Envisioning the Future, One Step at a Time

Supplementary Material

A. Additional Implementation Details

We provide more context on implementation details of our main model described in the paper. Please also refer to the supplementary model code, which contains extensive further comments, for reference.

A.1. Transformer Block

We implement our transformer [30, 107] blocks primarily following the standard Llama [101, 102]-style block architecture in a similar setup as Baumann et al. [10]. Specifically, we use pre-normalization with RMSNorm [121], omit bias terms in linear layers, and use rotary positional embeddings [97] in an axial setup with scaled cosine similarity attention following Crowson et al. [27]. Our feedforward network setup does not follow Llama's SwiGLU [93] activation, but instead uses the more classical GELU [46], while still retaining the omission of bias terms. We observed that both choosing GELU with the typical $\tanh$ approximation as the activation and omitting the GLU-style [93] gating leads to small speed improvements without significant decreases in quality. Importantly, we implement a fully fused parallel transformer layer, where cross-attention and self-attention are combined into a single attention across both kinds of tokens, and projections are shared between the attention and feedforward network, as described in the main paper.

A.2. Posterior Flow Matching Head

Our flow matching posterior head follows similar high-level hyperparameters as Li et al. [60], with three layers of width 1024. Unlike them, we use a standard flow matching [65] objective instead of the DDPM [47] formulation and perform substantial architectural changes to enable efficient sampling. Each block is a standard pre-LayerNorm [4] FFN block with GELU [46] activation.

Conditioning. We implement conditioning such that every component can be cached. Typically, conditioning would be implemented with a local, per-layer MLP that projects a conditioning vector into channel scales, shifts, and, optionally, output gating coefficients. This causes a large number of extra kernel launches, which, as this head will perform tens to hundreds of forward passes per AR sampling step, would cause significant wall-clock overhead. Instead, we precompute all scales and shifts centrally once. Additionally, we factorize the conditioning on flow matching time τ and the conditioning on the parameters $\mathbf{z}_t^{(i)}$ additively, such that the time conditioning can be precomputed offline once, and the parameter conditioning can be computed once per sampling loop, further reducing computational overhead. Conditioning inside each block is implemented via predicted scale and shift on the output of each pre-LayerNorm [4]. We do not perform output gating.

Input Value "Scale Cascade". For the posterior FM head, we use an input scale cascade to stabilize training when modeling motion. Practically, this is implemented as a logarithmically spaced set of scale coefficients

$$\mathbf{s} = \exp(\text{linspace}(\log(0.1), \log(1e5), \text{num} = 512)), \quad (1)$$

with $\text{linspace}(\min, \max, \text{num})$ denoting the standard numpy/PyTorch operation, using which the features for the noisy input x_τ are computed component-wise as

$$[\tanh(\mathbf{s} \cdot x_{\tau,0}) | \tanh(\mathbf{s} \cdot x_{\tau,1})]\mathbf{W}_{in}^\top, \quad (2)$$

with $[\cdot|\cdot]$ denoting channelwise concatenation, and $\mathbf{W}_{in}$ being the output projection to the transformer's hidden dimension.

Sampling. For sampling, we solve the ODE parametrized by the FM head using an Euler solver with uniform spacing of flow matching time τ, matching our training setting of sampling from a uniform distribution $\tau \sim \mathcal{U}[0, 1]$. Unless specifically noted otherwise, we use 50 sampling steps. During AR sampling, we simply sample one motion sample from the posterior, update the latest position of that trajectory, and then sample the next step defined by the AR factorization, while also conditioning on this new information. This process can be started from partial motion information, initial motion hints (pokes), or no prior motion information.

A.3. Hyperparameters

Tab. A provides a comprehensive list of hyperparameters that describe our training setup and model configuration. We train the open-set motion model for 400k steps with a peak learning rate of 3×10^{-5}. We train with a linear learning rate warmup of 5000 steps, after which we apply a linear learning rate schedule. The training setup for the Billiard simulation is similar, but trajectory positions are obtained from the Billiard physics engine [31] and thus represent ground truth motion instead of tracker annotations. Further, we focus on longer-horizon prediction in the Billiard setup. We train the model to predict 50 timesteps, where each timesteps corresponds to a $\Delta t = 0.01\,s$ interval for 300k iterations.

A.4. Training Data

We use three sources of training data for our models.

