NoMaD: **N**avigati**o**n with Goal-**Ma**sked **D**iffusion

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Motivation and Goal

Robotic navigation in unfamiliar environments requires:

- Task-oriented navigation — reaching specified goals
- Task-agnostic exploration — discovering and mapping new areas

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The Challenge

These two objectives are typically handled by *separate systems*.

Exploration can be decomposed into:

- **Local Exploration:** Learning short-horizon control policies for diverse actions
- **Global Planning:** Using those policies to achieve long-horizon, goal-directed behavior

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Key Question

Can a *single model* unify both tasks — exploration and navigation?

What is NoMaD?

NoMaD is a transformer-based diffusion policy designed for long-horizon, memory-efficient navigation.

It supports both:

- **Goal-conditioned navigation** — moving towards a specified visual goal
- **Open-ended exploration** — learning diverse behaviors without explicit goals

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`+ Diffusion Policies`

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It combines a transformer backbone to encode the high-dimensional visual stream, with diffusion models that predict a sequence of future actions in a generative manner.

Visual Goal-Conditioned Navigation

Backbone: ViNT (Visual Navigation Transformer)
How does ViNT work?

- Recieves: A sequence of past and current observations $o_t = o_{t-P:t}$
- **Visual Encoder:** Each observation is processed using an EfficientNet-B0 encoder to extract feature embeddings.

Overview of NoMaD Architecture

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`EfficientNet?`

- A new method of Scaling CNNs to improve accuracy and efficiency
- It uses a **compound scaling** to uniformly scale all dimensions of depth, width, and resolution.

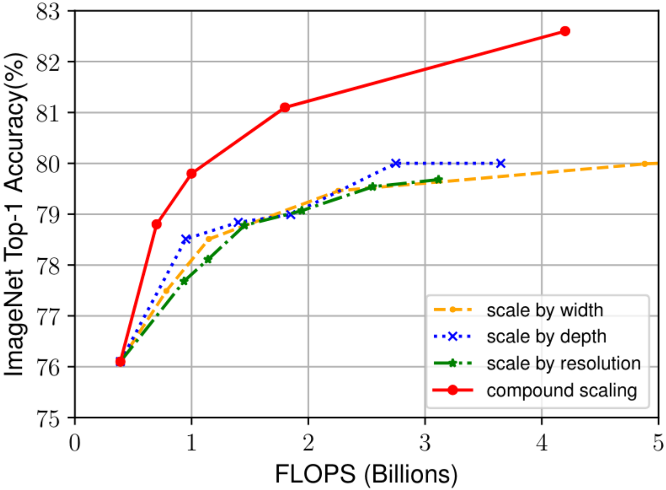


Figure: Compound Scaling

EfficientNet

Use Network Architecture Search (NAS) to find the best baseline network (EfficientNet-B0)

Optimization Objective:

$$\mathrm{ACC}(m) \times \left[\frac{\mathrm{FLOPS}(m)}{T}\right]^{w}$$

- ACC(m): accuracy of model m
- FLOPS(m): floating point operations
- T: target FLOPS
- $w = -0.07$: controls trade-off between accuracy and FLOPS

EfficientNet Scaling

Compound Scaling

EfficientNet introduces a principled way to scale up CNNs using a single compound coefficient ϕ.

- Simultaneously scales:
  - Network depth d
  - Width w
  - Input resolution r
- Scaling formulas:

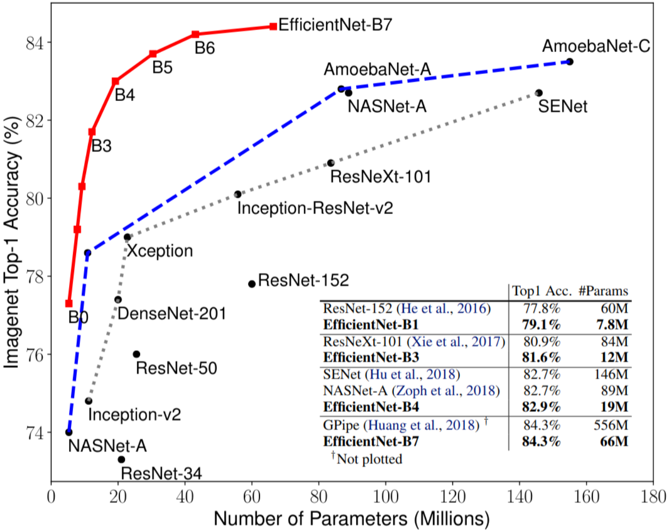
$$d = \alpha^{\phi}, \quad w = \beta^{\phi}, \quad r = \gamma^{\phi}$$

- Constants α, β, and γ are determined via grid search.

