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EvalCrafter: Benchmarking and Evaluating Large Video Generation Models

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Project Page: http://evalcrafter.github.io

Abstract

The vision and language generative models have been overgrown in recent years. For video generation, various open-sourced models and public-available services have been developed to generate high-quality videos. However, these methods often use a few metrics, e.g., *FVD [57] or IS [46], to evaluate the performance. We argue that it is hard to judge the large conditional generative models from the simple metrics since these models are often trained on very large datasets with multi-aspect abilities. Thus, we propose a novel framework and pipeline for exhaustively evaluating the performance of the generated videos. Our approach involves generating a diverse and comprehensive list of 700 prompts for text-to-video generation, which is based on an analysis of real-world user data and generated with the assistance of a large language model. Then, we evaluate the state-of-the-art video generative models on our carefully designed benchmark, in terms of visual qualities, content qualities, motion qualities, and text-video alignment with 17 well-selected objective metrics. To obtain the final leaderboard of the models, we further fit a series of coefficients to align the objective metrics to the users' opinions. Based on the proposed human alignment method, our final score shows a higher correlation than simply averaging the metrics, showing the effectiveness of the proposed evaluation method.*

1. Introduction

The charm of the large generative models is sweeping the world, *e.g.*, the well-known ChatGPT and GPT4 [38] have shown human-level abilities in several aspects, including coding, solving math problems, and even visual understanding, which can be used to interact with our human beings using any knowledge in a conversational way. As for the generative models for visual content creation, Stable Diffusion

Figure 1. We propose EvalCrafter, a comprehensive framework for benchmarking and evaluating the text-to-video models, including the well-defined prompt types in grey and the multiple evaluation aspects in black circles.

(SD) [44] and SDXL [41] play very important roles since they are the most powerful publicly available models that can generate high-quality images from any text prompts.

Beyond text-to-image (T2I), taming diffusion model for video generation has also progressed rapidly. Early works (Imagen-Viedo [23], Make-A-Video [50]) utilize the cascaded models for video generation directly. Powered by the image generation priors in SD, LVDM [21] and MagicVideo [70] have been proposed to train the temporal layers to efficiently generate videos. Apart from the academic papers, several commercial services also can generate videos from text or images, *e.g.*, Gen2 [18] and PikaLabs [5]. Although we can not get the technique details of these services, they are not evaluated and compared with other methods. However, all current large text-to-video (T2V) models only use previous GAN-based metrics like FVD [57] for evaluation, which only concerns the distribution matching between the generated video and the real videos, other than the pairs between the text prompt and the generated video. Differently, we argue that a good evaluation method should consider the

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metrics in different aspects, *e.g.*, the motion quality and the temporal consistency. Also, similar to the large language models (LLMs), some models are not publicly available and we can only get access to the generated videos, which further increases the difficulties in evaluation. Although the evaluation has progressed rapidly in the large generative models, including the areas of LLM [38], MLLM [33], and T2I [26], it is still hard to directly use these methods for video generation. The main problem here is that different from T2I or dialogue evaluation, motion and consistency are very important to video generation which previous works ignore.

We make the very first step to evaluate the general T2V models. In detail, we first build a comprehensive prompt list containing various everyday objects, attributes, and motions. To achieve a balanced distribution of well-known concepts, we start from the well-defined meta types of the real-world knowledge and utilize the knowledge of the LLM, *i.e.*, ChatGPT [38], to extend our meta-prompt to a wide range. Besides the prompts generated by the model, we also select the prompts from real-world users and T2I prompts. After that, we obtain the metadata (*e.g.*, color, size, *etc.*) from the prompt for further evaluation. Second, we assess the performance of large T2V models from four aspects, *i.e.*, video quality, text-video alignment, motion quality, and temporal consistency. For each aspect, we employ several objective metrics as evaluation measures, and we conduct a user study to human scores w.r.t. these four aspects. After that, we train coefficients of the regression model for each aspect, aligning evaluation scores with user preferences. This enables us to obtain the final model scores and evaluate new videos using the trained coefficients.

Overall, we summarize the contribution of our paper as:

- We make the first step of evaluating the large T2V model and build a comprehensive prompt list with detailed annotations for T2V evaluation.
- We consider the aspects of the video visual quality, video motion quality, video temporal consistency, and text-video alignment for the evaluation of video generation. For each aspect, we align the opinions of humans and also verify the effectiveness of the proposed metric by correlation analysis.
- During the evaluation, we also discuss several conclusions and findings, which might also contribute to further innovation and development of T2V models.

2. Related Work

2.1. Text-to-Video Generation and Evaluation

Text-to-video (T2V) generation aims to create videos from text prompts. Early works used Variational AutoEncoders (VAEs [29]) or generative adversarial networks (GANs [20]) but often yielded low-quality or domain-specific results, such as faces [67] or landscapes [51, 64]. Recent methods leverage advancements in diffusion models [24, 25, 61] and large-scale text-image pretraining [43] to improve generation quality. Examples include Make-A-Video [50], Imagen-Video [23], LVDM [21], Align Your Latent [9], and MagicVideo [70]. Commercial and non-commercial entities have also shown interest in T2V generation, with online services like Gen1 [18], Gen2 [18], and open-source models such as ZeroScope [6], ModelScope [58]. Discord-based servers like Pika-Lab [5] and Morph Studio [4] have demonstrated competitive results.

However, a fair and detailed benchmark for evaluating these methods is still lacking. Existing metrics like FVD [57], IS [46], and CLIP similarity [43] may perform well on previous in-domain T2I generation methods but do not adequately assess alignment with input text, motion quality, and temporal consistency, which are crucial for T2V.

2.2. Evaluations on Large Generative Models

Evaluating the large generative models [38, 41, 44, 55, 56] is a big challenge for both the NLP and vision tasks. For the LLMs, current methods design several metrics in terms of different abilities, question types, and user platform [15, 22, 62, 69, 71]. More details of LLM evaluation and Multi-model LLM evaluation can be found in recent surveys [11, 68]. Similarly, the evaluation of the multi-modal generative model also draws the attention of the researchers [8, 63]. For example, Seed-Bench [33] generates the VQA for multi-modal LLM evaluation.

For the models in visual generation tasks, Imagen [45] only evaluates the model via user studies. DALL-Eval [14] assesses the visual reasoning skills and social basis of the T2I model via both user and object detection algorithm [10]. HRS-Bench [7] proposes a holistic and reliable benchmark by generating the prompt with ChatGPT [38] and utilizing 17 metrics to evaluate the 13 skills of the T2I model. TIFA [26] proposes a benchmark utilizing the visual question answering (VQA). However, these methods still work for T2I evaluation or language model evaluation. For T2V evaluation, we further consider the quality of motion and temporal consistency.

3. Benchmark Construction

Our benchmark aims to create a trustworthy prompt list to evaluate the abilities of various T2V models fairly. To this end, we first collect and analyze large-scale real-world users' prompts. After that, we propose an automatic pipeline to generate a prompt list with high diversity. Since video generation is time-consuming, we collect 700 prompts as our initial version for evaluation with careful annotation. In

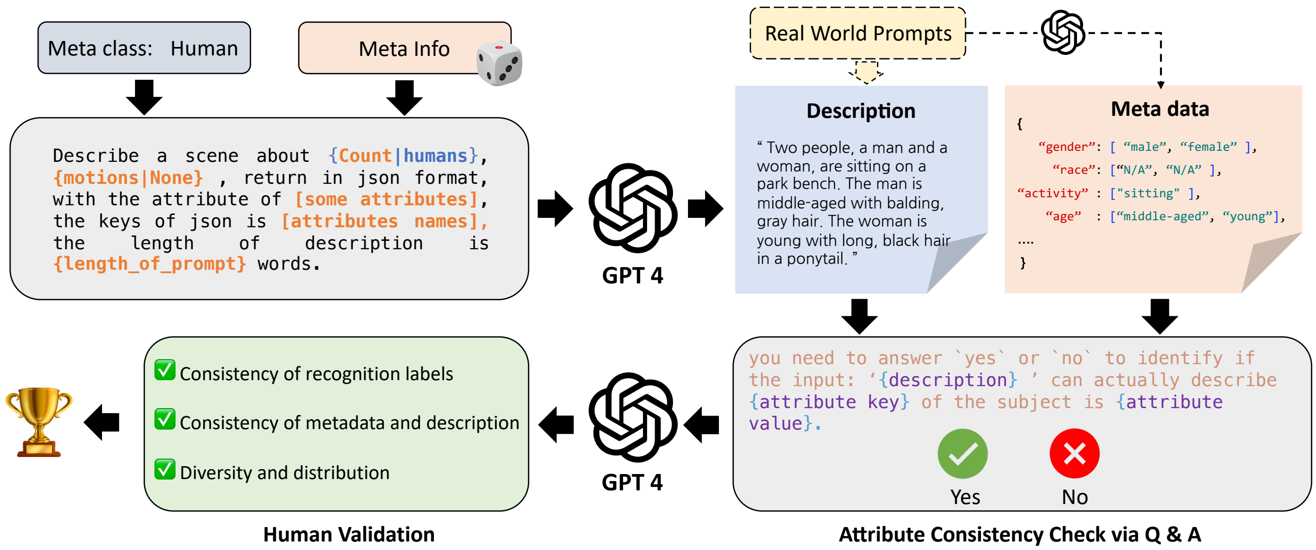

Figure 2. We aim to generate a trustworthy benchmark with detailed prompts for text-to-video evaluation by computer vision model and users. We show the pipeline above.