Open-set Video Data. To train our model for open-world motion generation, we source diverse videos from the internet, while ensuring no overlap with our evaluation data. We

Parameter	Value		
	Open-set		Billiard
Dataset	Open-Set Videos	Open-Set Video 3→2D	Billiard Simulations
Number of clips	10M	1.5M	–
Tracker	TapNext [123]	V-DPM [98]	Ground-truth
Tracker position seeding	1024 random positions	16,641 grid positions	random ball starting positions
Flow scale	$[-1, 1]$	$[-1, 1]$	$[-1, 1]$
Image size	512×512	512×512	512×512
Training track number	16	16	16
Training timesteps	16	16	50
Batch size	128	128	128
Optimizer	AdamW [67]	AdamW [67]	AdamW [67]
Betas	(0.09, 0.99)	(0.09, 0.99)	(0.09, 0.99)
Peak learning rate	3×10^{-5}	3×10^{-5}	3×10^{-5}
Learning rate schedule	linear decay to 10^{-8}	linear decay to 10^{-8}	linear decay to 10^{-8}
Warm-up steps	5k	5k	5k
Total steps	400k	400k	300k
Precision	bfloat16 AMP	bfloat16 AMP	bfloat16 AMP
Total Parameters	665M	665M	665M
GPUs	16 Nvidia H200	16 Nvidia H200	16 Nvidia H200s
Training Time	20 h	20 h	20 h
Depth	24	24	24
Width	1024	1024	1024
Head dim	128	128	128
Normalization	RMSNorm	RMSNorm	RMSNorm
FFN expand factor	4	4	4
Activation	GELU	GELU	GELU
Positional Encoding	see Sec. 3	see Sec. 3	see Sec. 3
Static scene conditioning	Adaptive Norm [48]	–	–
Denoiser width	1024	1024	1024
Denoiser depth	3	3	3

Table A. Hyperparameters of our main models and training setup.

then apply an off-the-shelf tracker [123] to obtain pseudo ground-truth annotations. For training, we center crop images to square resolution, cropping in both axis slightly to avoid border points for which the tracker commonly fails. We then resize frames to a uniform 512×512 resolution.

Reprojected 3D Data. Large-scale open-set videos typically suffer from ego camera motion, limiting the interpretability of trajectories. We aim to train a motion model, predicting interpretable static camera trajectories on unconstrained video data for scalability. We thus apply V-DPM [98] a 3D tracker that also estimates camera motion to open-set videos. Then, we reproject tracks into the first camera view, resulting in stabilized trajectories without camera motion interference. We apply the same center crop and resize.

Billiard Data. Training data for the Billiard simulation is obtained using a billiard physics simulation [31]. Ball positions and velocity are sampled randomly while ensuring balls do not overlap with other balls or the border. The physics engine produces future positions of balls, which are used as tracks to train the model.

A.5. Benchmark Construction

To create the OWM dataset, we source 95 permissively licensed videos from Pexels[1] that have been verified to have a static camera and cover a large variety of different kinds of motion from different kinds of entities (e.g., people, vehicles, animals, objects, ...). We prioritize structured or kinematically constrained dynamics (*e.g.*, articulated bodies, rigid object movement) and avoid stochastic or disconnected movement (*e.g.*, excessive background movement, excessively unconstrained motion). We further manually annotate a start frame and select points of interest on moving objects. Ground truth trajectories are obtained with TAPNext [123] and the tracking quality is manually verified.

We complement our dataset with samples from existing solid mechanics benchmarks with known high complexity. For this purpose, we obtain 97 samples from Physics-IQ [69] (subset "solid mechanics") and 134 samples from Physion [11] (excluding the "Drape" subset because of it's focus on soft-body collisions). We manually verify the correctness of motion in the Physion subset, as we observed some examples with unrealistic physical simulation. We, again, manually select starting frames and query points, and verify the correctness of motion annotations for all the additional samples.

A.6. Metrics

Open-World Motion Prediction. For the open-world and physical motion prediction benchmark, we rely on a simple MSE objective between the ground truth trajectory points $\mathbf{p}_{gt}$ and the predicted trajectory $\mathbf{p}_{pred}$ by evaluated methods, where $\mathbf{p}$ is a sequence of T 2D points $\mathbf{p} \in \mathbb{R}^{T\times 2}$. The ground truth is obtained by applying TapNext [123] to the full original video. As in a given initial configuration, multiple outcomes could be reasonable, we give each method the chance to produce an ensemble of predictions, whereby the ensemble size is $N_{ens} = 5$ for the **Best-of-5** setting and N_{ens} depends on the throughput of each method in the **Best-in-5min** setting. Throughput is calculated using best effort, meaning we utilize optimized implementations and lower-precision calculations when possible.