Subject to constraint:

$$\alpha \cdot \beta^2 \cdot \gamma^2 \approx 2$$

Ensures that the model scales within a fixed computational budget.



	Top1 Acc.	#Params
ResNet-152 (He et al., 2016)	77.8%	60M
EfficientNet-B1	**79.1%**	**7.8M**
ResNeXt-101 (Xie et al., 2017)	80.9%	84M
EfficientNet-B3	**81.6%**	**12M**
SENet (Hu et al., 2018)	82.7%	146M
NASNet-A (Zoph et al., 2018)	82.7%	89M
EfficientNet-B4	**82.9%**	**19M**
GPipe (Huang et al., 2018) †	84.3%	556M
EfficientNet-B7	**84.3%**	**66M**

† Not plotted

Figure: Accuracy on imagenet

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- Recieves: A sequence of past and current observations $o_t = o_{t-P:t}$
- **Visual Encoder:** Each observation is processed using an EfficientNet-B0 encoder to extract feature embeddings.
- **Goal Fusion:** The current and goal images are combined using a goal-fusion encoder.
- **Transformer Attention:** These fused features (tokens) are passed through a Transformer model to generate a context vector c_t.
- **Predictions:** The context vector is used to predict:
  -A distribution over future actions: $a_t = f_a(c_t)$
  -An estimate of temporal distance to the goal: $d(o_t, o_g) = f_d(c_t)$

Extending to Long-Horizon Planning with Topological Memory

However, ViNT is inherently goal-conditioned—it cannot operate in the absence of a goal image, limiting its ability to explore autonomously.

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Solution

To enable open-ended exploration, NoMaD incorporates a Topological Memory $\mathcal{M}$:

1. Nodes represent previously encountered visual observations.
2. Edges represent traversable paths, established using ViNT's predicted distances.

This enables:

- **Subgoal Planning:** The model can plan a sequence of subgoals to reach a target location.
- **Frontier Exploration:** The model can autonomously explore new areas by identifying frontiers in the topological map.

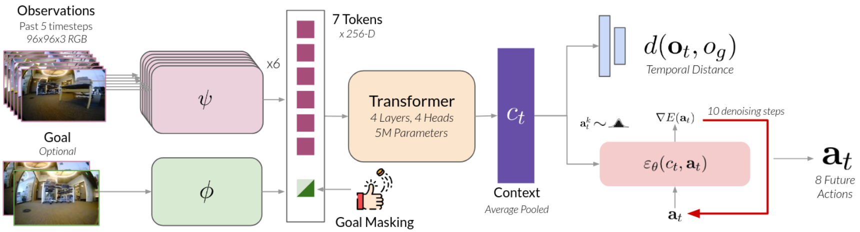
NoMaD = {EfficientNet + Vision Transformer} ← ViNT
+ Diffusion Policies

Nomad builds upon ViNT by:

Attention based Goal Masking:

Introduces a binary mask m, and modifies the context vector c_t as:

$$c_t = f(\psi(o_i), \phi(o_t, o_g), m)$$



Overview of NoMaD Architecture

`NoMaD = {EfficientNet + Vision Transformer}` $\leftarrow$ `ViNT`
`+ Diffusion Policies`

Diffusion Policies:

To model complex, multimodal action distributions, NoMaD employs a diffusion model to approximate the conditional distri- bution of the next action as: $p(a_t|c_t)$.

1. Forward Process: Start with a real action a_t^0 and add gaussian noise to it over multiple steps.

$$a_t^k = \sqrt{\alpha_k} a_t^{k-1} + (\sqrt{1-\alpha_k})\epsilon$$

where:

- $\epsilon \sim \mathcal{N}(0,\mathrm{I})$ is a random noise
- α_k is a noise scheduler (eg square cosine)
- By step K, the action is almost pure noise.

