Motion Binary Latent Diffusion

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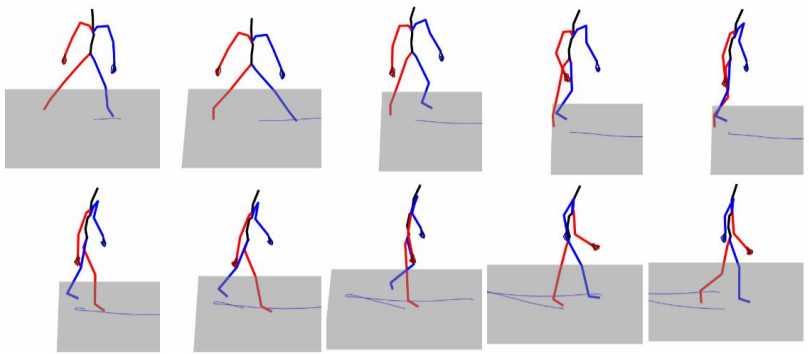
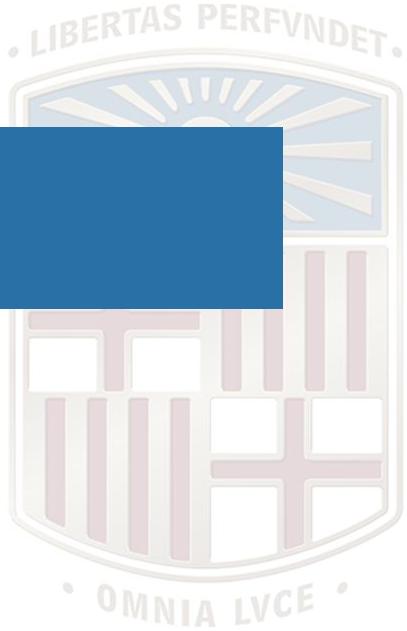


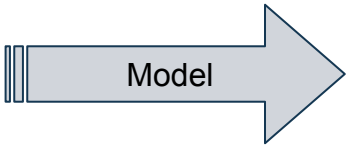
Introduction

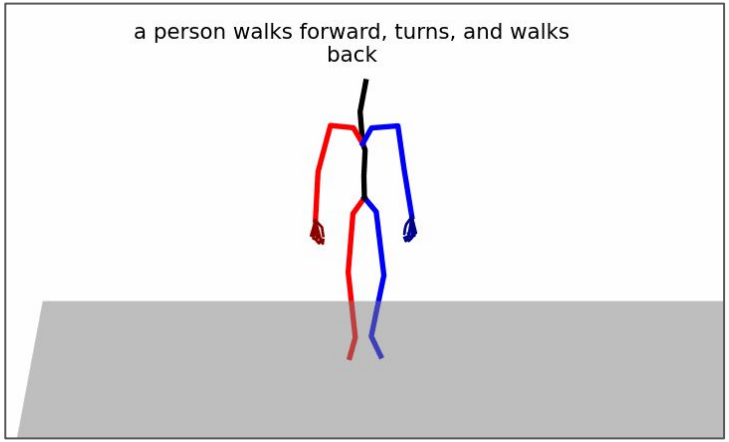


Problem definition

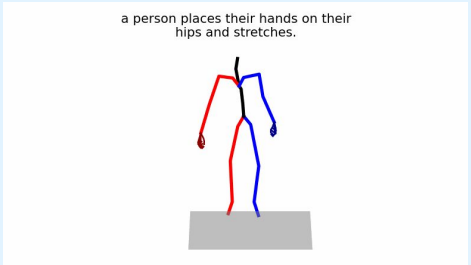
Text-to-motion: *“Design and train a model to generate plausible, natural and diverse range of human motion sequences, based on an input prompt text.”*

“a person walks forward, turns, and walks back”



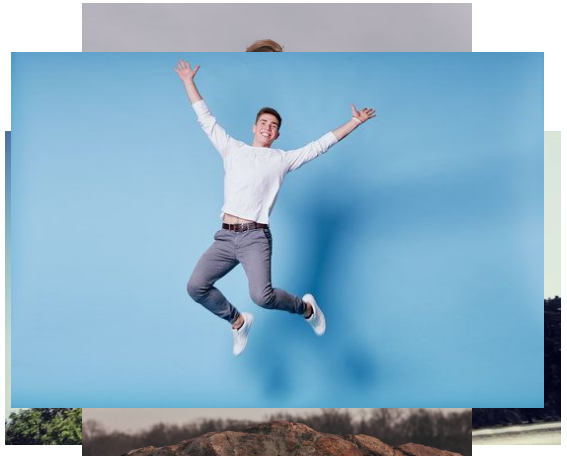


Motivation



Challenges

Data Scarcity:	Expensive, requires expertise, resource intensive, low accuracy …
Motion Complexity:	Physic laws, anatomy, intention, personality, …
NLP vs Motion:	Map between language and motion, semantic and meaning
Many-to-many:	many motions ←→ many descriptions