Method	Ver.	Abilities†	Resolution	FPS	Open Source	Length	Speed*	Motion	Camera
ModelScope	23.03	T2V	256×256	8	✓	4s	0.5 min	-	-
VideoCrafter	23.04	T2V	256×256	8	✓	2s	0.5 min	-	-
ZeroScope	23.06	T2V & V2V	1024×576	8	✓	4s	3 min	-	-
ModelScope-XL	23.08	I2V & V2V	1280×720	8	✓	4s	8 min+	-	-
Show-1	23.10	T2V	576×320	8	✓	4s	10 min	-	-
Hotshot-XL	23.10	T2V	672×384	8	✓	1s	10 s	-	-
VideoCrafter1	23.10	I2V & T2V	1024×576	8	✓	2s	3 min	-	-
Floor33 Pictures	23.08	T2V	1280×720	8	-	2s	4 min	-	-
PikaLab	23.09	I2V OR T2V	1088×640	24	-	3s	1 min	✓	✓
Gen2	23.09	I2V OR T2V	896×512	24	-	4s	1 min	✓	✓

Table 1. The difference in the available diffusion-based text-to-video models. † We majorly evaluate the method of text-to-video generation (T2V). For related image-to-video generation model (I2V), *i.e.*, ModelScope-XL, we first generate the image by Stable Diffusion v2.1 and then perform image-to-video on the generated content.

this section, we introduce the details of the construction of our benchmark.

Real-World Data Collection. To better understand the types of prompts we should generate, we collect prompts from real-world T2V generation discord users, including the FullJourney [2] and PikaLab [5]. In total, we gather over 600k prompts with corresponding videos and filter them to 200k by removing repeated and meaningless prompts.

Through analyzing the collected data including aspects like prompt length and word frequency, we get to know that most of the prompts contain 3 to 40 words. Besides, we identify four meta-subject classes for T2V generation: `human`, `animal`, `object`, and `landscape`. For each type, we consider the motions and styles of each type, the relationship between the current metaclass and other metaclasses, and the `motion` and `camera motion` to construct the benchmark. We give more details in the supplementary materials.

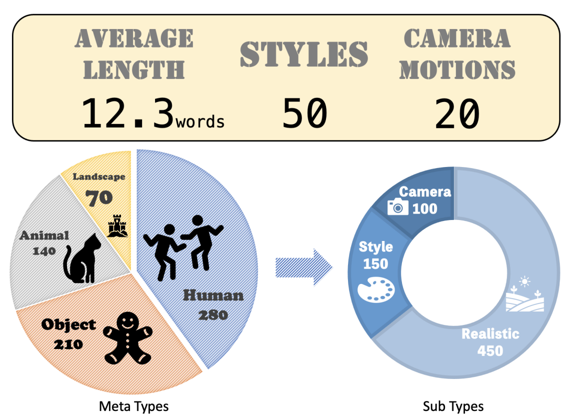

Figure 3. The analysis of the proposed benchmark. Each meta type contains 3 sub-types to increase the generated videos' diversity.

General Recognizable Prompt Generation. Based on the metaclasses identified in the previous step, we generate the recognizable prompts with the help of a LLM and human input. As shown in Fig 2, for each kind of metaclass, we ask GPT-4 [38] to describe the scenes about this metaclass and its attributes with randomly sampled meta information. This way, we get the ground truth for the computer vision models for evaluation. However, we find that GPT-4 is not perfect for this task, as the generated attributes are not very consistent with the generated description. Thus, we involve a self-check in the benchmark building process where we use GPT-4 to identify the similarities between the generated description and each metadata. Finally, we filter the prompts by ourselves to ensure each prompt is correct and meaningful for T2V generation.

In addition to the automatically generated prompts, we also integrate prompts from real-world users and available T2I evaluation prompts, such as DALL-Eval [14] and Draw-Bench [45]. We filter and generate the metadata using GPT-4, choose suitable prompts with corresponding meta-information as shown in Fig. 2, and check the consistency of the meta-information.

Benchmark Overview. Overall, we get over 700 prompts in the metaclasses of `human`, `animal`, `objects`, and `landscape`. Each class contains the natural scenes, the stylized prompts, and the results with explicit camera motion controls. We give a brief view of the benchmark in Fig. 3. To increase the diversity of the prompts, our benchmark contains 3 different sub-types, where we have a total of 50 styles and 20 camera motion prompts. We randomly add them in 250 prompts of the whole benchmark. Our benchmark contains an average length of 12.3 words per prompt, which is similar to the real-world prompts we collected.

4. Evaluation Metrics

Different from previous FID [47] based evaluation metrics, we evaluate the T2V models in different aspects, including the visual quality of the generated video, the text-video alignment, the motion quality, and temporal consistency. Below, we give the detailed metrics.

4.1. Overall Video Quality Assessment

We focus on the visual quality of the generated video, which is crucial for user appeal. As distribution-based methods like FVD [57] require ground truth videos, we argue they are unsuitable for general T2V generation cases.

Video Quality Assessment (VQA$_A$, VQA$_T$). We employ the Dover [60] method to assess generated video quality in terms of aesthetics and technicality. The technical rating measures common distortions like noise and artifacts. Dover [60] is trained on a large-scale dataset with labels ranked by real users. We denote the aesthetic and technical scores as VQA$_A$ and VQA$_T$, respectively.

Inception Score (IS). We also use the inception score [46] as a video quality assessment index, following previous T2V generation papers. The inception score evaluates GAN [20] performance using a pre-trained Inception Network [53] on the ImageNet [17] dataset. A higher inception score indicates more diverse generated content.

4.2. Text-Video Alignment

We evaluate the alignment of input text and generated video in various aspects, including global text prompts, content correctness, and specific attributes. The details of each score are as follows.

Text-Video Consistency (CLIP-Score). We use the CLIP-Score to quantify the discrepancy between input text prompts and generated videos. Using the pretrained `ViT-B/32` CLIP model [43] as a feature extractor, we obtain frame-wise image embeddings and text embeddings, and compute their cosine similarity. The overall CLIP-Score is then derived by averaging individual scores across all frames.

Image-Video Consistency (SD-Score). We propose a new metric, SD-Score, to compare the generated quality with frame-wise SD [44], considering that most current video diffusion models are fine-tuned on a base SD with a larger scale dataset. Using SDXL [41], we generate N_1 images $\{d_k\}_{k=1}^{N_1}$ for every prompt and extract visual embeddings in both generated images and video frames. We calculate the embedding similarity between the generated videos and SDXL images, which helps address the concept forgetting problems when fine-tuning the T2I diffusion model to video models. The final SD-Score is calculated as:

$$S_{SD} = \frac{1}{M}\sum_{i=1}^{M}(\frac{1}{N}\sum_{t=1}^{N}(\frac{1}{N_1}\sum_{k=1}^{N_1}\mathcal{C}(emb(x_t^i), emb(d_k^i)))). \tag{1}$$

where x_t^i is the t-th frame of the i-th video, $\mathcal{C}(\cdot,\cdot)$ is the cosine similarity function, $emb(\cdot)$ means CLIP embedding, M is the total number of testing videos, and N is the total number of frames in each video, where $N_1 = 5$.

Text-Text Consistency (BLIP-BLEU). We also consider the evaluation between the generated text descriptions of the video and the input prompt. We utilize BLIP2 [35] for caption generation and use BLEU [40] for evaluation of text alignment:

$$S_{BB} = \frac{1}{M}\sum_{i=1}^{M}(\frac{1}{N_2}\sum_{k=1}^{N_2}\mathcal{B}(p^i, l_k^i)), \tag{2}$$

where p^i is the i-th prompt, $\mathcal{B}(\cdot,\cdot)$ is the BLEU similarity scoring function, $\{l_k^i\}_{k=1}^{N_2}$ are BLIP2 generated captions for i-th video, and N_2 is set to 5 experimentally.

Object and Attributes Consistency (Detection-Score, Count-Score and Color-Score). We employ SAM-Track [13] to analyze the correctness of the video content.

We evaluate T2V models on the existence of objects, as well as the correctness of color and count of objects in text prompts. Specifically, we assess the Detection-Score, Count-Score, and Color-Score as follows:

1. *Detection-Score* (S_{Det}): Measures average object presence across videos, calculated as:

$$S_{Det} = \frac{1}{M_1} \sum_{i=1}^{M_1} \left(\frac{1}{K} \sum_{k=1}^{K} \sigma_{t_k}^i \right), \tag{3}$$

where M_1 is the number of prompts with objects, K is the number of frames where detection is performed, and $\sigma_{t_k}^i$ is the detection result for frame t_k in video i (1 if an object is detected, 0 otherwise). In our approach, we perform detection every $I = 5$ frames. Therefore, $K = \lceil \frac{N}{I} \rceil$.

2. *Count-Score* (S_{Count}): Evaluates average object count difference, calculated as:

$$S_{Count} = \frac{1}{M_2} \sum_{i=1}^{M_2} \left(1 - \frac{1}{K} \sum_{k=1}^{K} \frac{\left| c_{t_k}^i - \hat{c}^i \right|}{\hat{c}^i} \right), \tag{4}$$

where M_2 is the number of prompts with object counts, $c_{t_k}^i$ is the detected object count at frame t_k in video i, and $\hat{c}^i$ is the ground truth object count for video i.