Billiard Planning. We calculate throughput similarly under optimized settings. To calculate the planning accuracy, we use the best action found during rollouts using the principle from Eq. (8). Then, we perform rollouts of the true Billiard simulation using the found action as the initial motion, while all balls except the action ball are initialized as stationary. A selected action is counted as correct if the target ball at least touches or covers the predefined goal position within the allocated time frame. If not the selected action is counted as incorrect. The accuracy is then calculated by dividing the number of correct actions $N_{correct}$ by the total number of trials N_{total}.

A.7. Baselines

Open-World Baselines. For the open-world and physics evaluation, we compare against five state-of-the-art video generation models: MAGI-1 4.5B [100], Wan2.2 I2V-A14B [112], CogVideo-X 1.5 5B-I2V [118], SkyReels V2 DF 1.3B 540P [24], and Stable Video Diffusion 1.1 (SVD) [16]. We utilize the implementation provided in the diffusers [109, 114] library for Wan, CogVideo-X, SkyReels,

[1] https://www.pexels.com/

and SVD. For MAGI, no diffusers implementation is available as of the writing of the paper, therefore we instead adopt the official repository and checkpoint and use the provided 4.5B distill+quant variant. All models except MAGI are run in I2V mode. Thus, they receive the last known image as conditioning and are tasked to simulate the video rollout. As multiple continuations are possible, we sample the Best-out-of-5 and Best-in-5min motion, respectively, giving the models the chance to explore multiple possible outcomes under uncertainty. For MAGI-1, we run the model in video-2-video mode and provide frames preceding the last known frame as hint conditioning. We subsequently apply TapNext [123] tracking to generated videos to obtain predicted trajectories, which we use to compute metrics.

Billiard Baselines. We compare billiard action search performance against four video generation baselines and two trajectory prediction baselines, which we implement and train from scratch to ensure fair comparison. We match the training setup as closely as possible to the setup for our model.

Video generation models are implemented as image-conditioned spatio-temporal Diffusion Transformers [76]. For efficiency, we utilize latent diffusion [82] and perform diffusion in the latent space of the pretrained VAE from Stable Diffusion-XL [80]. Image-conditioning is achieved by cross-attending to the VAE-produced tokens of the start image. We train four variants of video diffusion models, differing along two axes to cover a variety of previous approaches. Our video diffusion models either use auto-regressive generation or full sequence diffusion. In the former setting, the image conditioning is auto-regressively updated to include the prior N_{hist} images. The auto-regressive video generation model then generates the single next frame, conditioned on the history of previous images. The full sequence diffusion approach, on the other hand, is conditioned solely on the initial image and generates the full video from a single noise sample $x_1 \in \mathbb{R}^{T\times H\times W\times C}$. The models further differ in how they are informed about motion prompts. The *Images to Video* variants receive an additional second conditioning image to which they cross-attend. Note that this is natively supported by AR video generation models, while full sequence diffusion requires modification. Therefore, these models can infer the initial motion from visual cues. The *poke-cond.* models receive the instantaneous flow as an additional conditioning similar to our method. The flow and positions are first embedded using Fourier Embeddings and then passed through a small-scale MLP before being pooled into a fixed-size vector with a linear layer for multiple trajectories. The model is then conditioned on the flow embedding using Adaptive Layer Normalization [4, 48]. We use L-sized DiT backbones [76] for our experiments and train the video diffusion models until convergence.

For the full trajectory diffusion baseline, we ensure a fair comparison by reusing our motion models' backbone, but replacing the auto-regressive point-wise diffusion head with a DiT [76]. The training setup and motion model hyperparameters are consistent with our standard setup; however, we ensure that the model always receives only the first step flow.

For the FPT [10] baseline, we utilize the official implementation. Note that all other models predict step-wise motion, while FPT samples future positions in a single step. We align the horizon of the FPT baseline with that of the step-wise models and predict the final position of the balls at the end of the prediction window.

B. Additional Ablations

In the following, we elaborate further on design choices in our implementation.

B.1. Number of Function Evaluations

We test the impact of using more evaluations of the denoising flow matching head on the endpoint error (EPE) in the Billiard setting. Results in Tab. B show that our approach yields lower endpoint error with more function evaluations. Beyond 10 function evaluations, the benefits begin to diminish. Therefore, for our main evaluations in Sec. 5 we use 50 evaluations to balance quality and speed.

NFEs	Mean-best-of-5-EPE
1	0.00361
5	0.00143
10	0.00140
25	<u>0.00139</u>
50	**0.00138**

Table B. **Inference Time Scaling:** Our approach achieves lower End-Point-Error in the Billiard simulation with more function evaluations of the diffusion head.