Overview of NoMaD Architecture

`NoMaD = {EfficientNet + Vision Transformer}` $\leftarrow$ `ViNT`
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2. Reverse Denoising: starting from pure noise $a_t^k \sim \mathcal{N}(0, I)$, it denoises step by step to recover the final clean action a_t^0.
Each denoising step is :

$$a_t^{k-1} = \alpha(\alpha_t^k - \gamma_k.\epsilon_\theta(c_t, a_t^k, k)) + \mathcal{N}(0, \sigma^2.I)$$

Where:

- Here, ϵ_θ is the noise prediction network conditioned on the context c_t, which may or may not include the goal depending on m.
  - It is a 1D conditional U-Net with 15 CNN layers.
  - Input:Noisy action a_t^k, Context vector c_t, and the diffusion step k.
  - the predicted noise vector $\hat{\epsilon}_k$,During training, it is compared to the true noise added earlier.
- γ, α, σ are scheduler constants.

Overview of NoMaD Architecture

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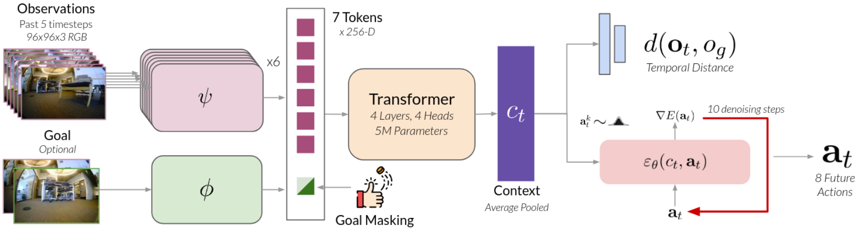
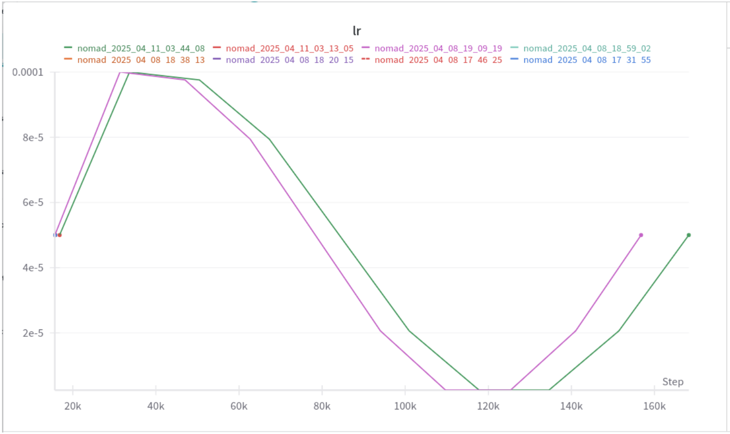
3. Action Decoder: The denoised action a_t^0 is then passed through a low-level action decoder to generate the final action a_t.

- The decoder maps the denoised action to a low-level control command for the robot.
- It can be a simple feedforward network or a more complex recurrent network.



Training Details and Experiments

- Datasets used: Sacson/HuRoN, parts of RECON and SCAND
- Batch size: 47, Epochs: 10
- Optimizer: AdamW, Lr: 10^{-4}
- Scheduler: Cosine annealing



Training Details and Experiments

- Goal Masking Probability: $p_m = 0.5$
- Diffusion Steps: 10
- Noise Scheduler: Square Cosine

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Training Objective

- **Diffusion Loss:** Measures the difference between the predicted and true noise.
- **Distance Loss:** Measures the difference between the predicted and true distance to the goal.

$$\mathcal{L}_{NoMaD}(\phi, \psi, f, \theta, f_d) = MSE(\epsilon^k, \epsilon_\theta(c_t, a_t^0 + \epsilon^k, k)) + \lambda . MSE(d(o_t, o_g), f_d(c_t))$$

where:

- We set λ to 10^{-4}
- ψ, ϕ correspond to the visual encoders for the observation and goal images.
- f corresponds to the transformer layers, θ to diffusion parameters,
- f_d corresponds to the temporal distance predictor.

Training Visualization with wandb

Why Weights & Biases (wandb)?

We used wandb to log training progress, visualize losses, and monitor both model behavior and system resources (e.g., GPU/CPU utilization) throughout experimentation. Metrics such as **action loss**, **goal prediction error**, and the **learning rate schedule** were automatically tracked and visualized, which helped with debugging and plotting out results.

