating open-domain images with video diffusion priors. In *European Conference on Computer Vision*, pages 399–417. Springer, 2024.

- [16] Jiaqi Xu, Xinyi Zou, Kunzhe Huang, Yunkuo Chen, Bo Liu, MengLi Cheng, Xing Shi, and Jun Huang. Easyanimate: A high-performance long video generation method based on transformer architecture. *arXiv preprint arXiv:2405.18991*, 2024.
- [17] Hong-Xing Yu, Haoyi Duan, Charles Herrmann, William T Freeman, and Jiajun Wu. Wonderworld: Interactive 3d scene generation from a single image. In *Proceedings of the Computer Vision and Pattern Recognition Conference*, pages 5916–5926, 2025.
- [18] Hong-Xing Yu, Haoyi Duan, Junhwa Hur, Kyle Sargent, Michael Rubinstein, William T Freeman, Forrester Cole, Deqing Sun, Noah Snavely, Jiajun Wu, et al. Wonderjourney: Going from anywhere to everywhere. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 6658–6667, 2024.
- [19] Jaeyoung Chung, Suyoung Lee, Hyeongjin Nam, Jaerin Lee, and Kyoung Mu Lee. Luciddreamer: Domain-free generation of 3d gaussian splatting scenes. *arXiv preprint arXiv:2311.13384*, 2023.
- [20] Paul Engstler, Andrea Vedaldi, Iro Laina, and Christian Rupprecht. Invisible stitch: Generating smooth 3d scenes with depth inpainting. In *2025 International Conference on 3D Vision*, pages 457–468. IEEE, 2025.
- [21] Lukas Höllerin, Ang Cao, Andrew Owens, Justin Johnson, and Matthias Nießner. Text2room: Extracting textured 3d meshes from 2d text-to-image models. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 7909–7920, 2023.
- [22] Jingbo Zhang, Xiaoyu Li, Ziyu Wan, Can Wang, and Jing Liao. Text2nerf: Text-driven 3d scene generation with neural radiance fields. *IEEE Transactions on Visualization and Computer Graphics*, 30(12):7749–7762, 2024.
- [23] Sherwin Bahmani, Ivan Skorokhodov, Victor Rong, Gordon Wetzstein, Leonidas Guibas, Peter Wonka, Sergey Tulyakov, Jeong Joon Park, Andrea Tagliasacchi, and David B Lindell. 4d-fy: Text-to-4d generation using hybrid score distillation sampling. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 7996–8006, 2024.
- [24] Sherwin Bahmani, Xian Liu, Wang Yifan, Ivan Skorokhodov, Victor Rong, Ziwei Liu, Xihui Liu, Jeong Joon Park, Sergey Tulyakov, Gordon Wetzstein, et al. Tc4d: Trajectory-conditioned text-to-4d generation. In *European Conference on Computer Vision*, pages 53–72. Springer, 2024.
- [25] Haiyu Zhang, Xinyuan Chen, Yaohui Wang, Xihui Liu, Yunhong Wang, and Yu Qiao. 4diffusion: Multi-view video diffusion model for 4d generation. *Advances in Neural Information Processing Systems*, 37:15272–15295, 2024.
- [26] Dejia Xu, Hanwen Liang, Neel P Bhatt, Hezhen Hu, Hanxue Liang, Konstantinos N Plataniotis, and Zhangyang Wang. Comp4d: Llm-guided compositional 4d scene generation. *arXiv preprint arXiv:2403.16993*, 2024.
- [27] Yifan Zhang, Chunli Peng, Boyang Wang, Puyi Wang, Qingcheng Zhu, Zedong Gao, Eric Li, Yang Liu, and Yahui Zhou. Matrix-game: Interactive world foundation model. *arXiv*, 2025.
- [28] Tim Brooks, Bill Peebles, Connor Holmes, Will DePue, Yufei Guo, Li Jing, David Schnurr, Joe Taylor, Troy Luhman, Eric Luhman, et al. Video generation models as world simulators. *OpenAI Blog*, 1:8, 2024.
- [29] Niket Agarwal, Arslan Ali, Maciej Bala, Yogesh Balaji, Erik Barker, Tiffany Cai, Prithvijit Chattopadhyay, Yongxin Chen, Yin Cui, Yifan Ding, et al. Cosmos world foundation model platform for physical ai. *arXiv preprint arXiv:2501.03575*, 2025.
- [30] Bingyi Kang, Yang Yue, Rui Lu, Zhijie Lin, Yang Zhao, Kaixin Wang, Gao Huang, and Jiashi Feng. How far is video generation from world model: A physical law perspective. In *Proceedings of the 42nd International Conference on Machine Learning*, 2025.
- [31] Fanqing Meng, Jiaqi Liao, Xinyu Tan, Wenqi Shao, Quanfeng Lu, Kaipeng Zhang, Yu Cheng, Dianqi Li, Yu Qiao, and Ping Luo. Towards world simulator: Crafting physical commonsense-based benchmark for video generation. In *Proceedings of the 42nd International Conference on Machine Learning*, 2025.
- [32] Jiannan Xiang, Guangyi Liu, Yi Gu, Qiyue Gao, Yuting Ning, Yuheng Zha, Zeyu Feng, Tianhua Tao, Shibo Hao, Yemin Shi, et al. Pandora: Towards general world model with natural language actions and video states. *arXiv preprint arXiv:2406.09455*, 2024.
- [33] Xiaoyu Shi, Zhaoyang Huang, Fu-Yun Wang, Weikang Bian, Dasong Li, Yi Zhang, Manyuan Zhang, Ka Chun Cheung, Simon See, Hongwei Qin, et al. Motion-i2v: Consistent and controllable image-to-video generation with explicit motion modeling. In *ACM SIGGRAPH 2024 Conference Papers*, pages 1–11, 2024.