3. *Color-Score* (S_{Color}): Assesses average color accuracy, calculated as:

$$S_{Color} = \frac{1}{M_3} \sum_{i=1}^{M_3} \left(\frac{1}{K} \sum_{k=1}^{K} s_{t_k}^i \right), \tag{5}$$

where M_3 is the number of prompts with object colors and $s_{t_k}^i$ is the color accuracy result for frame t_k in video i (1 if the detected color matches the ground truth color, 0 otherwise).

Human Analysis (Celebrity ID Score). Human is important for the generated videos as shown in our collected real-world prompts. To this end, we evaluate the correctness of human faces using DeepFace [48], a popular face analysis toolbox. We calculate the distance between the generated celebrities' faces and real images of the celebrities.

$$S_{CIS} = \frac{1}{M_4} \sum_{i=1}^{M_4} \left(\frac{1}{N} \sum_{t=1}^{N} \left(\min_{k \in \{1, \ldots, N_3\}} \mathcal{D}(x_t^i, f_k^i) \right) \right), \tag{6}$$

where M_4 is the number of prompts that contain celebrities, $\mathcal{D}(\cdot, \cdot)$ is the Deepface's distance function, $\{f_k^i\}_{k=1}^{N_3}$ are collected celebrities images for i-th prompt, and $N_3 = 3$.

Text Recognition (OCR-Score) Another hard case for visual generation is to generate text in the input prompt. To examine the abilities of current T2V models for text generation, we utilize the widely used toolbox PaddleOCR [39] to detect the English text from generated videos. Then, similar to HRS-Bench [7], we calculate Word Error Rate (WER) [30], Normalized Edit Distance (NED) [52], Character Error Rate (CER) [37], and get the average.

4.3. Motion Quality

For video, we believe the motion quality is a major difference from other domains, such as image. To this end, we consider the quality of motion as one of the main evaluation metrics in our evaluation system. Here, we consider two different motion qualities introduced below.

Action Recognition (Action-Score). For videos about humans, we can easily recognize the common actions via pre-trained models. We use the MMAction2 toolbox [16] and the pre-trained VideoMAE V2 model [59] to infer human actions in generated videos. We take the classification accuracy as our Action-Score, focusing on Kinetics 400 action classes [27].

Average Flow (Flow-Score). We also consider the general motion information of the video. To this end, we use RAFT [54], to extract the dense flows of the video in every two frames. Then, we calculate the average flow on these frames to obtain the average flow score of every specific generated video clip since some methods are likely to generate still videos that are hard to be identified by the temporal consistency metrics.

Amplitude Classification Score (Motion AC-Score). Based on the average flow, we further identify whether the motion amplitude in the generated video is consistent with the amplitude specified by the text prompt. To this end, we set an average flow threshold ρ that if surpasses ρ, one video will be considered large, and here ρ is set to 5 based on our subjective observation.

4.4. Temporal Consistency

Temporal consistency is also a very valuable field in our generated video. To this end, we involve several metrics for calculation. We list them below.

Warping Error. We first consider the warping error, which is widely used in previous blind temporal consistency methods [31, 32, 42]. In detail, we first obtain the optical flow of each two frames using the pre-trained optical flow estimation network [54], then, we calculate the pixel-wise differences between the warped image and the predicted image. We calculate the warp differences on every two frames and calculate the final score using the average of all the pairs.

Semantic Consistency (CLIP-Temp). Besides pixel-wise error, we also consider the semantic consistency between every two frames, which is also used in previous video editing works [18, 42]. Specifically, we consider the cosine similarity of the embeddings of each two consecutive frames $(emb(x_t), emb(x_{t+1}))$ of the generated videos and then get the averages on each two frames.

Face Consistency. Similar to CLIP-Temp, we evaluate the human identity consistency of the generated videos. Specifically, we select the first frame x_1 as the reference and calculate the cosine similarity of $emb(x_1)$ with $\{emb(x_t)\}_{t=2}^{N}$. Then, we average the similarities as the final score.

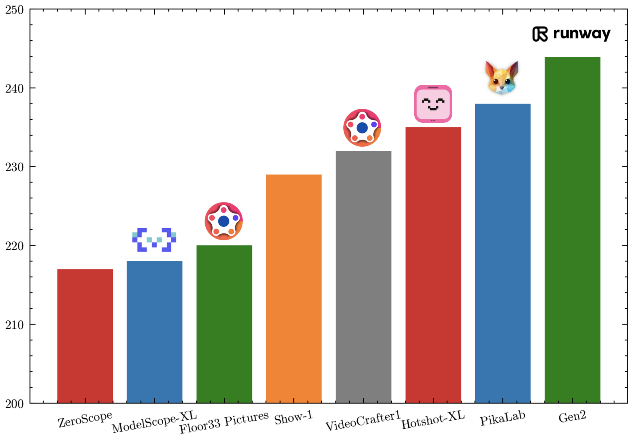

Figure 4. Overall comparison results on our EvalCrafter benchmark.

	Visual Quality	Text-Video Alignment	Motion Quality	Temporal Consistency
ModelScope	53.09 (7)	54.46 (7)	52.47 (7)	57.80 (6)
ZeroScope	53.41 (6)	51.21 (8)	53.61 (4)	58.91 (5)
Floor33 Pictures	58.78 (5)	61.32 (4)	49.16 (8)	50.24 (8)
PikaLab	60.77 (3)	55.80 (6)	55.77 (2)	**65.41 (1)**
Gen2	**62.51 (1)**	60.98 (5)	**56.43 (1)**	64.41 (2)
VideoCrafter1	60.85 (2)	61.95 (2)	53.08 (5)	55.89 (7)
Show-1	52.19 (8)	**62.07 (1)**	53.74 (3)	60.83 (3)
Hotshot-XL	60.38 (4)	61.52 (3)	52.98 (6)	59.96 (4)

Table 2. Human-preference aligned results from four different aspects, with the rank of each aspect in the brackets.

4.5. User Opinion Alignments

Besides the above objective metrics, we evaluate user opinions through studies focusing on five main aspects: (1) *Video Quality*, indicating the quality of the generated video where a higher score shows less blur, noise, or other visual degradation; (2) *Text and Video Alignment*, examining the relationships between the generated video and the input text-prompt, requiring users to evaluate the correctness of generated motions; (3) *Motion Quality*, requiring users to identify the correctness of the generated motions from the video. (4) *Temporal Consistency*, assessing frame-wise consistency, varying from *Motion Quality*, which needs users to give a rank for high-quality movement; (5) *Subjective likeness*, similar to the aesthetic index, a higher value indicates the generated video generally achieves human preference, and we leave this metric used directly.

For evaluation, we generate videos using the provided prompts benchmark on five state-of-the-art methods of ModelScope [58], ZeroScope [6], Gen2 [18], Floor33 [1], and PikaLab [5], getting 2.5k videos in total. For a fair comparison, we change the aspect ratio of Gen2 and PikaLab to $16 : 9$ to suitable other methods. Also, since PikaLab can not generate the content without the visual watermark, we add the watermark of PikaLab to all other methods for a fair comparison. We also consider that some users might not understand the prompt well, for this purpose, we use SDXL [41] to generate three reference images of each prompt to help the users understand better, which also inspires us to design an SD-Score to evaluate the models' text-video alignments. For each metric, we ask 7 users to give opinions between 1 to 5, where a large value indicates better alignments. The video sequence has been randomly shuffled before being given to users, and we get 8647 feedback scores in total. Finally, after filtering, we keep 1024 most objective and professional scores as illustrated in Fig. ??.

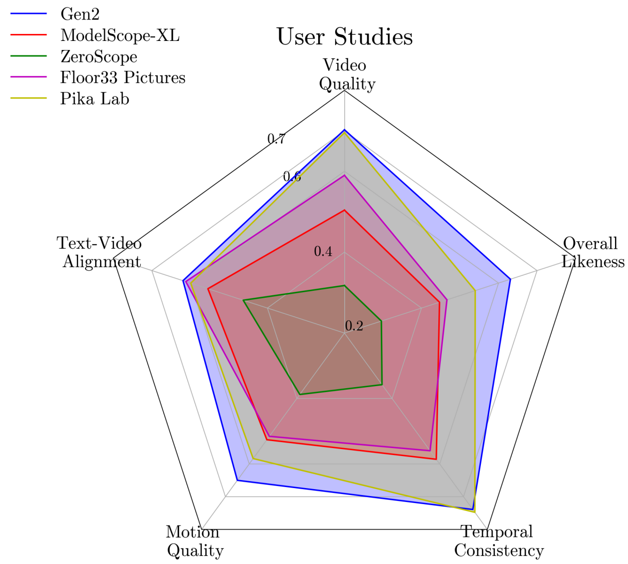

Figure 5. The raw ratings from our user study.

Upon collecting user data, we proceed to perform human alignment for our evaluation metrics, with the goal of establishing a more reliable and robust assessment of T2V algorithms. Initially, we conduct alignment on the data using the mentioned individual metrics above to approximate human scores for the user's opinion in specific aspects. Similar to the works of the evaluation of natural language processing [19, 34], we employ a linear regression model to fit the parameters in each dimension. Specifically, we randomly choose 80% samples from four different methods as the fittings samples and left the rest 20% samples to verify the effectiveness of the proposed method. The coefficient parameters are obtained by minimizing the residual sum of squares between the human labels and the prediction from the linear regression model. In the subsequent stage, we integrate the aligned results of these four aspects and calculate the total score to obtain a comprehensive final score.