Figure: QR code to project dashboard

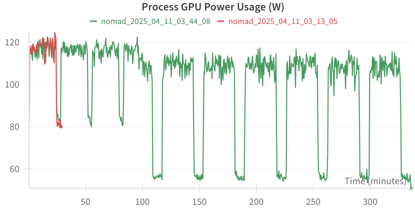
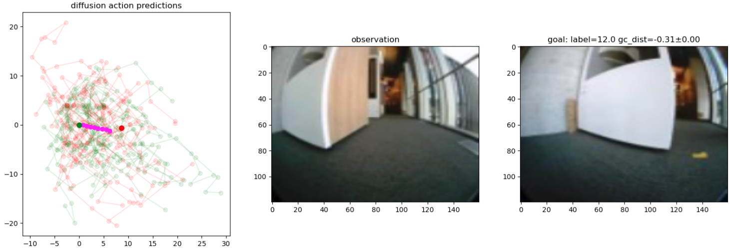


Figure: GPU power usage during training

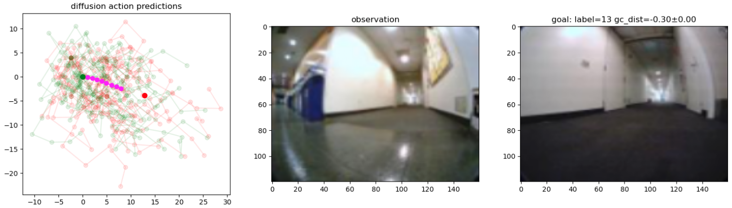
Action Samples generated by NoMaD

During Training



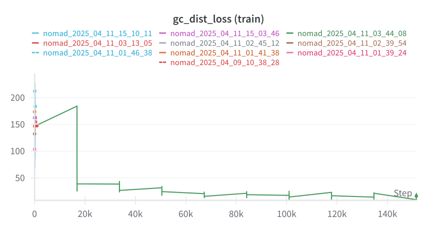
Action Samples generated by NoMaD

During Testing

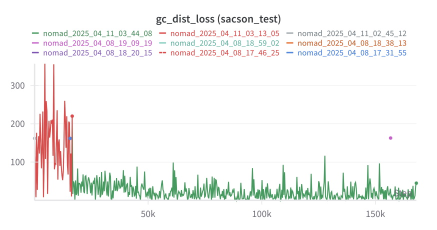


Experiments and Results

Distance Loss (Goal Conditioned)



(a) Distance Loss on Training Set



(b) Distance Loss on Validation Set

Figure: Distance loss comparison between training and validation sets under goal-conditioned evaluation.

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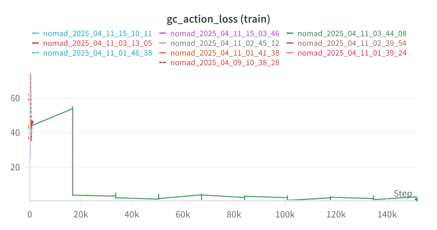
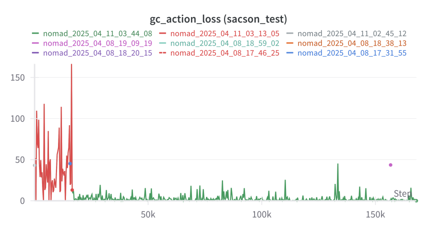
Action Loss (Goal Conditioned)



(a) Action Loss on Training Set

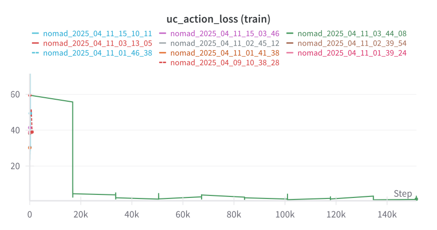


(b) Action Loss on Validation Set

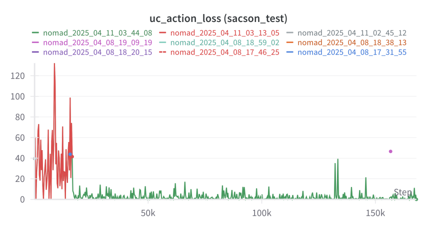
Figure: Action loss comparison between training and validation sets under goal-conditioned evaluation.