- [34] Zhengqi Li, Richard Tucker, Forrester Cole, Qianqian Wang, Linyi Jin, Vickie Ye, Angjoo Kanazawa, Aleksander Holynski, and Noah Snavely. Megasam: Accurate, fast, and robust structure and motion from casual dynamic videos. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2025.
- [35] Sili Chen, Hengkai Guo, Shengnan Zhu, Feihu Zhang, Zilong Huang, Jiashi Feng, and Bingyi Kang. Video depth anything: Consistent depth estimation for super-long videos. In *Proceedings of the Computer Vision and Pattern Recognition Conference*, pages 22831–22840, 2025.
- [36] Luigi Piccinelli, Yung-Hsu Yang, Christos Sakaridis, Mattia Segu, Siyuan Li, Luc Van Gool, and Fisher Yu. Unidepth: Universal monocular metric depth estimation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 10106–10116, 2024.
- [37] Khurram Soomro, Amir Roshan Zamir, and Mubarak Shah. Ucf101: A dataset of 101 human actions classes from videos in the wild. *arXiv preprint arXiv:1212.0402*, 2012.
- [38] Aliaksandr Siarohin, Stéphane Lathuilière, Sergey Tulyakov, Elisa Ricci, and Nicu Sebe. First order motion model for image animation. *Advances in neural information processing systems*, 32, 2019.
- [39] Wei Xiong, Wenhan Luo, Lin Ma, Wei Liu, and Jiebo Luo. Learning to generate time-lapse videos using multi-stage dynamic generative adversarial networks. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 2364–2373, 2018.
- [40] Andreas Rossler, Davide Cozzolino, Luisa Verdoliva, Christian Riess, Justus Thies, and Matthias Nießner. Faceforensics++: Learning to detect manipulated facial images. In *Proceedings of the IEEE/CVF international conference on computer vision*, pages 1–11, 2019.
- [41] Shenghai Yuan, Jinfang Huang, Yongqi Xu, Yaoyang Liu, Shaofeng Zhang, Yujun Shi, Rui-Jie Zhu, Xinhua Cheng, Jiebo Luo, and Li Yuan. Chronomagic-bench: A benchmark for metamorphic evaluation of text-to-time-lapse video generation. *Advances in Neural Information Processing Systems*, 37:21236–21270, 2024.
- [42] Hao Zhu, Wayne Wu, Wentao Zhu, Liming Jiang, Siwei Tang, Li Zhang, Ziwei Liu, and Chen Change Loy. Celebv-hq: A large-scale video facial attributes dataset. In *European conference on computer vision*, pages 650–667. Springer, 2022.
- [43] Max Bain, Arsha Nagrani, Gülcin Varol, and Andrew Zisserman. Frozen in time: A joint video and image encoder for end-to-end retrieval. In *Proceedings of the IEEE/CVF international conference on computer vision*, pages 1728–1738, 2021.
- [44] Yi Wang, Yinan He, Yizhuo Li, Kunchang Li, Jiashuo Yu, Xin Ma, Xinhao Li, Guo Chen, Xinyuan Chen, Yaohui Wang, et al. Internvid: A large-scale video-text dataset for multimodal understanding and generation. In *The Twelfth International Conference on Learning Representations*, 2023.
- [45] Bin Lin, Yunyang Ge, Xinhua Cheng, Zongjian Li, Bin Zhu, Shaodong Wang, Xianyi He, Yang Ye, Shenghai Yuan, Liuhan Chen, et al. Open-sora plan: Open-source large video generation model. *arXiv preprint arXiv:2412.00131*, 2024.
- [46] Xueyang Wang, Xiya Zhang, Yinheng Zhu, Yuchen Guo, Xiaoyun Yuan, Liuyu Xiang, Zerun Wang, Guiguang Ding, David Brady, Qionghai Dai, et al. Panda: A gigapixel-level human-centric video dataset. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 3268–3278, 2020.
- [47] Tomás Soucek and Jakub Lokoc. Transnet v2: An effective deep network architecture for fast shot transition detection. In *Proceedings of the 32nd ACM International Conference on Multimedia*, pages 11218–11221, 2024.
- [48] Chenlong He, Qi Zheng, Ruoxi Zhu, Xiaoyang Zeng, Yibo Fan, and Zhengzhong Tu. Cover: A comprehensive video quality evaluator. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) Workshops*, pages 5799–5809, June 2024.
- [49] Aaron Hurst, Adam Lerer, Adam P Goucher, Adam Perelman, Aditya Ramesh, Aidan Clark, AJ Ostrow, Akila Welihinda, Alan Hayes, Alec Radford, et al. Gpt-4o system card. *arXiv preprint arXiv:2410.21276*, 2024.
- [50] Shuai Bai, Keqin Chen, Xuejing Liu, Jialin Wang, Wenbin Ge, Sibo Song, Kai Dang, Peng Wang, Shijie Wang, Jun Tang, et al. Qwen2. 5-vl technical report. *arXiv preprint arXiv:2502.13923*, 2025.