B.2. Trajectory ID Embedding

As outlined in Sec. 3 we draw random, (nearly) orthogonal trajectory embeddings $\text{id}_{\text{traj}}^{(i)} \sim \mathcal{U}(\mathbb{S}^{d-1})$ to indicate trajectory correspondence to the model. Other, more common approaches would be to use no explicit embedding and instead only rely on positional embeddings, or to use a learnable trajectory embedding with a fixed-size codebook.

We compare these options in Tab. C on the Billiard simulation data. We find that our randomized embeddings outperform both learnable embeddings (likely attributable to a reduction in the likelihood of the model learning position-related biases) and the setting with no extra embeddings. Importantly, unlike learnable embeddings, the model is capable of zero-shot trajectory number extrapolation from 16 (the number observed during training) to larger and smaller numbers, with minimal performance degradation.

Traj. Emb.	Num. Traj.	Mean-best-of-5-EPE
No Emb.	8	0.00116
	16	0.00150
	24	0.00277
Learnable	8	0.00112
	16	0.00149
	24	not possible
Ours	8	**0.00108**
	16	**0.00141**
	24	**0.00263**

Table C. **Trajectory ID Embedding:** Our trajectory ID embeddings provide lower end-point-error in billiard simulations and enable zero-shot generalization to *both* increased and reduced number of trajectories.

B.3. Multi-Step Reasoning

T	Δt	Num. Steps	Mean-best-of-5-EPE
0.5	0.01	50	**0.00141**
0.5	0.05	10	0.00999
0.5	0.5	1	0.02823

Table D. **Reasoning in multiple steps.** We compare predicting 0.5 s into the future using models trained with different step sizes. Our standard method integrates 50 steps, while the other models perform fewer steps. Therefore, these models require fewer auto-regressive steps, yet have to model more of the dynamics internally.

Our approach predicts the motion over a short time horizon Δt in one step and then auto-regressively samples movement to predict motion over the entire time horizon T, thus factorizing the full motion prediction over ΔT into a sequence of small-step predictions. In theory, a motion model with infinite capacity should be able to predict the final position of all scene elements in a single step by internally accounting for all potential interactions. However, we argue that predicting step-wise motion is a substantially more practically viable task when not assuming abundant model capacity. We investigate this assumption by comparing model variants in the Billiard setting.

We compare our standard model, predicting $\Delta t = 0.01\,s$ into the future per step, against variants predicting over a larger Δt. We perform a 0.5 s rollout (making the largest-step model perform predictions over the full horizon T in a single step, as in [10]) and evaluate the end-point-error of each model. The results in Tab. D show that multi-step motion prediction improves modeling performance, with overall improved performance for smaller step intervals. The single-step model performs significantly worse than both multi-step variants, mirroring the planning results in Tab. 2. We attribute this failure to the complexity of internally modeling and accounting for all interactions in a large Δt timeframe.

B.4. Classic Trajectory Forecasting Setting

We explore our approach's efficacy in classic trajectory forecasting settings in a *zero-shot* setting. We compare on the canonical ETH-UCY [58, 77] benchmark following the setting of Trajectron++ [87]. All baselines are trained exclusively on in-domain data, while we apply our model zero-shot. The baselines directly operate on tracked abstract agents in a 2D top-down view space (obtained from the camera-space tracks via projection), while we operate directly on the original images, as our model uses that as the input. Since the given homographies are not accurate for reprojecting back into the camera space, we manually annotate correspondences and fit homographies, obtaining the equivalent tracks in camera space, which serve as input and output space for our model. ETH generally annotates people's heads, while UCY seems to rely on people's feet. This does not matter in a top-down view, as the head will typically be in the same 2D position as the feet, but it matters in camera space. We annotate homographies to follow the ETH convention. Metrics are computed in the original 2D top-down space directly following the baselines.

We show results in Tab. E. Despite not being trained for this setting, our method achieves competitive results with canonical task-specific baselines. This demonstrates that our much more generic approach can still perform well even in specific settings. With additional finetuning on sufficiently large-scale in-domain data, results should further improve significantly.

B.5. OWM Breakdown

We report metrics for subsets of OWM focusing on specific kinds of motion in Tab. F. Our model is competitive with substantially larger video baselines for all subsets, including intricate multi-agent interactions. In the time constraint setting our method achieves the best results across all subsets as it's fast inference allows to explore a much larger variety of potential futures.

C. Additional Qualitative Samples

Benchmark samples. We provide qualitative samples from the OWM benchmark (Fig. A), Physics-IQ subset (Fig. B), and Physion subset (Fig. C) with the **Best-out-of-5** motion annotation for our approach and all baseline methods.