5. Results

We conduct the evaluation on our benchmark prompts, where each prompt has a metafile for additional information as the answer of evaluation. We then generate the videos using all available high-resolution T2V models, including the ModelScope [58], Floor33 Pictures [1], and ZeroScope [6], Show-1 [66], Hotshot-XL [3], and VideoCrafter1 [12]. We

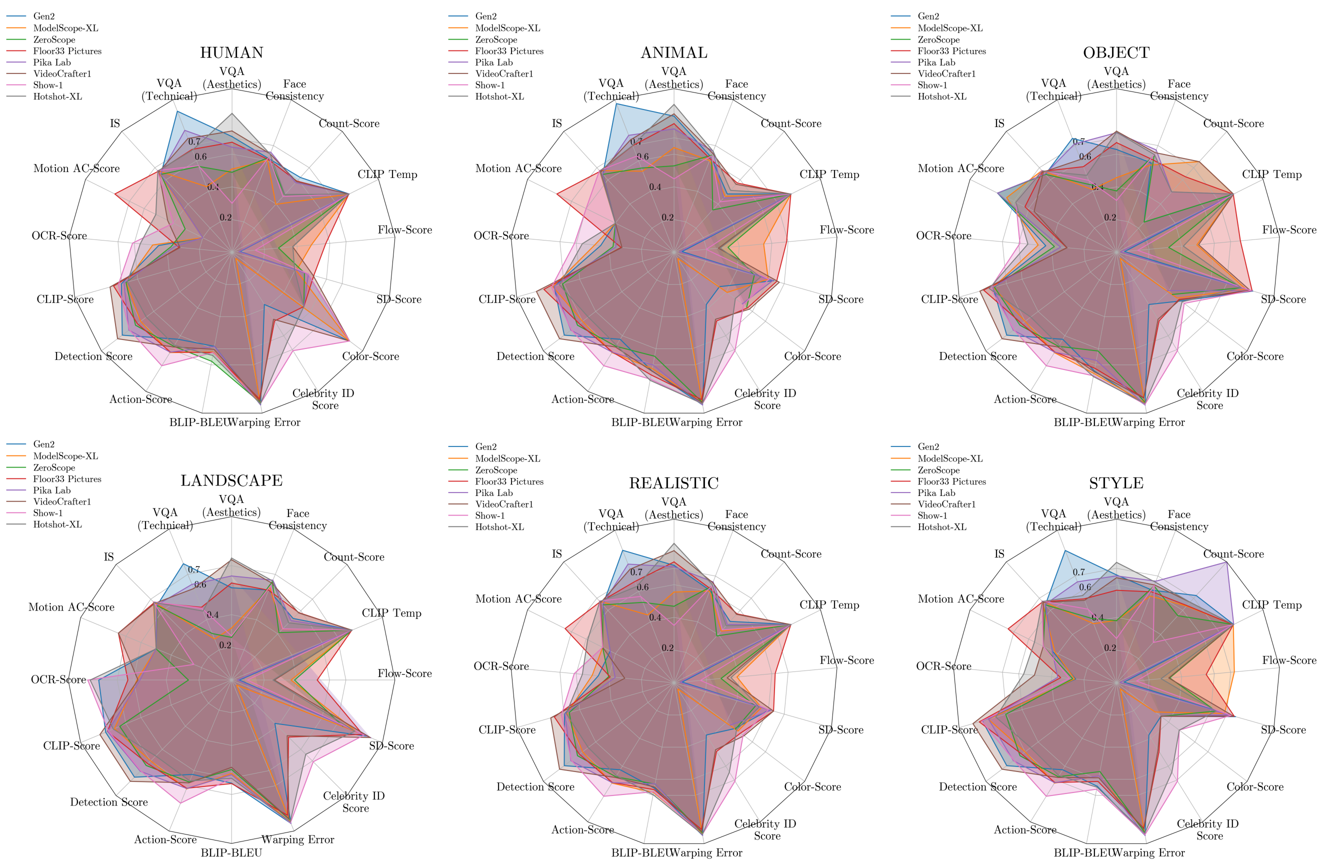

Figure 6. ***Raw results in different aspects.*** We consider 4 main meta types (`animal`, `human`, `landscape`, `object`) to evaluate the performance of the meta types of the generated video, where each type contains several prompts with fine-grained attribute labels. For each prompt, we also consider the style of the video, yet more diverse prompts. as shown in `realistic` and `style` figure above. (The metrics values are normalized for better visualization, the Warping Error, Celebrity ID Score, and OCR-Score by $1-$ so that large values indicate better performance.)

keep all the hyper-parameters, such as classifier-free guidance, as the default value. For the service-based model, we evaluate the performance of the representative works of Gen2 [18] and PikaLab [5]. They generate at least 512p videos with high-quality watermark-free videos. We run all available models on an NVIDIA A100 for speed comparison. We first show the overall human-aligned results in Fig. 4, with also the different aspects of our benchmark in Table 2, which gives us the final and the main metrics of our benchmark. Finally, as in Fig. 6, we give the results of each method on 4 different meta types (*i.e.*, `animal`, `human`, `landscape`, `object`) and two different types of videos (*i.e.*, `realistic`, `style`) in our benchmark.

5.1. Analysis on Human Preference Alignment

To demonstrate the effectiveness of our model in aligning with human scores, we calculate Spearman's rank correlation coefficient [65] and Kendall's rank correlation coefficient [28], both of which are non-parametric measures of rank correlation. These coefficients provide insights into the magnitude and direction of the association between our method results and human scores, as listed in Table. 3. From this table, the proposed weighting method shows a better correlation on the unseen 20% samples than directly averaging.

5.2. Findings

Finding #1: Single dimension evaluation is insufficient for nowadays T2V models. Models' rankings in Table. 2 vary significantly across different aspects, emphasizing the importance of a multi-aspect evaluation approach for a comprehensive understanding of model performance.

Finding #2: Meta type evaluation is necessary. As shown in Fig. 6, models perform differently in various meta types, highlighting the importance of evaluating their abilities by meta type. For example, Gen2 [18] behaves better than Floor33 Pictures [1] w.r.t. VQA_A in `human`, `animal`, and `style` videos. Contrarily, it falls behind Floor33 Pictures in `landscape`, `object`, and `realistic` ones.

Finding #3: Users prioritize visual appeal over T2V alignment. As shown in ??, despite Gen2 [18] performing relatively badly in T2V alignment, it surpasses all other models in `Subjective Likeness`. We argue that it is because users prefer videos with better visual appeal like good visual quality and high temporal consistency.

Finding #4: All methods cannot perform camera motion control directly using text prompt. Although some additional hyper-parameters can be set as additional control handles for Gen2 [18] and PikaLab [5], all current T2V models still lack the understanding of open-world prompts, like camera motion.

Finding #5: Resolution doesn't correlate much with visual appeal. As shown in Table. 1 and Table. 2, Gen2 [18] and Hotshot-XL [3] have small resolutions but are both competitive in visual quality.

Finding #6: Larger motion amplitude doesn't ensure user preference. In our study, most videos that users are fond of are with slight movements, such as those videos generated by PikaLab [5] and Gen2 [18].

Finding #7: Generating text remains challenging. Most methods struggle to generate high-quality and consistent text from prompts, as evident from OCR-Scores. Raw results of all metrics are given in supplementary materials.

Finding #8: Many models can sometimes generate completely wrong videos. From our study, we find quite a number of failure cases like severe noises and distortion from our baseline models such as ZeroScope [6], ModelScope [58] and Floor33 Pictures [1]. We argue that it could be viewed as a catastrophic forgetting problem [49], as we know many current T2V models are finetuned from base models like SD [44]. We present our detailed qualitative results in supplementary materials.

Finding #9: Effective metrics and not that effective metrics. Metrics like Warp Error, CLIP-Temp, VQA_T, and VQA_A seem to perform well as they all have high correlations with human scores shown in Table. 3. However, some metrics are not as good as we think. The Clip-Score especially, which is a widely used metric in previous works [18, 23, 50], only has Spearsman's ρ 6.3 and Kendall's ϕ 4.3 compared to BLIP-BLEU in the same aspects has 26.7 and 19.0. Detailed correlation results can be found in the supplementary materials.

Finding #10: All current models are not satisfactory enough. From our objective evaluation and subjective observation, we argue that T2V models nowadays still have lots to improve. Even for the best model in our evaluation, Gen2 [18] also has limitations like struggling with complex scenes, instruction following, and entity details.

5.3. Limitation

Although we have already made a step in evaluating the T2V generation, there are still many challenges. *(i)* Currently, we only collect 700 prompts as the benchmark, where the real-world situation is very complicated. More prompts will show a more general benchmark. *(ii)* Evaluating the motion quality of the general senses is also hard. However, in the era of multi-model LLM and large video foundational models, we believe better and larger video understanding models will be released and we can use them as our metrics. *(iii)* The labels used for alignment are collected from only fewer human annotators, which may introduce some bias in the results. To address this limitation, we plan to expand the pool of annotators and collect more diverse scores to ensure a more accurate and unbiased evaluation.