- [51] Woosuk Kwon, Zhuohan Li, Siyuan Zhuang, Ying Sheng, Lianmin Zheng, Cody Hao Yu, Joseph E. Gonzalez, Hao Zhang, and Ion Stoica. Efficient memory management for large language model serving with pagedattention. In *Proceedings of the ACM SIGOPS 29th Symposium on Operating Systems Principles*, 2023.
- [52] Will Reese. Nginx: the high-performance web server and reverse proxy. *Linux Journal*, 2008(173):2, 2008.
- [53] Zachary Teed, Lahav Lipson, and Jia Deng. Deep patch visual odometry. *Advances in Neural Information Processing Systems*, 36:39033–39051, 2023.
- [54] Jianyuan Wang, Minghao Chen, Nikita Karaev, Andrea Vedaldi, Christian Rupprecht, and David Novotny. Vggt: Visual geometry grounded transformer. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2025.
- [55] Lihe Yang, Bingyi Kang, Zilong Huang, Xiaogang Xu, Jiashi Feng, and Hengshuang Zhao. Depth anything: Unleashing the power of large-scale unlabeled data. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 10371–10381, 2024.
- [56] Yi Wang, Kunchang Li, Xinhao Li, Jiashuo Yu, Yinan He, Guo Chen, Baoqi Pei, Rongkun Zheng, Zun Wang, Yansong Shi, et al. Internvideo2: Scaling foundation models for multimodal video understanding. In *European Conference on Computer Vision*, pages 396–416. Springer, 2024.
- [57] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, 12:2825–2830, 2011.
- [58] Ziqi Huang, Yinan He, Jiashuo Yu, Fan Zhang, Chenyang Si, Yuming Jiang, Yuanhan Zhang, Tianxing Wu, Qingyang Jin, Nattapol Chanpaisit, et al. Vbench: Comprehensive benchmark suite for video generative models. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 21807–21818, 2024.
- [59] Ziqi Huang, Fan Zhang, Xiaojie Xu, Yinan He, Jiashuo Yu, Ziyue Dong, Qianli Ma, Nattapol Chanpaisit, Chenyang Si, Yuming Jiang, et al. Vbench++: Comprehensive and versatile benchmark suite for video generative models. *arXiv preprint arXiv:2411.13503*, 2024.
- [60] Vincent Sitzmann, Semon Rezchikov, Bill Freeman, Josh Tenenbaum, and Fredo Durand. Light field networks: Neural scene representations with single-evaluation rendering. *Advances in Neural Information Processing Systems*, 34:19313–19325, 2021.