Qualitatively, our approach predicts motion that is on par with state-of-the-art video generation approaches in open-world settings, found in the OWM benchmark. Comparing on Physics-IQ [69], video generation approaches tend to predict overly simplified, physically implausible trajectories, whereas our method is able to capture the complexity of real-world physical interactions. For Physion [11], state-of-the-art video generation models hallucinate overly complex motion, whereas our approach is able to capture the rigid

Method	ETH		Hotel		Zara01		Zara02	
	Deterministic	Best-of-20	Deterministic	Best-of-20	Deterministic	Best-of-20	Deterministic	Best-of-20
SocialLSTM [2]	1.09/2.35	–	0.79/1.76	–	0.47/1.00	–	0.56/1.17	–
SocialGAN [39]	–	0.81/1.52	–	0.72/1.61	–	0.34/0.69	–	0.34/0.69
Trajectron [49]	–	0.59/1.14	–	0.35/0.66	–	0.43/0.83	–	0.43/0.83
Trajectron++ [87]	**0.71**/1.66	0.39/0.83	**0.22/0.46**	**0.12/0.19**	**0.39/0.77**	**0.15/0.33**	**0.23/0.59**	**0.11/0.25**
Ours (zero-shot)	0.81/**1.50**	**0.31/0.80**	0.30/0.54	0.17/0.30	0.79/1.75	0.53/1.21	0.58/1.30	0.40/0.91

Table E. **Zero-shot Comparison with Closed-Domain Trajectory Forecasting on ETH-UCY [58, 77].** All numbers (except ours) are sourced from Trajectron++ [87]. Note that some sequences from UCY are missing due to missing RGB videos. Values are (following Trajectron++) (min-){ADE/FDE}, "–" means not reported by Trajectron++. In the "deterministic" setting, we sample from our model once with fixed seed.

Method	Rigidity				Number of Agents				Agents with Free Will				Avg. Rank		Throughput SAMPLES/MIN↑	Params↓
	Rigid		Non-rigid		Single-Agent		Multi-Agent		w/ Free Will		w/o Free Will					
	N=5↓	T=5MIN↓	N=5↓	T=5MIN↓	N=5↓	T=5MIN↓	N=5↓	T=5MIN↓	N=5↓	T=5MIN↓	N=5↓	T=5MIN↓	N=5↓	T=5MIN↓		
MAGI-1	0.032	0.058	0.039	0.069	0.020	0.044	0.048	0.080	0.040	0.066	0.030	0.065	2.00	3.00	0.303	4.5B
Wan2.2 [112]	0.042	DNF	0.038	DNF	0.039	DNF	0.039	DNF	0.036	DNF	0.045	DNF	2.33	DNF	0.141	14B
CogVideo-X 1.5 [118]	0.051	DNF	0.051	DNF	0.041	DNF	0.052	DNF	0.049	DNF	0.054	DNF	4.50	DNF	0.051	5B
SkyReels V2 [24]	0.061	0.071	0.056	0.066	0.048	0.056	0.064	0.075	0.054	0.063	0.065	0.076	5.50	3.00	0.304	1.3B
SVD 1.1 [16]	0.048	0.055	0.057	0.073	0.037	0.053	0.065	0.077	0.060	0.069	0.042	0.064	4.66	3.00	0.714	1.5B
Ours	0.031	0.007	0.039	0.016	0.036	0.008	0.044	0.017	0.037	0.014	0.044	0.011	2.00	1.00	2200	0.6B

Table F. **OWM Subset-wise Metrics.** Breakdown of Tab. 1 results. While orders of magnitude faster, our method is consistently competitive with state-of-the-art video models across not only the overall benchmark, but also when split across multiple properties (rigidity of motion, number of agents, presence of agents with free will).

body physics of the benchmark setting. Therefore, our approach is able to balance complexity and simplicity better than previous approaches making it applicable to a wider range of inference contexts.

Open-set samples. We provide samples for a variety of open-set conditioning images, sourced from the internet. Fig. D shows that our approach predicts motion informed by the context provided through the starting image. We provide two examples where we edit the image using nano banana and use the same motion hint. The qualitative samples show that for a person on a trampoline, more bouncy motion is predicted compared to a person jumping on a wooden floor. Further, a ball rolling across a table has a more straight trajectory compared to an egg rolling across the same table.

Fig. E shows samples generated with initial motion hints. The samples show that unrolling hinted trajectories results in consistent motion across entities and realistic long-term behaviour.

In Fig. F we provide samples generated without an initial motion hint. While the trajectories tend to be more simplistic, realistic motion is obtained based solely on the input image. Query points without motion hint are marked in grey.

Fig. G illustrates samples where only a single query point on the object received a hint, and motion for other queries has to be inferred from appearance alone. The results highlight that sampled motion is coherent across objects. Further, our model is able to capture multi-modal behaviour if two outcomes are realistic given the same input. Query points without motion hint are marked in grey while queries with motion hint are colored black.