Aspects	Methods	Spearsman's ρ	Kendall's ϕ
Visual Quality	VQA_A	42.1	30.5
	VQA_T	53.6	39.1
	Avg.	55.0	41.0
	Ours	**55.4**	**41.1**
Motion Amplitude	Motion AC	-22.1	-16.4
	Flow-Score	-43.3	-30.1
	Avg.	-38.2	-27.7
	Ours	**45.0**	**32.4**
Temporal Consistency	CLIP-Temp	49.8	35.7
	Warping Error	69.0	51.7
	Avg.	54.4	38.9
	Ours	**56.7**	**41.5**
TV Alignment	CLIP-Score	6.3	4.3
	BLIP-BLEU	26.7	19.0
	Avg.	31.9	**22.7**
	Ours	**32.3**	22.5

Table 3. ***Correlation Analysis.*** Correlations between some objective metrics and human judgment on text-to-video generations. We use Spearsman's ρ and Kendall's ϕ for correlation calculation.

6. Conclusion

Exploring the capabilities of large generative models is crucial for improving model design and utilization. In this paper, we take the first step towards evaluating large, high-quality T2V models by constructing a comprehensive prompt benchmark for T2V assessment. We also provide several objective evaluation metrics to measure T2V model performance concerning video quality, text-video alignment, temporal consistency, and motion quality. Furthermore, we conduct human alignment to correlate user scores with objective metrics, resulting in accurate evaluation metrics for T2V methods. Our experiments demonstrate that the proposed methods effectively align with user opinions, thus providing a reliable assessment of T2V approaches. We believe this comprehensive evaluation benchmark will serve as a foundation and foster development for future research.

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Appendices

Appendix Contents

A. Detailed Analysis of Real-World User Data

In this section, we present a detailed analysis of the real-world user data collected from text-to-video (T2V) generation discord users, including the FullJourney [2] and PikaLab [5]. We provide insights into the distribution of prompt lengths, important words, and meta classes.

A.1. Prompt Length Distribution

Fig. 7 (a) shows the distribution of prompt lengths in the real-world user data. We find that 90% of the prompts contain words in the range of $[3, 40]$. This observation helps us determine the appropriate length for the prompts in our benchmark.

A.2. Important Words in Prompts

Fig. 7 (b) presents a word cloud of all words in the real-world user data. From this word cloud, we can observe the most frequent words in the prompts and gain insights into the key concepts that users request in T2V generation.

A.3. Meta Classes in Prompts

Fig. 7 (c) shows the distribution of noun types in the real-world user data. We use WordNet [36] to identify the meta classes. Excluding communication, attribute, and cognition words, we find that artifacts (human-made objects), humans, animals, and locations (landscapes) play important roles in the prompts. We also include the most important word `style` from Fig. 7 (b) in the meta classes.

Based on this analysis, we divide the T2V generation into four meta-subject classes: `human`, `animal`, `object`, and `landscape`. This classification helps us create a diverse and representative benchmark for evaluating T2V models.

B. Quantitative Results

In this part, we present the quantitative results of our evaluation benchmark. We have conducted experiments on various state-of-the-art video generative models and assessed their performance using 17 objective metrics. We provide the raw results of every metric for each model and the correlations between metrics and human labels. The results are illustrated in two tables. The first table (Table 4) shows the raw results of every metric for each model. The second table (Table 5) displays the correlations between metrics and human labels.

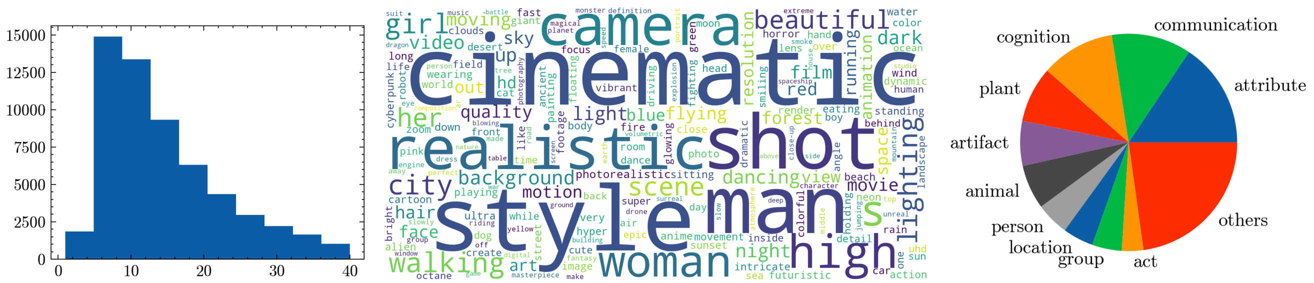
B.1. Raw Results of Every Metric for Every Model

Table 4 shows the raw results of all 17 introduced metrics for each of the evaluated models. All metrics are expressed as percentages, except for Warping Error and Flow-Score. The table is organized as follows:

- The first column lists the metrics used for evaluation.
- The following columns display the raw results for each model, including ModelScope [58], Floor33 Pictures [1], and ZeroScope [6], Show-1 [66], Hotshot-XL [3], VideoCrafter1 [12], Gen2 [18], and PikaLab [5].
- Arrows next to the metric names indicate whether higher (↑) or lower (↓) values are better for that particular metric. For Flow-Score, the arrow is replaced with a rightwards arrow (→) as it is a neutral metric.

B.2. Correlations Between Metrics and Human Labels

In addition to the raw results, Table 5 presents the correlation analysis between objective metrics and human judgment on T2V generations. We use Spearman's ρ and Kendall's ϕ for correlation calculation. The table is organized into four sections, representing the four aspects of the evaluation: visual quality, motion amplitude, temporal consistency, and



(a) Prompt length distribution. (b) All words cloud (c) types of noun

Figure 7. The analysis of the real-world prompts from PikaLab Server [5].

Metrics	Gen2	ModelScope	Pika	Floor33	ZeroScope	VideoCrafter	Show-1	Hotshot
$\text{VQA}_A \uparrow$	59.44	40.06	59.09	58.7	34.02	66.18	23.19	71.54
$\text{VQA}_T \uparrow$	76.51	32.93	64.96	52.64	39.94	58.93	44.24	50.52
IS $\uparrow$	14.53	17.64	14.81	17.01	14.48	16.43	17.65	17.29
CLIP-Temp $\uparrow$	99.94	99.74	99.97	99.6	99.84	99.78	99.77	99.74
Warping Error $\downarrow$	0.0008	0.0162	0.0006	0.0413	0.0193	0.0295	0.0067	0.0091
Face Consistency $\uparrow$	99.06	98.94	99.62	99.08	99.33	99.48	99.32	99.48
Action-Score $\uparrow$	62.53	72.12	71.81	71.66	67.56	68.06	81.56	66.8
Motion AC-Score $\uparrow$	44.0	42.0	44.0	74.0	50.0	50.0	50.0	56.0
Flow-Score $\rightarrow$	0.7	6.99	0.5	9.26	4.5	5.44	2.07	5.06
CLIP-Score $\uparrow$	20.53	20.36	20.46	21.02	20.2	21.33	20.66	20.33
BLIP-BLUE $\uparrow$	22.24	22.54	21.14	22.73	21.2	22.17	23.24	23.59
SD-Score $\uparrow$	68.58	67.93	68.57	68.7	67.79	68.73	68.42	67.65
Detection-Score $\uparrow$	64.05	50.01	58.99	52.44	53.94	67.67	58.63	45.7
Color-Score $\uparrow$	37.56	38.72	34.35	41.85	39.25	45.11	48.55	42.39
Count-Score $\uparrow$	53.31	44.18	51.46	58.33	41.01	58.11	44.31	49.5
OCR-Score $\downarrow$	75.0	71.32	84.31	87.48	82.58	88.04	58.97	63.66
Celebrity ID Score $\downarrow$	41.25	44.56	45.21	40.07	46.93	40.18	37.93	38.58

Table 4. Raw results of 17 introduced metrics among the aspects of video quality, text-video alignment, motion quality, and temporal consistency. All metrics are expressed as percentages, except for Warping Error and Flow-Score.

text-video alignment. In each section, we compare various methods with our proposed evaluation method, which is highlighted in bold.

As can be seen from the table, our method consistently achieves higher correlation values compared to the average of other methods. This shows the effectiveness of our proposed evaluation method in aligning the objective metrics to users' opinions. For instance, in the visual quality aspect, our method obtains a Spearman's ρ of 55.4 and a Kendall's ϕ of 41.1, which are both higher than the average values of 55.0 and 41.0, respectively. Similar improvements can be observed in other aspects as well.

In addition to the findings mentioned earlier, we can observe that some metrics show negative correlations with human judgment, such as Color-Score and OCR-Score in the TV Alignment aspect. This indicates that these metrics may not be reliable for evaluating the alignment between text and video content in generative models. On the other hand, metrics like Detection-Score and Count-Score exhibit relatively higher correlations with human judgment, suggesting their potential usefulness in evaluating T2V alignment.

Overall, the results in Table 5 provide a comprehensive analysis of various objective metrics and their correlations with human judgment. These results can be valuable for researchers and practitioners in the field of T2V generation to select appropriate metrics for evaluating their models and to better understand the strengths and weaknesses of different evaluation methods.