NeurIPS Paper Checklist

1. Claims

Question: Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope?

Answer: [Yes]

Justification: The abstract contains our main claims including motivation, the high-quality long-form video dataset Sekai with diverse annotations.

Guidelines:

- The answer NA means that the abstract and introduction do not include the claims made in the paper.
- The abstract and/or introduction should clearly state the claims made, including the contributions made in the paper and important assumptions and limitations. A No or NA answer to this question will not be perceived well by the reviewers.
- The claims made should match theoretical and experimental results, and reflect how much the results can be expected to generalize to other settings.
- It is fine to include aspirational goals as motivation as long as it is clear that these goals are not attained by the paper.

2. Limitations

Question: Does the paper discuss the limitations of the work performed by the authors?

Answer: [Yes]

Justification: We have discussed the limitations in a individual section.

Guidelines:

- The answer NA means that the paper has no limitation while the answer No means that the paper has limitations, but those are not discussed in the paper.
- The authors are encouraged to create a separate "Limitations" section in their paper.
- The paper should point out any strong assumptions and how robust the results are to violations of these assumptions (e.g., independence assumptions, noiseless settings, model well-specification, asymptotic approximations only holding locally). The authors should reflect on how these assumptions might be violated in practice and what the implications would be.
- The authors should reflect on the scope of the claims made, e.g., if the approach was only tested on a few datasets or with a few runs. In general, empirical results often depend on implicit assumptions, which should be articulated.
- The authors should reflect on the factors that influence the performance of the approach. For example, a facial recognition algorithm may perform poorly when image resolution is low or images are taken in low lighting. Or a speech-to-text system might not be used reliably to provide closed captions for online lectures because it fails to handle technical jargon.
- The authors should discuss the computational efficiency of the proposed algorithms and how they scale with dataset size.
- If applicable, the authors should discuss possible limitations of their approach to address problems of privacy and fairness.
- While the authors might fear that complete honesty about limitations might be used by reviewers as grounds for rejection, a worse outcome might be that reviewers discover limitations that aren't acknowledged in the paper. The authors should use their best judgment and recognize that individual actions in favor of transparency play an important role in developing norms that preserve the integrity of the community. Reviewers will be specifically instructed to not penalize honesty concerning limitations.

3. Theory assumptions and proofs

Question: For each theoretical result, does the paper provide the full set of assumptions and a complete (and correct) proof?

Answer: [NA]

Justification: Our work is not related to theorems.

Guidelines:

- The answer NA means that the paper does not include theoretical results.
- All the theorems, formulas, and proofs in the paper should be numbered and cross-referenced.
- All assumptions should be clearly stated or referenced in the statement of any theorems.

- The proofs can either appear in the main paper or the supplemental material, but if they appear in the supplemental material, the authors are encouraged to provide a short proof sketch to provide intuition.
- Inversely, any informal proof provided in the core of the paper should be complemented by formal proofs provided in appendix or supplemental material.
- Theorems and Lemmas that the proof relies upon should be properly referenced.