Billiard samples. We show qualitative predictions from our model trained on billiard simulation data in Fig. H. We show the predicted simulation given an initial impulse in the upper row, and the ground truth simulation overlaid with the prediction in the lower row for each respective sample. Simulation time increases linearly from left to right. Our model is able to accurately predict the ground truth motion, up to stochastic uncertainties.

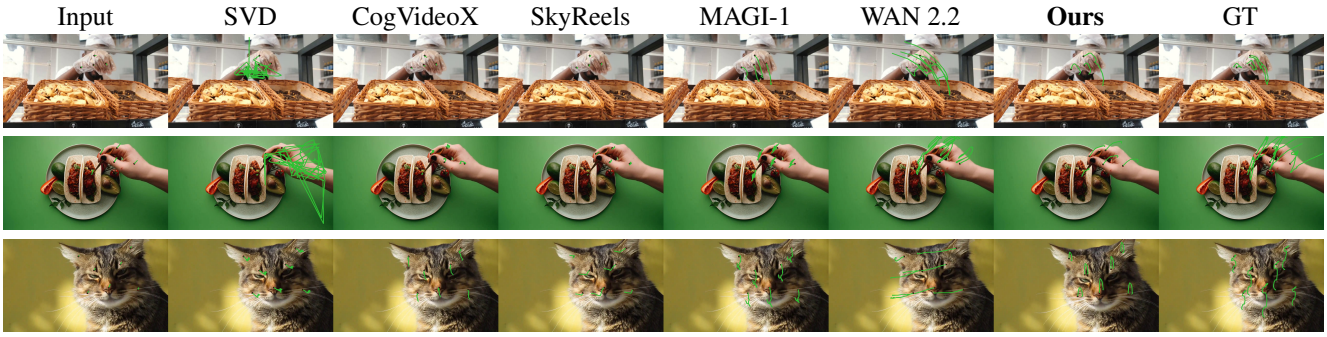

Figure A. **Qualitative comparison on OWM:** Our model produces motion samples that are qualitatively on par with much larger models such as WAN2.2 and MAGI-1.

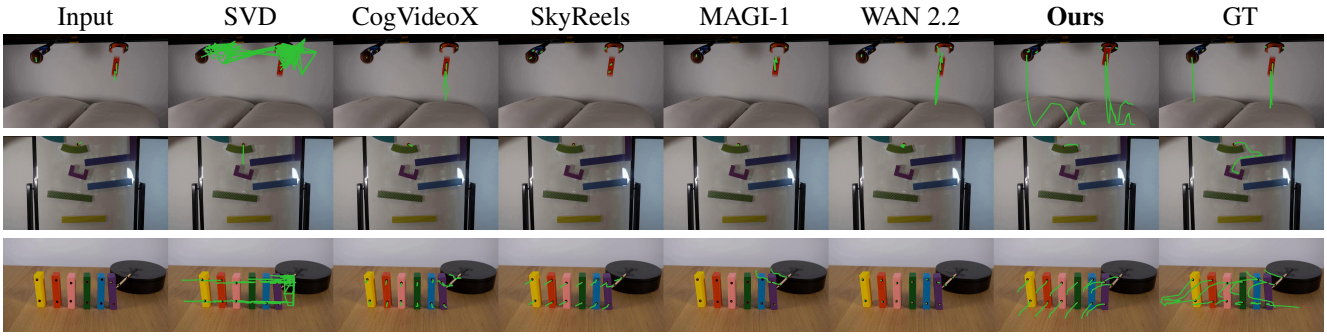

Figure B. **Qualitative comparison on Physics-IQ:** While video generation models fail to capture the complexity of object interactions and predict simplified or no motion, our approach captures realistic physical interactions.