Experiments and Results: Unconditioned Setting

Unconditioned Action Loss Evaluation



Training Set



Validation Set

The unconditioned action loss measures model accuracy in open-loop, goal-agnostic settings. Lower loss indicates better generalization in exploratory behavior.

Experiments and Results: Diffusion Loss

Training Performance

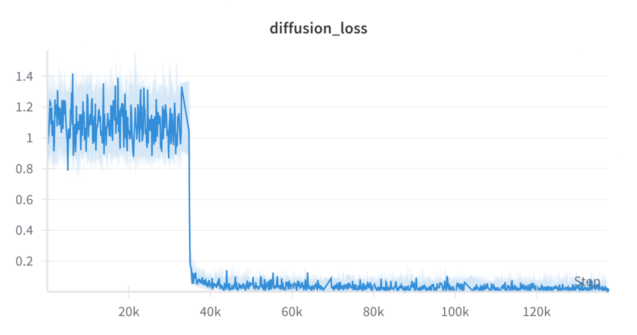
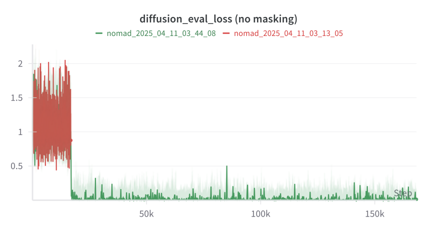


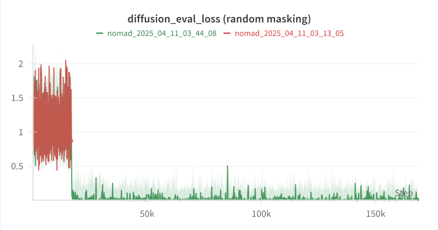
Figure: Diffusion loss over training batches. This loss reflects how well the model learns to denoise the trajectory samples using the learned conditional distribution.

Goal-Conditioned ($m = 0$)



All tokens receive goal signal.
Evaluates the robot's ability to follow a target.

Unconditioned ($m = 1$)

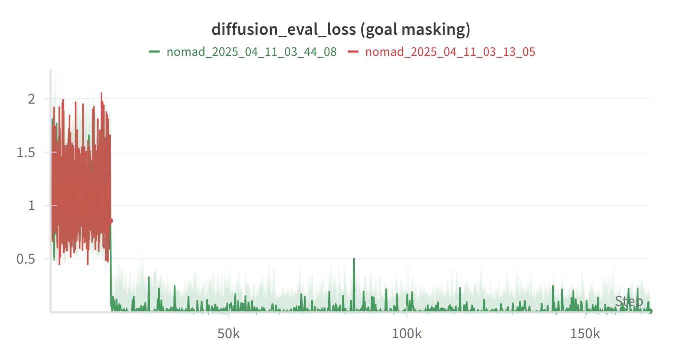


No goal information.
Evaluates purely exploratory navigation behavior.

We see that loss goes downstream in both cases.

Evaluation: Mixed Masking ($m \sim \mathcal{B}(0.5)$)

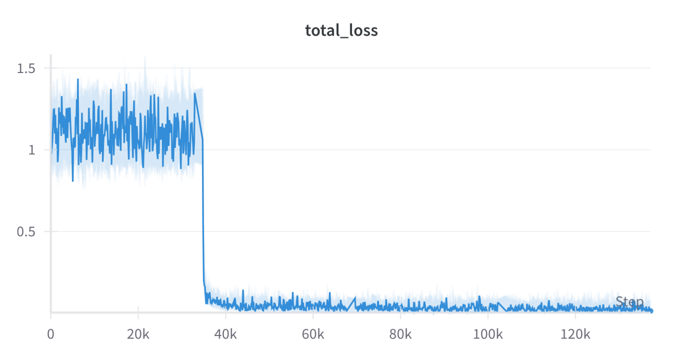
Stochastic Goal Conditioning



Description: Each token is randomly masked with probability 0.5. This encourages the model to balance between exploring and exploiting goal cues.