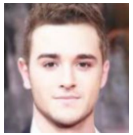
“a person is jumping”
“guy jumping”
“doing a backflip”
“laying upside-down”

Background

Diffusion Models	VQ-VAE

Diffusion Models

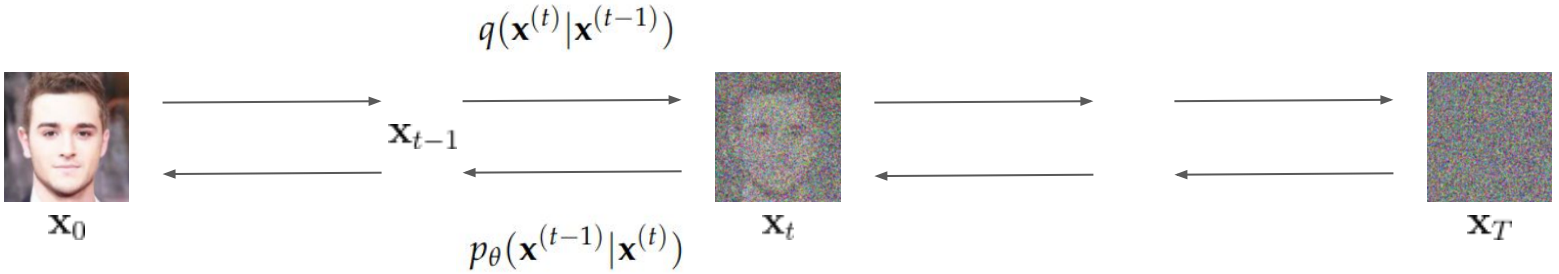
VQ-VAE



$\mathbf{x}_0$

	Gaussian	Binomial
Forward trajectory:	$q(\mathbf{x}^{(t)}\|\mathbf{x}^{(t-1)}) = \mathcal{N}(\mathbf{x}^{(t)}; \mathbf{x}^{(t-1)}\sqrt{1-\beta_t}, \mathbf{I}\beta_t)$	$q(\mathbf{x}^{(t)}\|\mathbf{x}^{(t-1)}) = \mathcal{B}(\mathbf{x}^{(t)}; \mathbf{x}^{(t-1)}(1-\beta_t) + 0.5\beta_t)$
Reverse trajectory:	$p_\theta(\mathbf{x}^{(t-1)}\|\mathbf{x}^{(t)}) = \mathcal{N}(\mathbf{x}^{(t-1)}; \mu_\theta(\mathbf{x}^{(t)}, t), \Sigma_\theta(\mathbf{x}^{(t)}, t))$	$p_\theta(\mathbf{x}^{(t-1)}\|\mathbf{x}^{(t)}) = \mathcal{B}(\mathbf{x}^{(t-1)}; \mathbf{b}_\theta(\mathbf{x}^{(t)}, t))$

Diffusion Models



Bayes' Rule: $q(\mathbf{x}^{(t-1)}|\mathbf{x}^{(t)}, \mathbf{x}^{(0)})$

	Gaussian	Binomial
Learning Objective:	$D_{\mathrm{KL}}(q(\mathbf{x}^{(t)}\|\mathbf{x}^{(t+1)}, \mathbf{x}^{(0)})\|\|p_\theta(\mathbf{x}^{(t)}\|\mathbf{x}^{(t+1)}))$	
Forward trajectory:		$q(\mathbf{x}^{(t)}\|\mathbf{x}^{(t-1)}) = \mathcal{B}(\mathbf{x}^{(t)}; \mathbf{x}^{(t-1)}(1-\beta_t) + 0.5\beta_t)$
Reverse trajectory:	$p_\theta(\mathbf{x}^{(t-1)}\|\mathbf{x}^{(t)}) = \mathcal{N}(\mathbf{x}^{(t-1)}; \mu_\theta(\mathbf{x}^{(t)}, t), \Sigma_\theta(\mathbf{x}^{(t)}, t))$	$p_\theta(\mathbf{x}^{(t-1)}\|\mathbf{x}^{(t)}) = \mathcal{B}(\mathbf{x}^{(t-1)}; \mathbf{b}_\theta(\mathbf{x}^{(t)}, t))$