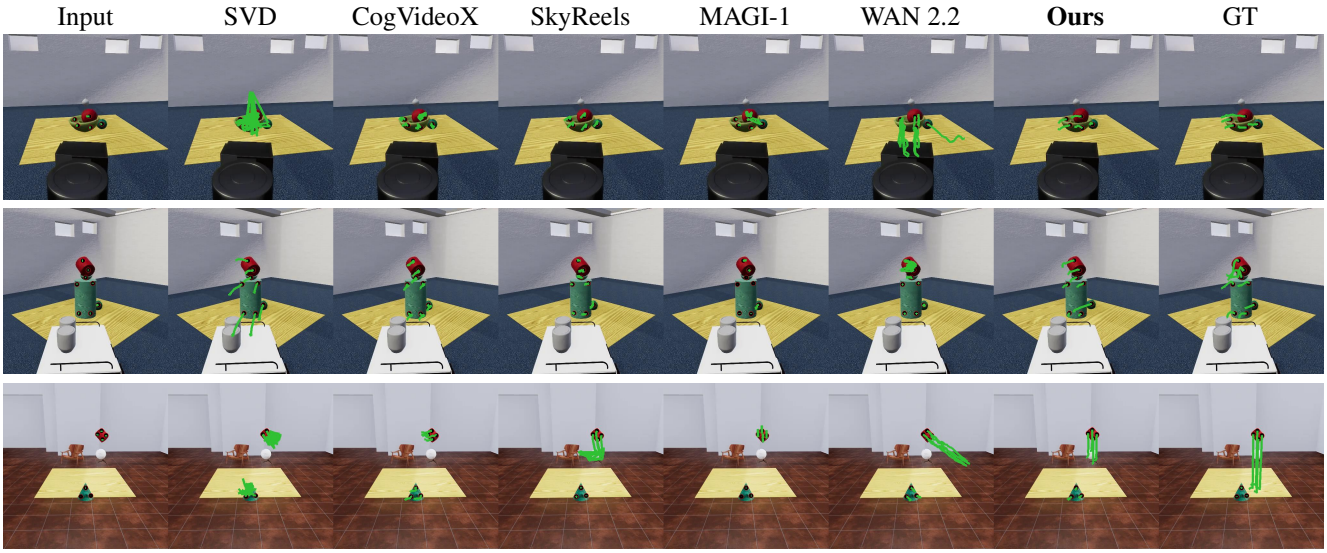

Figure C. **Qualitative comparison on Physion:** For simplified rigid body settings in Physion, video generation models hallucinate overly complex motion, while our approach is able to capture physical dynamics.

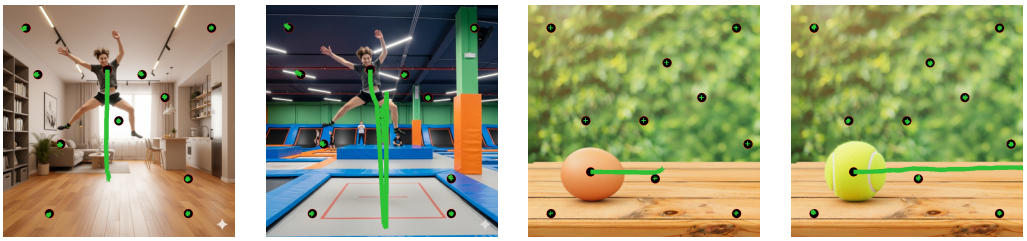

Figure D. **Context informed samples:** The above samples show our model's ability to take appearance information into account when predicting motion. In both comparisons, images were sampled with the same initial poke. Images where edited using nano banana for high similarity in appearance.

Figure E. **Hinted Samples** Our model is capable of producing complex, coherent, and appearance-informed motion given an initial motion hint.

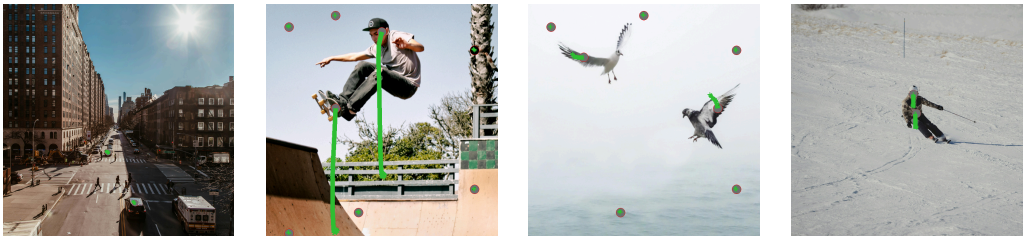

Figure F. **Un-hinted Samples** Given only appearance conditioning, our approach is able to produce physically correct and coherent motion, also show ing more complex understanding, such as that cars at an intersection should *not* move when pedestrians are blocking their path.

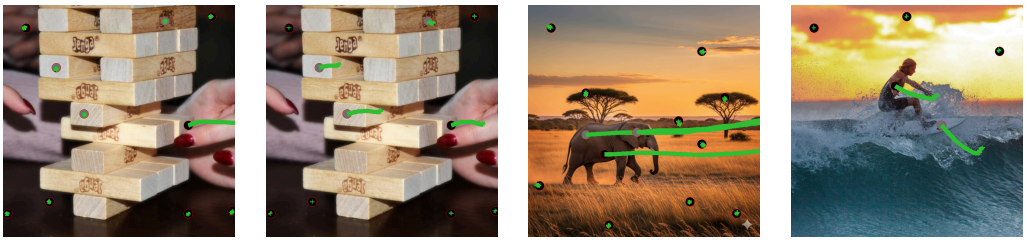

Figure G. **Partially-hinted Samples** Given only a single poke conditioning per example, our model produces coherent motion for queries on the same or linked objects. The Jenga example highlights that our model is able to capture multi-modality if two outcomes are possible given the same initial motion hint.