C. Qualitative Results

In this part, we present qualitative results of the evaluated T2V models for various aspects of video generation, taking into account the findings listed in the paper. The results are visualized in Fig. 11 to Fig. 13. We discuss the performance of each model in terms of camera motion control, content generation, motion generation, style generation, and task-

Aspects	Methods	Spearman	Kendall
Visual Quality	VQA_A	47.8	35.5
	VQA_T	53.6	39.1
	IS	9.9	4.3
	Avg.	54.9	40.9
	Ours	**55.4**	**41.1**
Motion Amplitude	Action-Score	-14.9	-10.4
	Motion AC	-22.1	-16.4
	Flow-Score	-43.3	-30.1
	Avg.	-38.2	-27.7
	Ours	**45.0**	**32.4**
Temporal Consistency	CLIP-Temp	49.7	35.7
	Warping Error	69.0	51.7
	Face Consistency	25.8	17.8
	Avg.	54.4	38.9
	Ours	**56.7**	**41.5**
TV Alignment	CLIP-Score	6.3	4.3
	BLIP-BLEU	26.7	19.0
	SD-Score	-2.8	-2.3
	Detection-Score	11.9	9.4
	Color-Score	-5.5	-3.9
	Count-Score	28.9	22.2
	OCR-Score	-8.3	-6.7
	Celebrity ID Score	-26.0	-19.8
	Avg.	31.9	**22.7**
	Ours	**32.3**	22.5

Table 5. ***Correlation Analysis.*** Whole results of correlations between objective metrics and human judgment on T2V generations. We use Spearman's ρ and Kendall's ϕ for correlation calculation.

specific generation.

C.1. Content Generation

In Fig. 9, we present the qualitative results of T2V models and SDXL [41] for four meta types of content generation: human, object, landscape, and animal. Finding #5 shows that resolution does not correlate much with visual appeal, as demonstrated by Gen2 [18] and Hotshot-XL [3], which have small resolutions but are both competitive in visual quality. Besides, we can also find that Gen2 [18] and PikaLab [5] are more distinguishable from SDXL [41] in both video content and style compared with other methods.

C.2. Motion Generation

Fig. 10 displays the qualitative results of T2V models with respect to motion generation. According to Finding #6, larger motion amplitude does not ensure user preference. In our study, most videos that users are fond of are those with slight movements, such as those generated by PikaLab [5] and Gen2 [18].

C.3. Style Generation

The qualitative results of T2V models concerning style generation are shown in Fig. 11. We can see from the figure that most methods have the ability to generate videos with specific styles, which may be inherited from base models. However, various methods like ZeroScope [6] and ModelScope [58] are also struggling to generate high-quality and consistent styled content from prompts.

C.4. Camera Motion Control

Fig. 12 shows the qualitative results of T2V models in terms of prompts with camera motion controls. As indicated by Finding #4, all methodss cannot perform camera motion control using text prompts, which indicates all T2V models lack the understanding of camera motion.

C.5. Task-Specific Generation

Finally, Fig. 13 presents the qualitative results of T2V models and SDXL [41] in terms of different tasks, *i.e.*, face generation, object generation with color, object generation with count, text generation, and activity generation. Finding #8 indicates that many models can sometimes generate completely wrong videos, with severe noises and distortions observed in baseline models like ZeroScope [6], ModelScope [58], and Floor33 Pictures [1]. This could be viewed as a catastrophic forgetting problem, as many current T2V models are finetuned from base models like SD [44].

In conclusion, the qualitative results presented in this appendix provide valuable insights into the strengths and weaknesses of different T2V models in various aspects of video generation. As stated in Finding #10, all current models are not satisfactory enough, and T2V models still have significant room for improvement. Even the best model in our evaluation, Gen2 [18], has limitations like struggling with complex scenes, instruction following, and entity details. These results, along with our proposed evaluation framework and pipeline, enable a more exhaustive and reliable assessment of the performance of large video generation models.

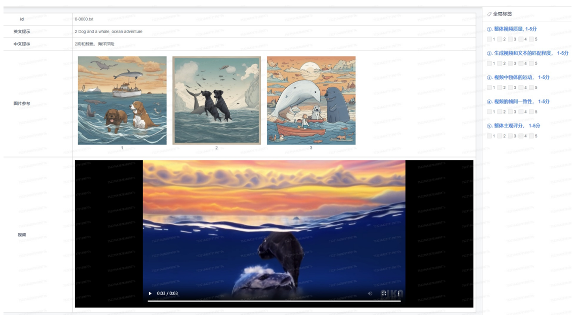
D. Additional Analysis and Explanations

D.1. Adequacy of 700 Prompts

As an initial attempt, one important reason to use these prompts is that we find the metrics tend to reach a plateau with the sample increased as in Fig. 8. Besides, concurrent benchmarks (*e.g.*, FETV (619 prompts overall), VBench (100 prompts per metric)) use a similar amount of prompts. From a practical view, T2V models' sampling speed is typically slow, a small but effective benchmark is crucial for fast evaluation of different methods.

D.2. User study's Demographics, Interface, and Adequacy

The interface is shown below. We use our internal AI-testing platform to find human raters. Each rater is asked to perform 100 tasks as pre-labeling, the annotator who has more than 90% accuracy will be marked as qualified. Otherwise, we will consider another supplier. Then, the qualified annotators will label the whole benchmark.



D.3. Crowdsourced Prompts & Dataset Dynamics

Our approach aims to capture a snapshot of current user expectations and model abilities. Besides, the benchmark is intended to be dynamic with periodic updates.

D.4. Motion Amplitude Metrics Discrepancy

It's mainly caused by user preferences on favoring subtle motions as stated by Finding #6, *e.g.*, Gen2 (always generate small motions) ranks 7th *w.r.t.* Motion AC-Score in Tab. 4, but it ranks 1st *w.r.t.* motion quality in user study, which resulted in Gen2 ranks 1st in Tab. 2.

D.5. Dependence on Pre-trained Models

As our initial attempt (also the whole community), pre-trained models provide a reference to find meaningful objective metrics. We will actively explore more straightforward metrics to avoid using pre-trained models, *e.g.*, training an end-to-end evaluation model for each aspect using more user opinions.

D.6. Costs of Evaluation

We agree that online evaluation is vital for model training. However, it is impossible to monitor T2V Models in the running process (even using FVD) since each video sample requires more than 2 minutes for generation. Our method is designed for offline evaluation (plays a similar role to previous FVD evaluation). The whole benchmark requires around 2 hours on an A100 GPU and at last 16 GB memory cost without any code optimization, which we think is more demanding than traditional methods such as FVD. However, FVD can only reflect one aspect of the T2V model and needs real video datasets as a reference.

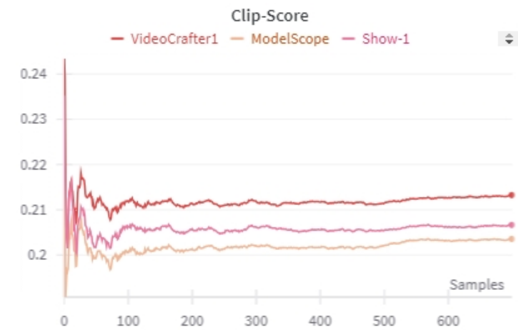


Figure 8. The stability of CLIP-Score with different prompts.

D.7. Benchmark Stability and Noise Variables

We give some stability analysis. First, as in Fig. 8, we find the objective scores are stable among different methods with the prompt increasing. Besides, we also try to introduce noise to the prompts, *i.e.*, adding, removing, or swapping words/symbols in 100 randomly selected prompts. Notably, the changes in all scores in Tab. 2 are marginal among the methods, with most variations below 0.2 points. The ranks remain consistent across all models.

D.8. Warping Error

The warping error assesses the discrepancy between the actual subsequent frame and its prediction, generated by warping the current frame using optical flow. The larger warping error means each frame changes dramatically, which is typically unwanted for real-world video. It also widely used previous blind video consistency methods [31] for temporal consistency metrics.

D.9. Discrepancy in User Study and Evaluation

This discrepancy arose from our endeavors to continuously update and enhance our prompt list. Our initial benchmark contains 512 prompts for user study, and we further expanded it to 700 prompts to make it more comprehensive and balanced. However, similar to Fig. 8, there are no significant changes in our results after the prompt increment. Therefore, we use the same user study result to avoid wasting resources as the initial version.