Diffusion Models | **VQ-VAE**

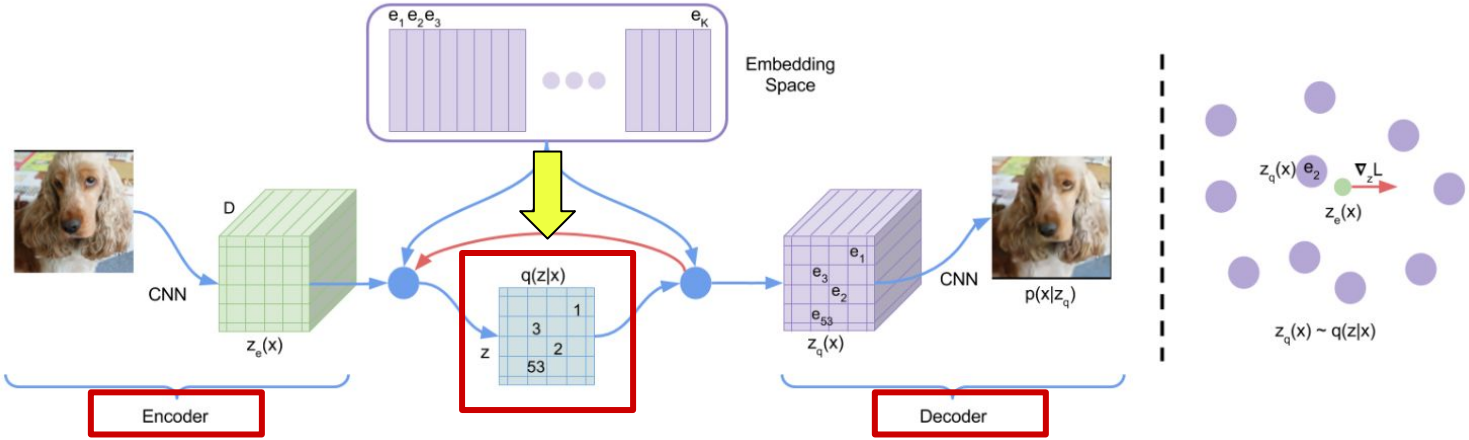


figure from [1]

Binary Latent Diffusion

figure from [1]

Binary Quantization

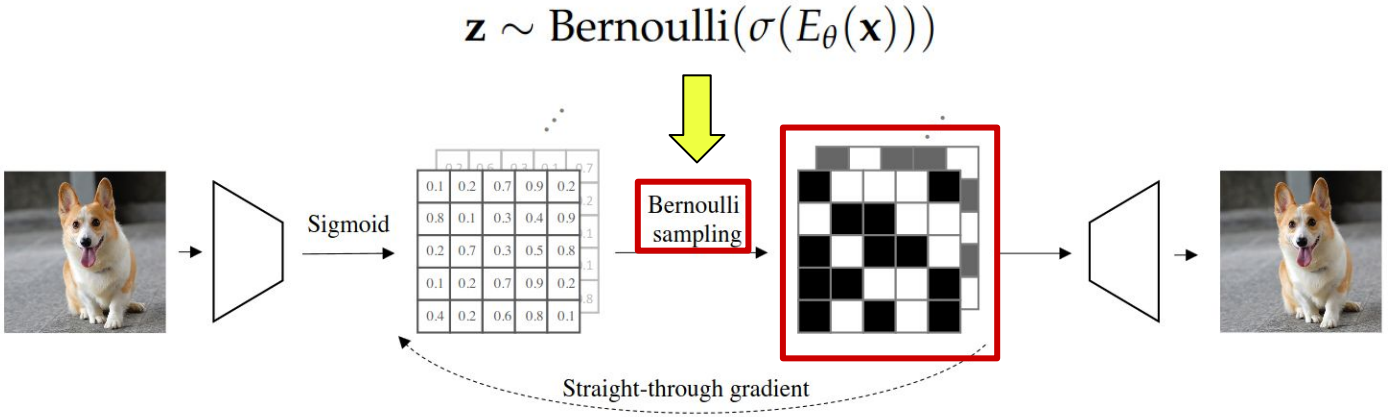
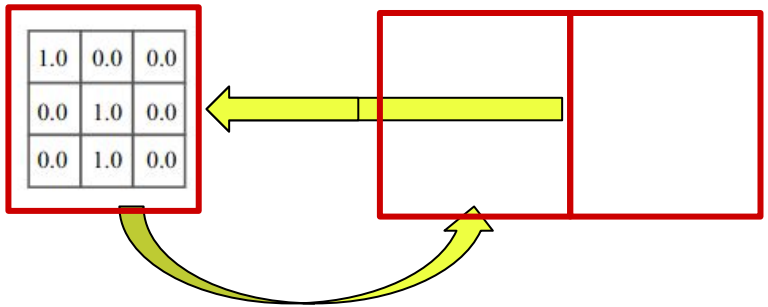


figure from [2]