4. Experimental result reproducibility

Question: Does the paper fully disclose all the information needed to reproduce the main experimental results of the paper to the extent that it affects the main claims and/or conclusions of the paper (regardless of whether the code and data are provided or not)?

Answer: [Yes]

Justification: We provide the implementation details of dataset curation and experiments.

Guidelines:

- The answer NA means that the paper does not include experiments.
- If the paper includes experiments, a No answer to this question will not be perceived well by the reviewers: Making the paper reproducible is important, regardless of whether the code and data are provided or not.
- If the contribution is a dataset and/or model, the authors should describe the steps taken to make their results reproducible or verifiable.
- Depending on the contribution, reproducibility can be accomplished in various ways. For example, if the contribution is a novel architecture, describing the architecture fully might suffice, or if the contribution is a specific model and empirical evaluation, it may be necessary to either make it possible for others to replicate the model with the same dataset, or provide access to the model. In general, releasing code and data is often one good way to accomplish this, but reproducibility can also be provided via detailed instructions for how to replicate the results, access to a hosted model (e.g., in the case of a large language model), releasing of a model checkpoint, or other means that are appropriate to the research performed.
- While NeurIPS does not require releasing code, the conference does require all submissions to provide some reasonable avenue for reproducibility, which may depend on the nature of the contribution. For example
 - If the contribution is primarily a new algorithm, the paper should make it clear how to reproduce that algorithm.
 - If the contribution is primarily a new model architecture, the paper should describe the architecture clearly and fully.
 - If the contribution is a new model (e.g., a large language model), then there should either be a way to access this model for reproducing the results or a way to reproduce the model (e.g., with an open-source dataset or instructions for how to construct the dataset).
 - We recognize that reproducibility may be tricky in some cases, in which case authors are welcome to describe the particular way they provide for reproducibility. In the case of closed-source models, it may be that access to the model is limited in some way (e.g., to registered users), but it should be possible for other researchers to have some path to reproducing or verifying the results.

5. Open access to data and code

Question: Does the paper provide open access to the data and code, with sufficient instructions to faithfully reproduce the main experimental results, as described in supplemental material?

Answer: [Yes]

Justification: We provide the youtube video urls and the code of the whole dataset curation pipeline. The complete data will be published after the paper is accepted.

Guidelines:

- The answer NA means that paper does not include experiments requiring code.
- Please see the NeurIPS code and data submission guidelines (<https://nips.cc/public/guides/CodeSubmissionPolicy>) for more details.
- While we encourage the release of code and data, we understand that this might not be possible, so “No” is an acceptable answer. Papers cannot be rejected simply for not including code, unless this is central to the contribution (e.g., for a new open-source benchmark).
- The instructions should contain the exact command and environment needed to run to reproduce the results. See the NeurIPS code and data submission guidelines (<https://nips.cc/public/guides/CodeSubmissionPolicy>) for more details.

- The authors should provide instructions on data access and preparation, including how to access the raw data, preprocessed data, intermediate data, and generated data, etc.
- The authors should provide scripts to reproduce all experimental results for the new proposed method and baselines. If only a subset of experiments are reproducible, they should state which ones are omitted from the script and why.
- At submission time, to preserve anonymity, the authors should release anonymized versions (if applicable).
- Providing as much information as possible in supplemental material (appended to the paper) is recommended, but including URLs to data and code is permitted.

6. Experimental setting/details

Question: Does the paper specify all the training and test details (e.g., data splits, hyperparameters, how they were chosen, type of optimizer, etc.) necessary to understand the results?

Answer: [NA]

Justification: We focus on the proposed Sekai dataset, and there are little experiments.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The experimental setting should be presented in the core of the paper to a level of detail that is necessary to appreciate the results and make sense of them.
- The full details can be provided either with the code, in appendix, or as supplemental material.

7. Experiment statistical significance

Question: Does the paper report error bars suitably and correctly defined or other appropriate information about the statistical significance of the experiments?