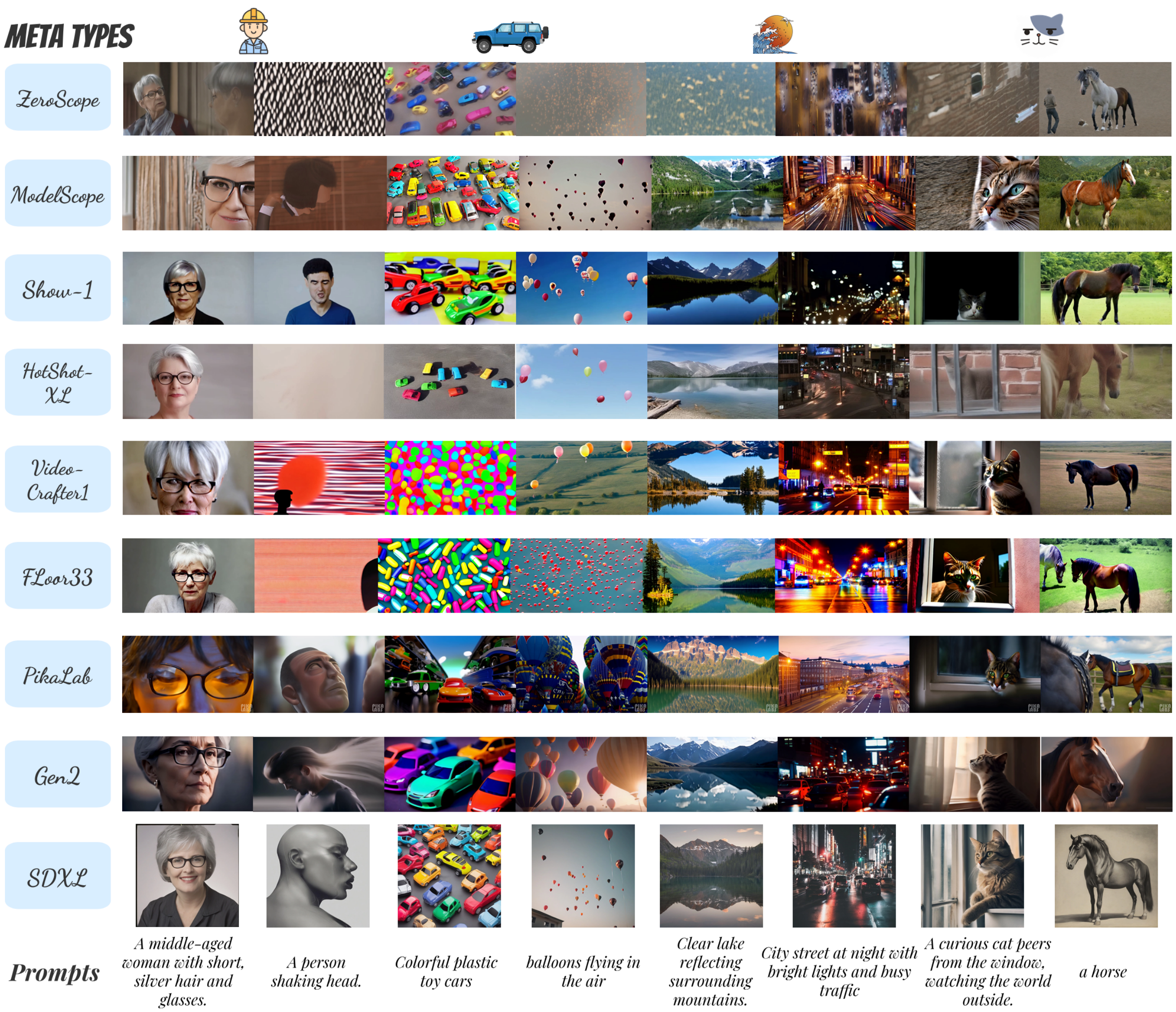


Figure 9. Qualitative results of T2V models in terms of four meta types (i.e., human, object, landscape, and animal)