Bernoulli Diffusion



Forward trajectory:

$$q(\mathbf{z}^{(t)}|\mathbf{z}^{(t-1)}) = \mathcal{B}(\mathbf{z}^{(t)}; \mathbf{z}^{(t-1)}(1-\beta_t) + 0.5\beta_t)$$

Reverse trajectory:

$$p_\theta(\mathbf{z}^{(t-1)}|\mathbf{z}^{(t)}) = \mathcal{B}(\mathbf{z}^{(t-1)}; f_\theta(\mathbf{z}^{(t)}, t))$$

Target:

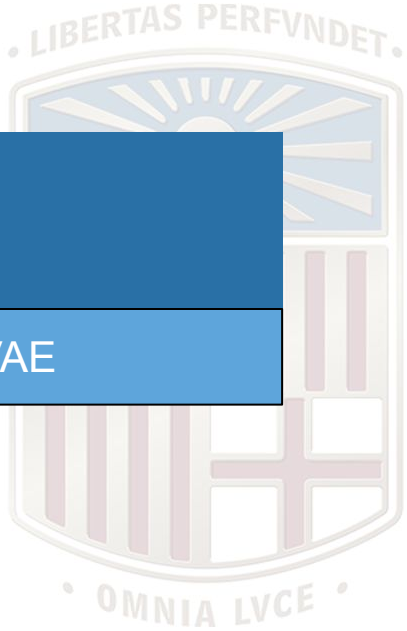
Original: $\hat{\mathbf{z}}^{(0)} = f_\theta(\mathbf{z}^{(t)}, t)$

Pflip: $\mathbf{z}^{(0)} \oplus \mathbf{z}^{(t)} = f_\theta(\mathbf{z}^{(t)}, t)$

figure from [2]