Answer: [NA]

Justification: We focus on the proposed Sekai dataset, and there are little experiments.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The authors should answer "Yes" if the results are accompanied by error bars, confidence intervals, or statistical significance tests, at least for the experiments that support the main claims of the paper.
- The factors of variability that the error bars are capturing should be clearly stated (for example, train/test split, initialization, random drawing of some parameter, or overall run with given experimental conditions).
- The method for calculating the error bars should be explained (closed form formula, call to a library function, bootstrap, etc.).
- The assumptions made should be given (e.g., Normally distributed errors).
- It should be clear whether the error bar is the standard deviation or the standard error of the mean.
- It is OK to report 1-sigma error bars, but one should state it. The authors should preferably report a 2-sigma error bar than state that they have a 96% CI, if the hypothesis of Normality of errors is not verified.
- For asymmetric distributions, the authors should be careful not to show in tables or figures symmetric error bars that would yield results that are out of range (e.g. negative error rates).
- If error bars are reported in tables or plots, The authors should explain in the text how they were calculated and reference the corresponding figures or tables in the text.

8. Experiments compute resources

Question: For each experiment, does the paper provide sufficient information on the computer resources (type of compute workers, memory, time of execution) needed to reproduce the experiments?

Answer: [NA]

Justification: We focus on the proposed Sekai dataset, and there are little experiments.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The paper should indicate the type of compute workers CPU or GPU, internal cluster, or cloud provider, including relevant memory and storage.
- The paper should provide the amount of compute required for each of the individual experimental runs as well as estimate the total compute.

- The paper should disclose whether the full research project required more compute than the experiments reported in the paper (e.g., preliminary or failed experiments that didn't make it into the paper).

9. Code of ethics

Question: Does the research conducted in the paper conform, in every respect, with the NeurIPS Code of Ethics <https://neurips.cc/public/EthicsGuidelines>?

Answer: [Yes]

Justification: Our work conforms with the NeurIPS Code of Ethics.

Guidelines:

- The answer NA means that the authors have not reviewed the NeurIPS Code of Ethics.
- If the authors answer No, they should explain the special circumstances that require a deviation from the Code of Ethics.
- The authors should make sure to preserve anonymity (e.g., if there is a special consideration due to laws or regulations in their jurisdiction).

10. Broader impacts

Question: Does the paper discuss both potential positive societal impacts and negative societal impacts of the work performed?

Answer: [NA]

Justification: There is no societal impact of our work performed.

Guidelines:

- The answer NA means that there is no societal impact of the work performed.
- If the authors answer NA or No, they should explain why their work has no societal impact or why the paper does not address societal impact.
- Examples of negative societal impacts include potential malicious or unintended uses (e.g., disinformation, generating fake profiles, surveillance), fairness considerations (e.g., deployment of technologies that could make decisions that unfairly impact specific groups), privacy considerations, and security considerations.
- The conference expects that many papers will be foundational research and not tied to particular applications, let alone deployments. However, if there is a direct path to any negative applications, the authors should point it out. For example, it is legitimate to point out that an improvement in the quality of generative models could be used to generate deepfakes for disinformation. On the other hand, it is not needed to point out that a generic algorithm for optimizing neural networks could enable people to train models that generate Deepfakes faster.
- The authors should consider possible harms that could arise when the technology is being used as intended and functioning correctly, harms that could arise when the technology is being used as intended but gives incorrect results, and harms following from (intentional or unintentional) misuse of the technology.
- If there are negative societal impacts, the authors could also discuss possible mitigation strategies (e.g., gated release of models, providing defenses in addition to attacks, mechanisms for monitoring misuse, mechanisms to monitor how a system learns from feedback over time, improving the efficiency and accessibility of ML).

11. Safeguards

Question: Does the paper describe safeguards that have been put in place for responsible release of data or models that have a high risk for misuse (e.g., pretrained language models, image generators, or scraped datasets)?

Answer: [Yes]

Justification: We access videos on Youtube, and Youtube has its own methods to avoid security safety risks.