Experiments and Results :Total Loss

Total Loss



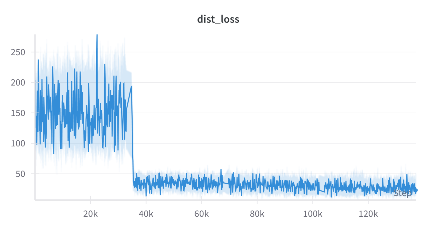
Description: The total loss combines both the diffusion and distance losses, providing a holistic measure of model performance.

Comparision with ViNT: Temporal Distance Loss

Motivation

ViNT serves as a strong baseline for visual navigation with transformer-based context encoding. We compare its distance prediction ability against NoMaD.

NoMaD Distance Loss



NoMaD achieves lower and more stable distance loss due to diffusion-based modeling and goal conditioning.

ViNT Distance Loss

ViNT performs comparably in early epochs but struggles with long-horizon distance regression.

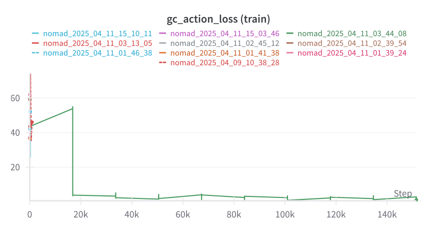
Observation: **NoMaD's diffusion-based decoder improves distance supervision** without sacrificing ViNT's transformer strengths.

ViNT vs NoMaD: Action Loss

Objective

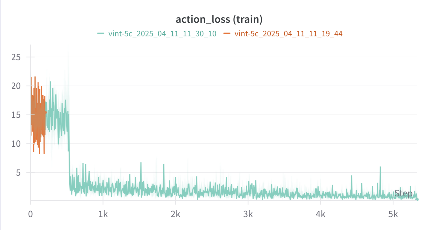
We compare the quality of predicted waypoints by measuring the Mean Squared Error (MSE) between predicted and ground-truth actions.

NoMaD Action Loss



NoMaD consistently achieves lower action loss, aided by the stochastic denoising process and goal-conditioned context.

ViNT Action Loss



ViNT shows slightly higher variance, and loss plateaus earlier due to MLP-based decoding.

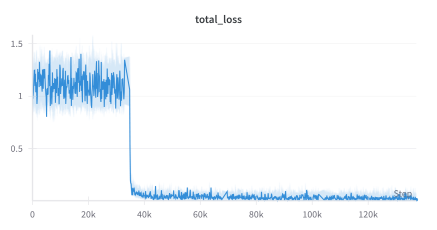
Observation: **NoMaD benefits from the expressiveness of diffusion decoding** in predicting fine-grained waypoint actions.

Comparison with ViNT: Total Loss

Motivation

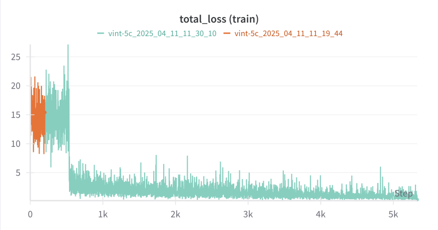
To assess the overall effectiveness of NoMaD vs. ViNT, we compare the combined loss: action prediction loss + temporal distance prediction loss.

NoMaD Total Loss



NoMaD achieves better convergence, with lower final loss due to richer diffusion-based decoding.

ViNT Total Loss



ViNT exhibits slower learning and higher loss, limited by direct MLP-based action prediction.

Takeaway: **NoMaD demonstrates improved learning dynamics and generalization.**

Challenges Faced

- CUDA out of memory errors were common during training, especially with larger batch sizes. We mitigated this by reducing the batch size and using gradient accumulation.
- The model was initially not being able to learn effectively, leading to high loss values. We debugged this by checking the data pipeline and ensuring that the input images were correctly preprocessed and normalized.
- The system in UG computational labs didnot have ROS installed, which was required to process the datasets. With the help of our TA, we used a docker file to set up a container with ROS and the required dependencies.
- The original codebase has several data-type related bugs which had to be fixed. For example, the original code was using torch.float32 for some tensors, while the model expected them to be in torch.float64. This caused several errors during training.
- The initial implementation caused several system crashes due to heavy computational load.