State-of-the-art

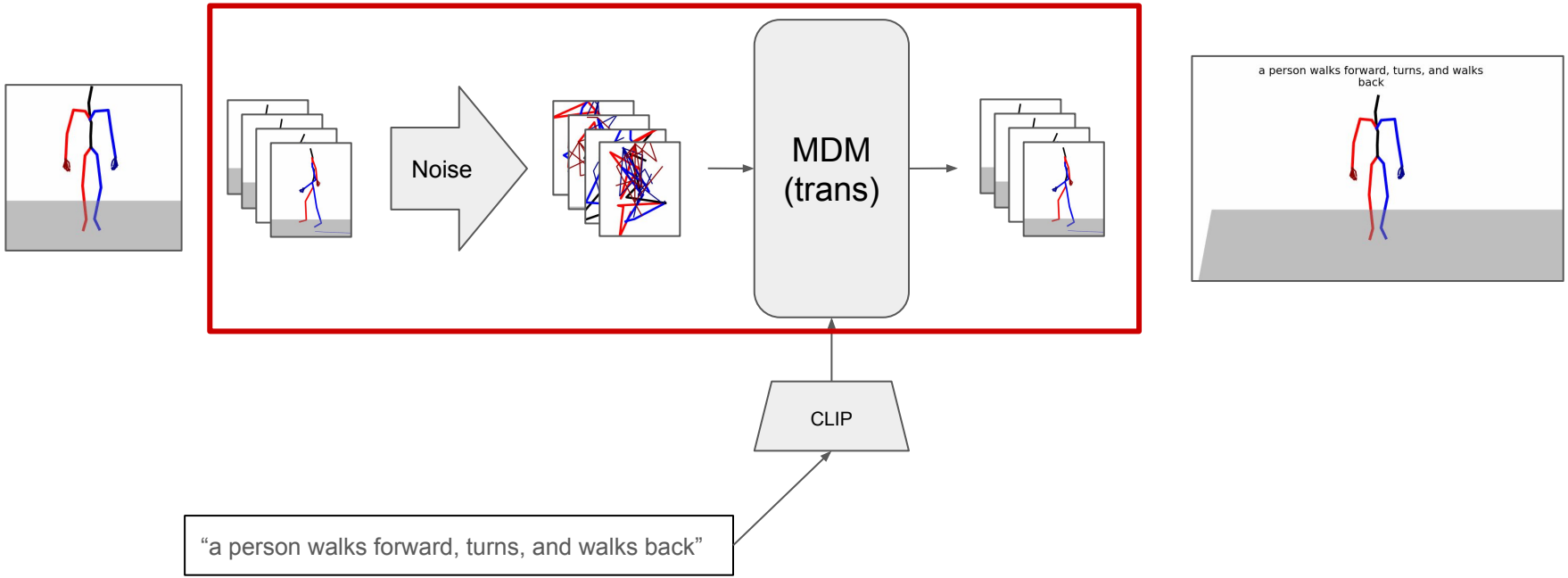
Diffusion Models	VQ-VAE



Diffusion Models

VQ-VAE

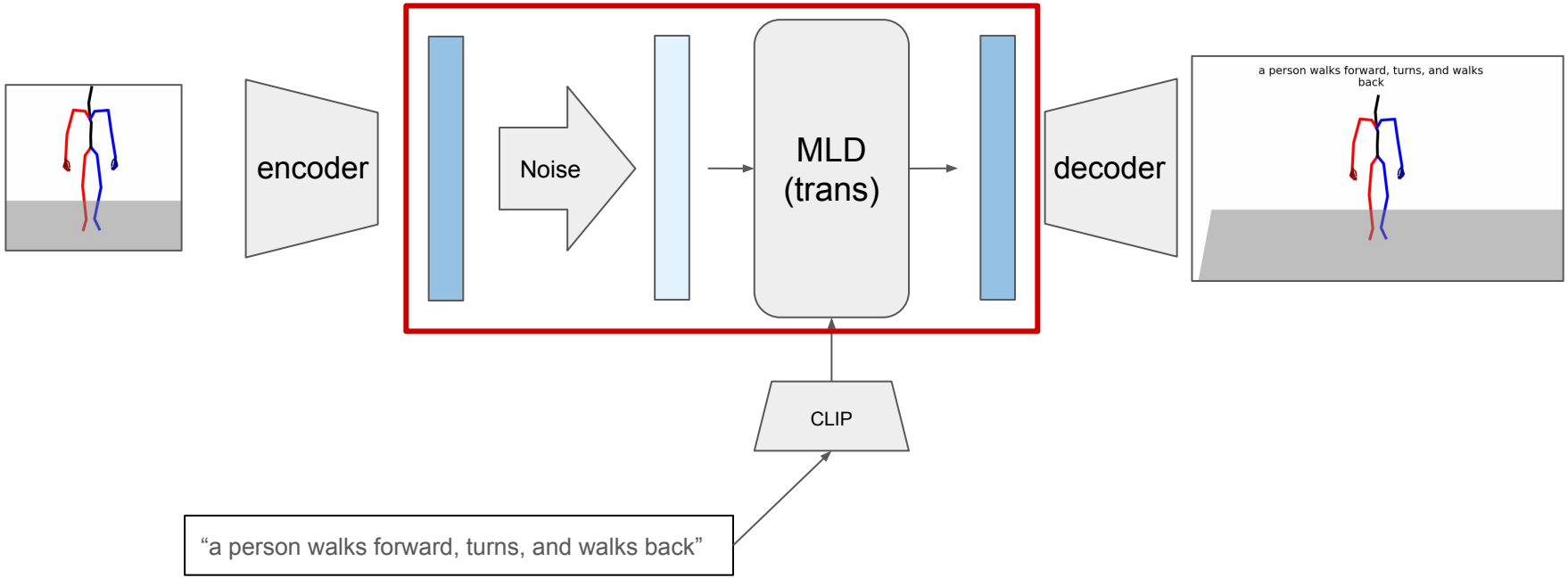
MDM:



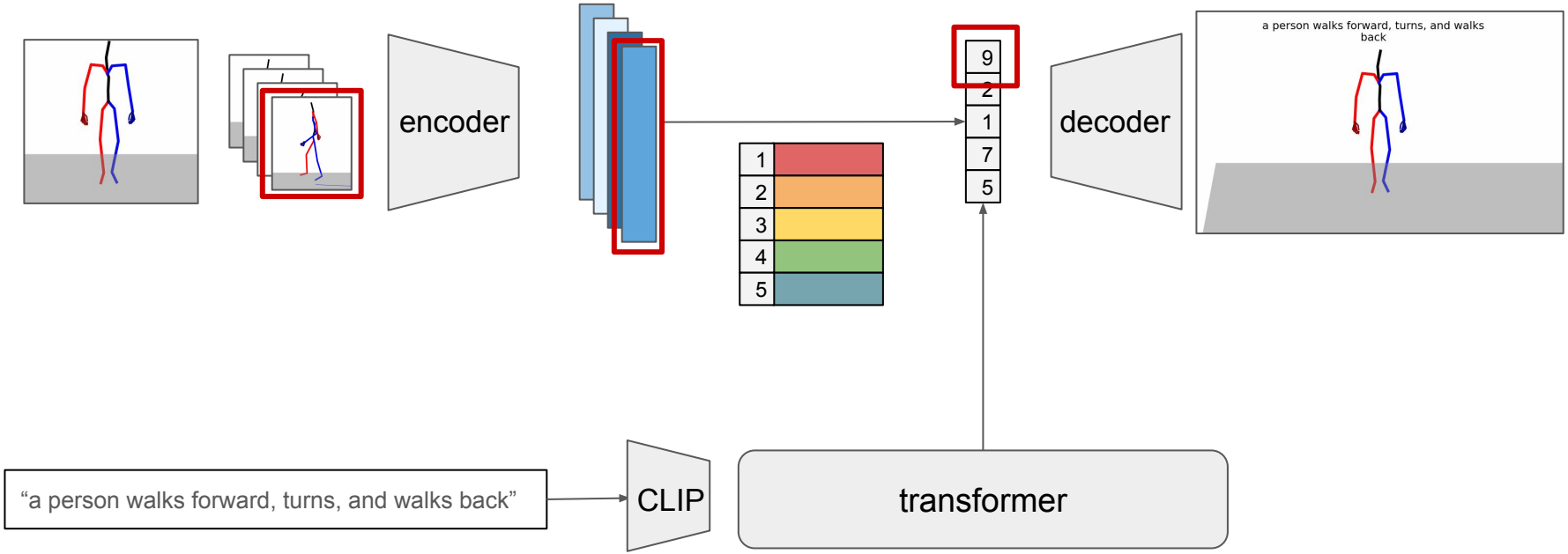
Diffusion Models

VQ-VAE

MLD:



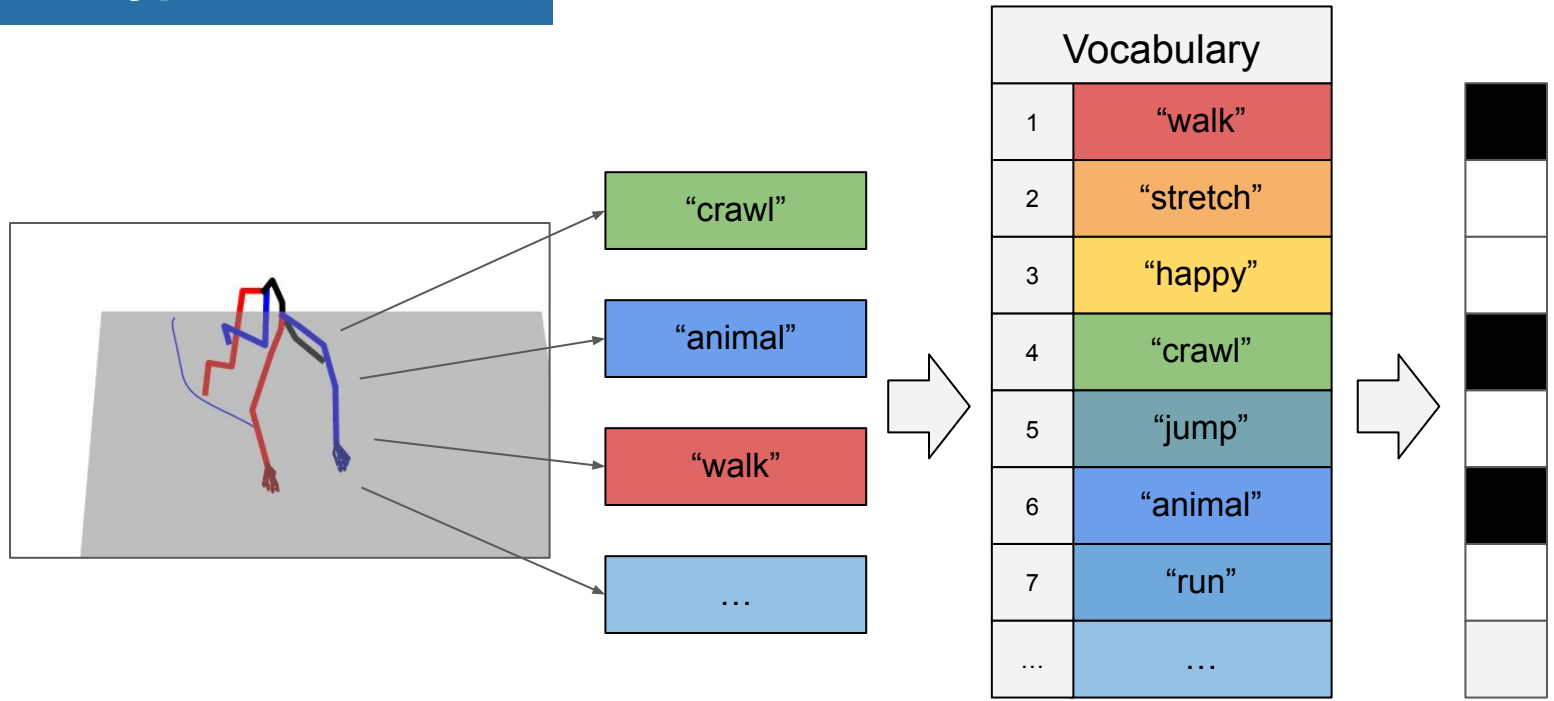
PoseGPT, T2M-GPT and MotionGPT:



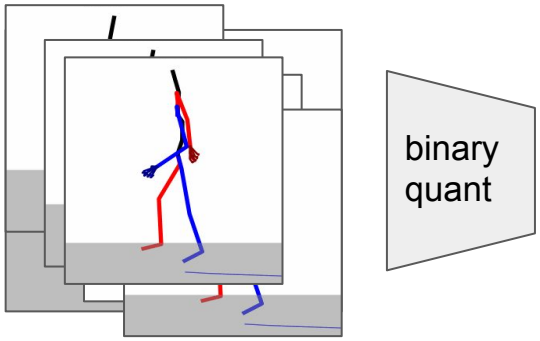
Methodology

MBVAE	MBLD

Hypothesis


“crawl”
“animal”
“walk”
…
Vocabulary
1
“walk”
2
“stretch”
3
“happy”
4
“crawl”
5
“jump”
6
“animal”
7
“run”
…
…

MBVAE | MBLD



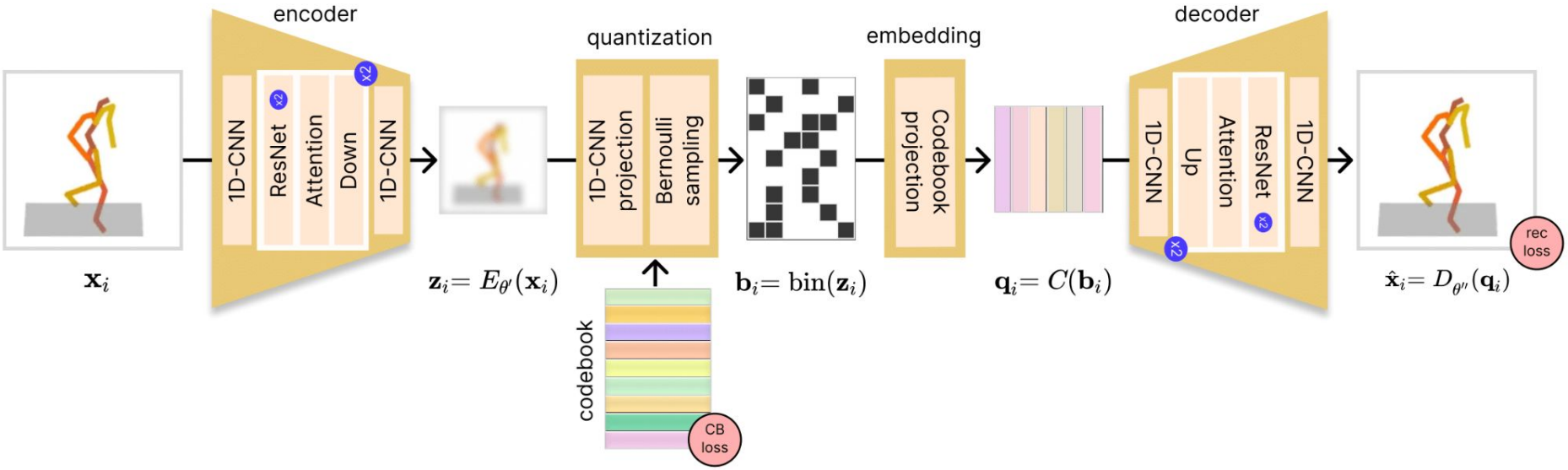
Frame-wise: per frame encoding.

Some-frames: chunks of frames encoding.

Full-sequence: entire motion encoding.