Guidelines:

- The answer NA means that the paper poses no such risks.
- Released models that have a high risk for misuse or dual-use should be released with necessary safeguards to allow for controlled use of the model, for example by requiring that users adhere to usage guidelines or restrictions to access the model or implementing safety filters.
- Datasets that have been scraped from the Internet could pose safety risks. The authors should describe how they avoided releasing unsafe images.

- We recognize that providing effective safeguards is challenging, and many papers do not require this, but we encourage authors to take this into account and make a best faith effort.

12. Licenses for existing assets

Question: Are the creators or original owners of assets (e.g., code, data, models), used in the paper, properly credited and are the license and terms of use explicitly mentioned and properly respected?

Answer: [Yes]

Justification: We've cited the original paper of the code and model we used.

Guidelines:

- The answer NA means that the paper does not use existing assets.
- The authors should cite the original paper that produced the code package or dataset.
- The authors should state which version of the asset is used and, if possible, include a URL.
- The name of the license (e.g., CC-BY 4.0) should be included for each asset.
- For scraped data from a particular source (e.g., website), the copyright and terms of service of that source should be provided.
- If assets are released, the license, copyright information, and terms of use in the package should be provided. For popular datasets, paperswithcode.com/datasets has curated licenses for some datasets. Their licensing guide can help determine the license of a dataset.
- For existing datasets that are re-packaged, both the original license and the license of the derived asset (if it has changed) should be provided.
- If this information is not available online, the authors are encouraged to reach out to the asset's creators.

13. New assets

Question: Are new assets introduced in the paper well documented and is the documentation provided alongside the assets?

Answer: [Yes]

Justification: We provide the youtube video urls and the code of the whole dataset curation pipeline. The complete assets will be published after the paper is accepted.

Guidelines:

- The answer NA means that the paper does not release new assets.
- Researchers should communicate the details of the dataset/code/model as part of their submissions via structured templates. This includes details about training, license, limitations, etc.
- The paper should discuss whether and how consent was obtained from people whose asset is used.
- At submission time, remember to anonymize your assets (if applicable). You can either create an anonymized URL or include an anonymized zip file.

14. Crowdsourcing and research with human subjects

Question: For crowdsourcing experiments and research with human subjects, does the paper include the full text of instructions given to participants and screenshots, if applicable, as well as details about compensation (if any)?

Answer: [NA]

Justification: There are no crowdsourcing experiments and research with human subjects.

Guidelines:

- The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
- Including this information in the supplemental material is fine, but if the main contribution of the paper involves human subjects, then as much detail as possible should be included in the main paper.
- According to the NeurIPS Code of Ethics, workers involved in data collection, curation, or other labor should be paid at least the minimum wage in the country of the data collector.

15. Institutional review board (IRB) approvals or equivalent for research with human subjects

Question: Does the paper describe potential risks incurred by study participants, whether such risks were disclosed to the subjects, and whether Institutional Review Board (IRB) approvals (or an equivalent approval/review based on the requirements of your country or institution) were obtained?

Answer: [NA]

Justification: There are no crowdsourcing experiments and research with human subjects.

Guidelines:

- The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
- Depending on the country in which research is conducted, IRB approval (or equivalent) may be required for any human subjects research. If you obtained IRB approval, you should clearly state this in the paper.
- We recognize that the procedures for this may vary significantly between institutions and locations, and we expect authors to adhere to the NeurIPS Code of Ethics and the guidelines for their institution.
- For initial submissions, do not include any information that would break anonymity (if applicable), such as the institution conducting the review.

16. Declaration of LLM usage

Question: Does the paper describe the usage of LLMs if it is an important, original, or non-standard component of the core methods in this research? Note that if the LLM is used only for writing, editing, or formatting purposes and does not impact the core methodology, scientific rigorousness, or originality of the research, declaration is not required.

Answer: [NA]

Justification: The usage of LLMs is not an important, original, or non-standard component in this work.

Guidelines:

- The answer NA means that the core method development in this research does not involve LLMs as any important, original, or non-standard components.
- Please refer to our LLM policy (<https://neurips.cc/Conferences/2025/LLM>) for what should or should not be described.