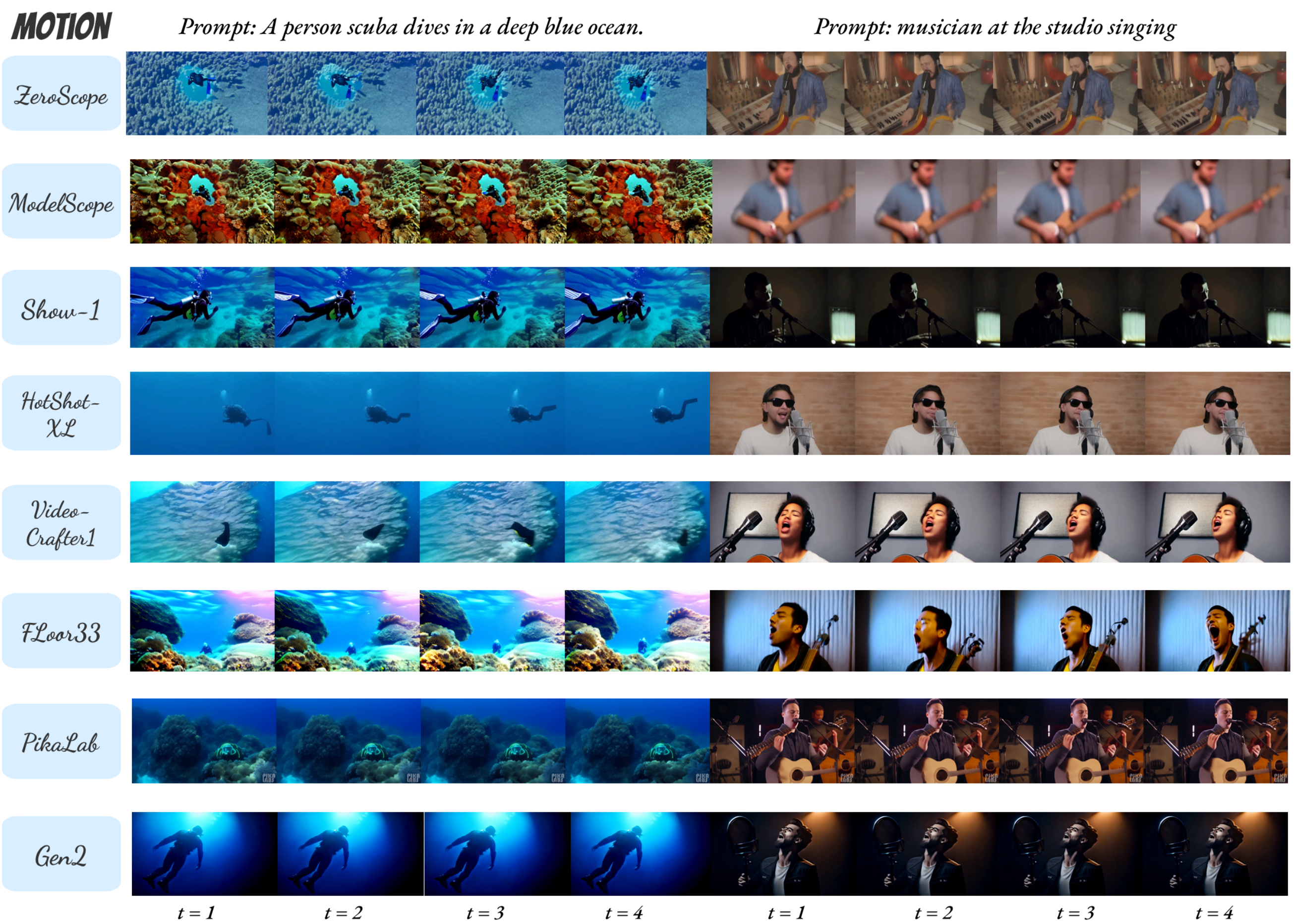


Figure 10. Qualitative results of T2V models w.r.t. motion generation

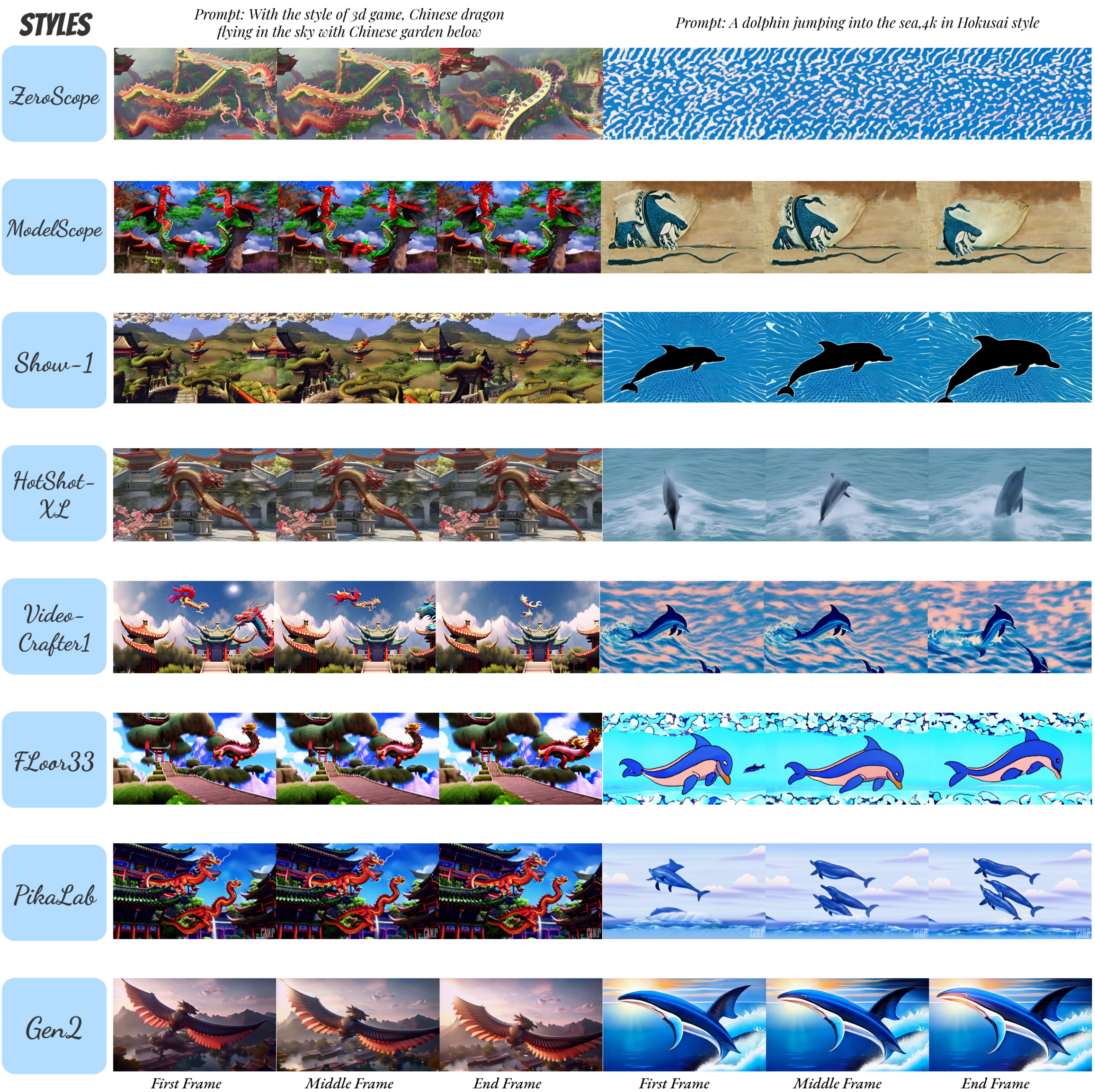


Figure 11. Qualitative results of T2V models w.r.t. style generation

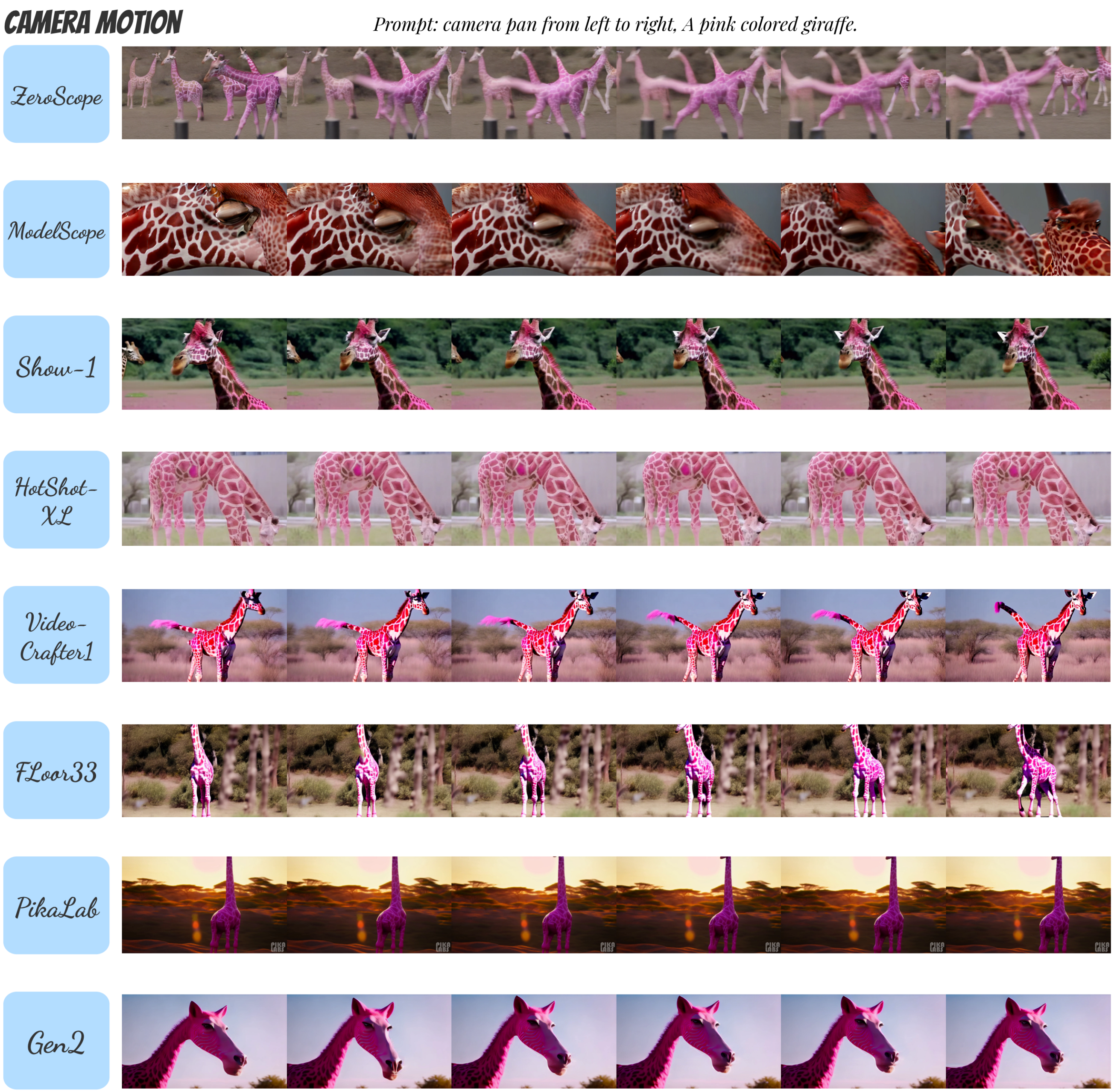


Figure 12. Qualitative results of T2V models in terms of prompts wtih camera motion controls

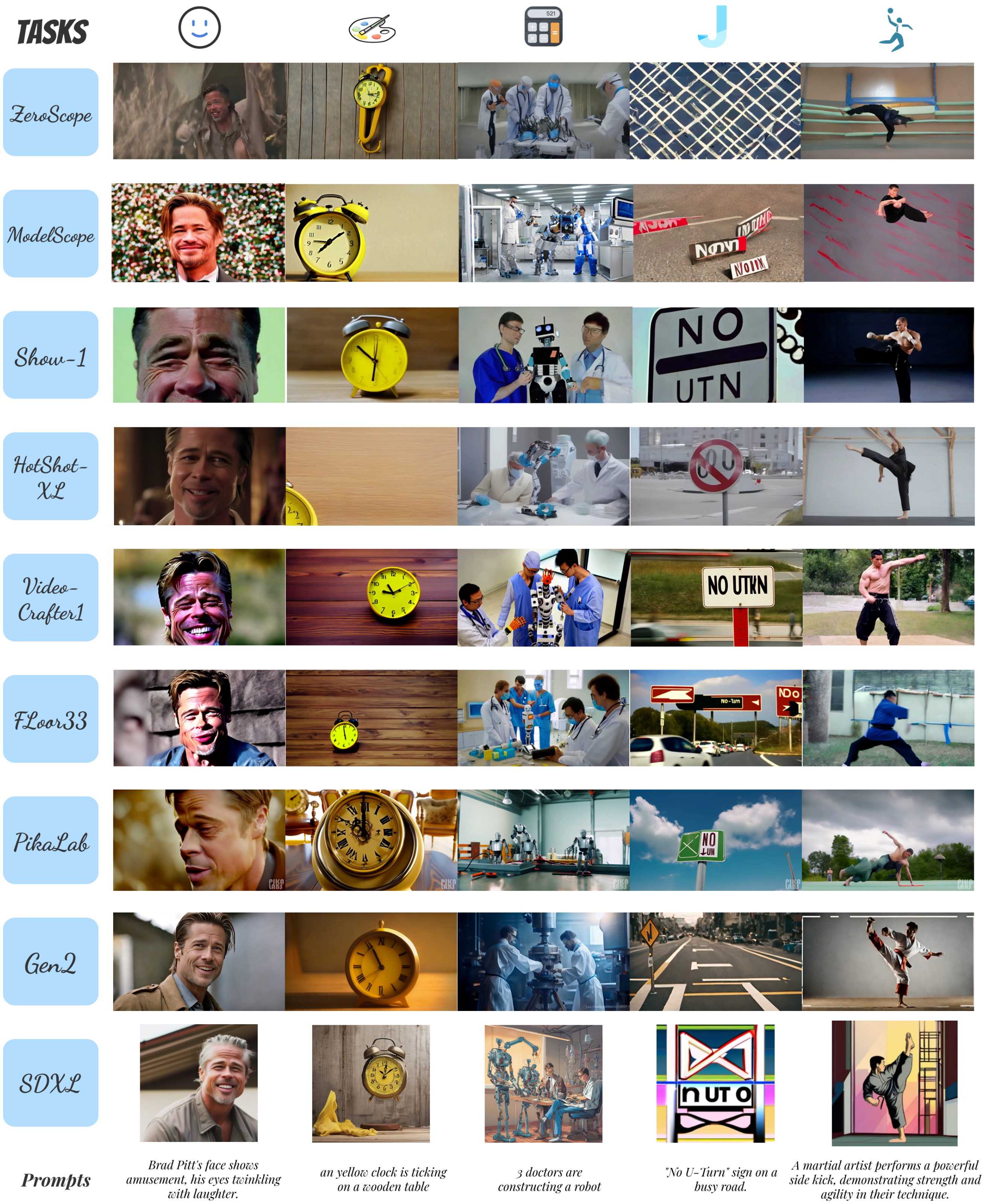


Figure 13. Qualitative results of T2V models in terms of different tasks (i.e., face generation, object generation with color, object generation with count, text generation, and activity generation)