Team Contributions

Abhishek Kumar Jha:

- Helped in Understanding the diffusion model
- Helped in solving the errors while training the NoMaD model

Namashivayaa V:

- Helped in Understanding the theory for the entire project
- Helped Extrating the data from the datasets
- Made the Appendices section of the Report

Team Contributions

Sehaj Ganjoo:

- Implemented the ViNT architecture
- Developed the goal fusion encoder
- Conducted experiments and analysis for comapring NoMaD and ViNT
- Made the Presentation and Report

Shobhnik Kriplani:

- Implemented the Tockenizer, embeddings and positional encodings from scratch
- Implemented the NoMaD architecture
- Developed the training pipeline
- Conducted experiments and analysis

Conclusion and Future Work

- Successfully trained NoMaD using diffusion for visual navigation
- Showed compatibility with ViNT-based perception
- Future work:
  - Deploy NoMaD on real robots and check performance on real world environments
  - Explore the use of NoMaD for other tasks like object detection and tracking
  - Explore how we can improve the current architecture.
  - Try larger ViTs and alternate decoders

Q&A

Thank You!

Appendices

Appendices

- Appendix A: Additional Results
- Appendix B: Implementation Details
- Appendix C: References

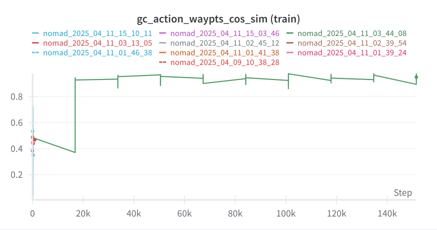
Appendix A: Additional Results

Additional Results

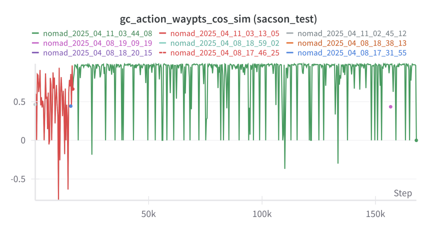
- Additional results and analysis of NoMaD's performance

Experiments and Results: Cosine Similarity

Goal-Conditioned Action Waypoints Cosine Similarity



Training Set

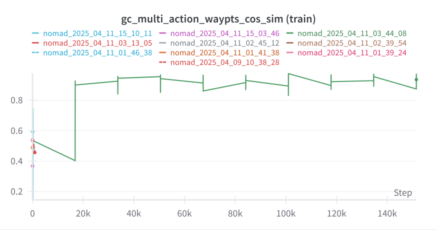


Validation Set

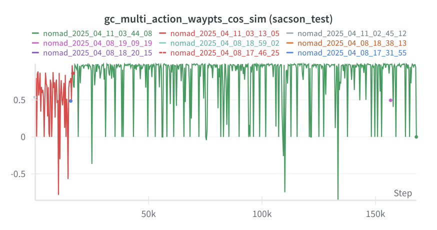
Cosine similarity evaluates directional alignment between predicted and ground-truth action waypoints. Higher values (~ 1.0) indicate better trajectory alignment under goal-conditioned settings.

Experiments and Results: Multi-Action Cosine Similarity

Goal-Conditioned Multi-Action Waypoints Cosine Similarity



Training Set

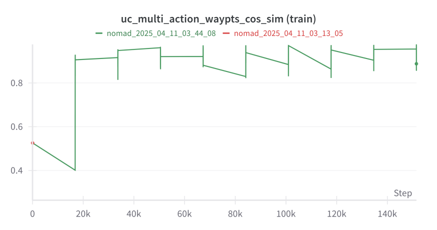


Validation Set

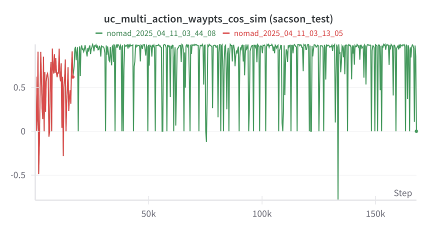
Multi-action cosine similarity compares the overall alignment of full predicted trajectory vectors with ground truth, rather than frame-by-frame. This provides a more holistic measure of long-horizon trajectory quality.

Experiments and Results: UC Multi-Action Cosine Similarity

Unconditioned Multi-Action Waypoints Cosine Similarity



Training Set



Validation Set

Cosine similarity across the full predicted trajectory in unconditioned setting. Higher similarity indicates better alignment with ground-truth behavior.