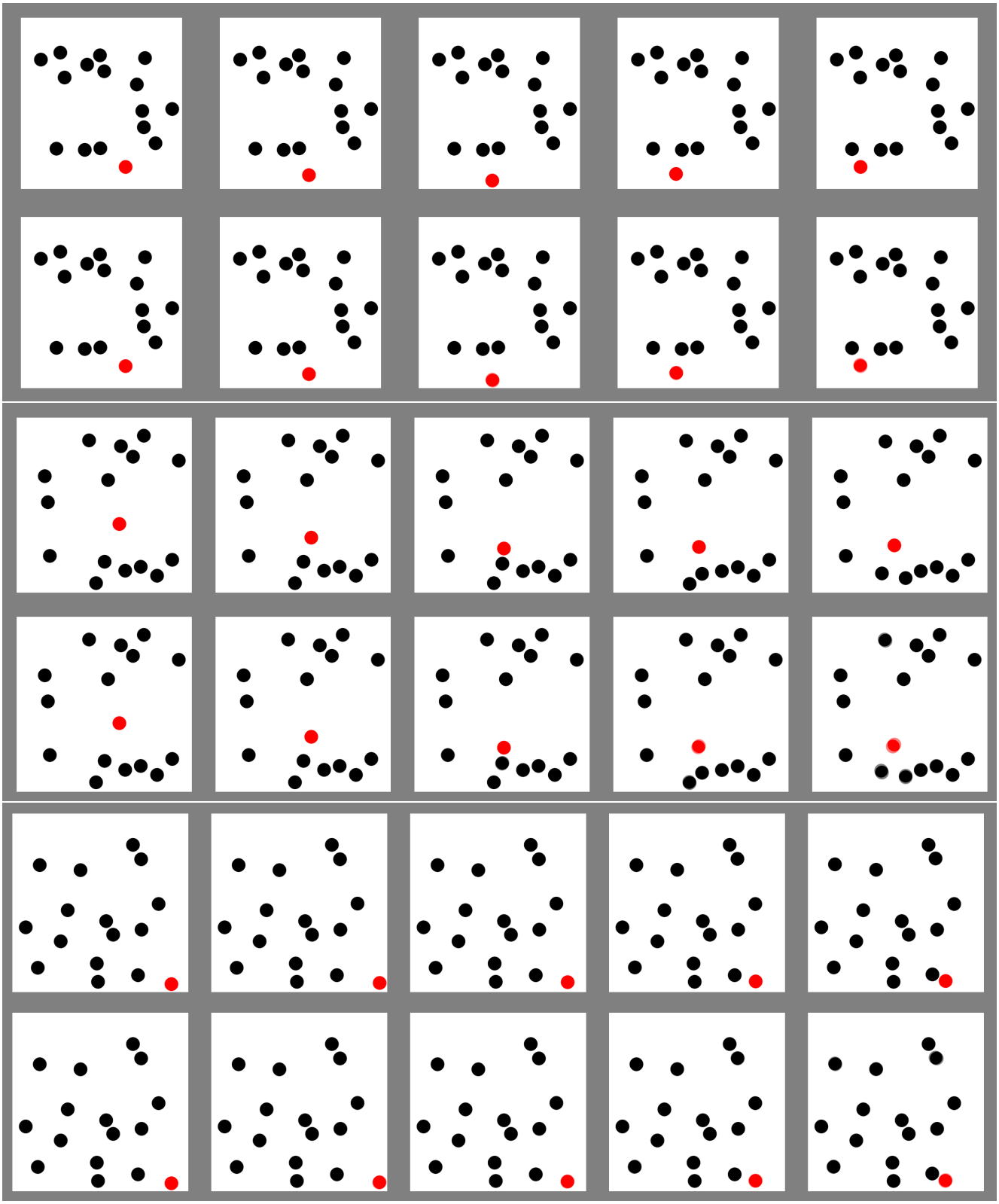

Figure H. **Qualitative samples on our billiard simulation.** The respective top row shows our model's prediction given an initial impulse for the ball marked in red, where we visualize the predicted trajectory state using a frame-wise renderer; the lower row shows an overlay of the ground truth simulation with the prediction to enable comparisons. Our model can successfully predict the observed motion up to minor stochastic details.

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