MBVAE | MBLD

Frame-wise



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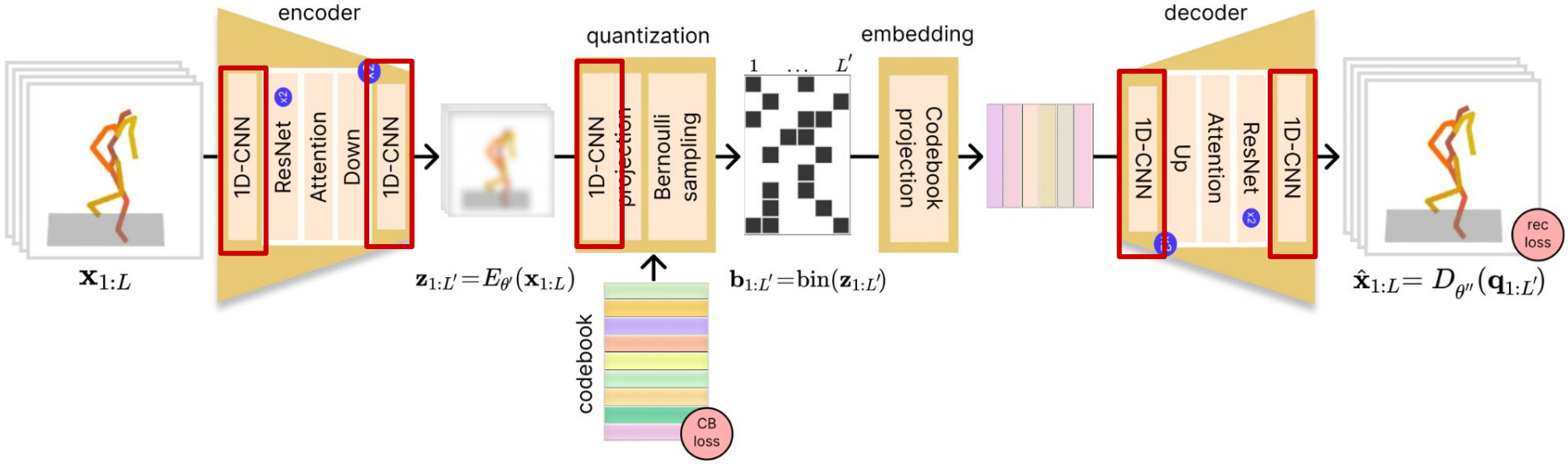
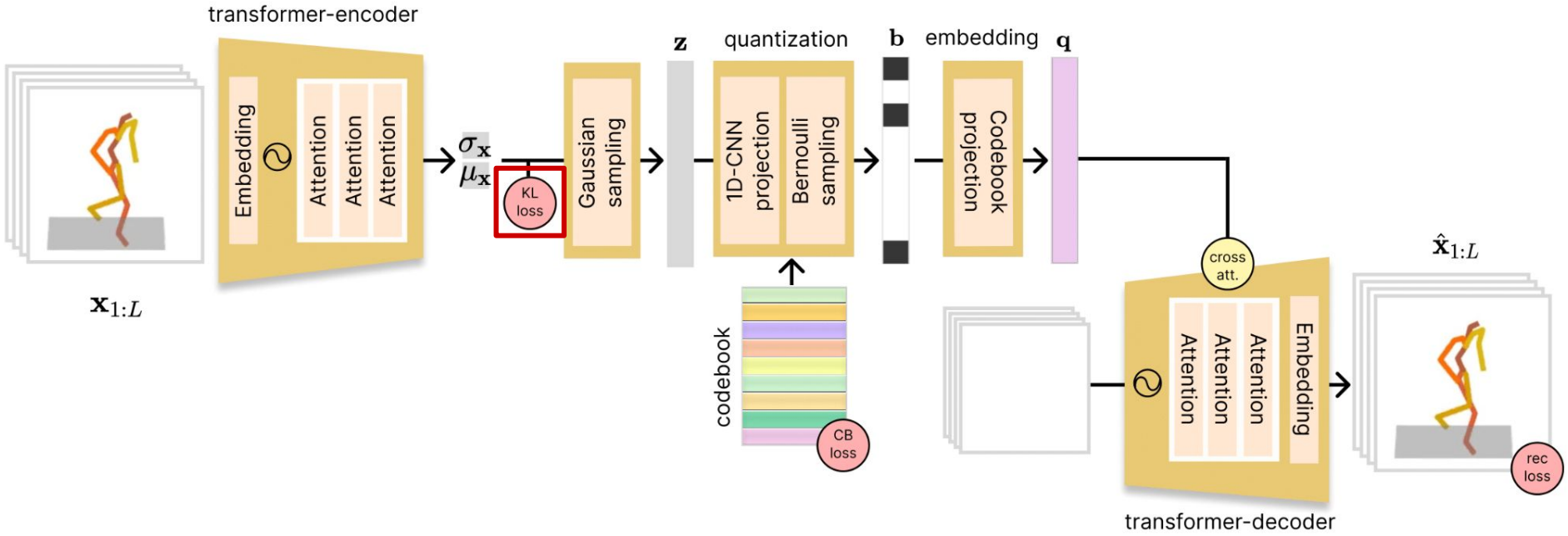
Some-frames

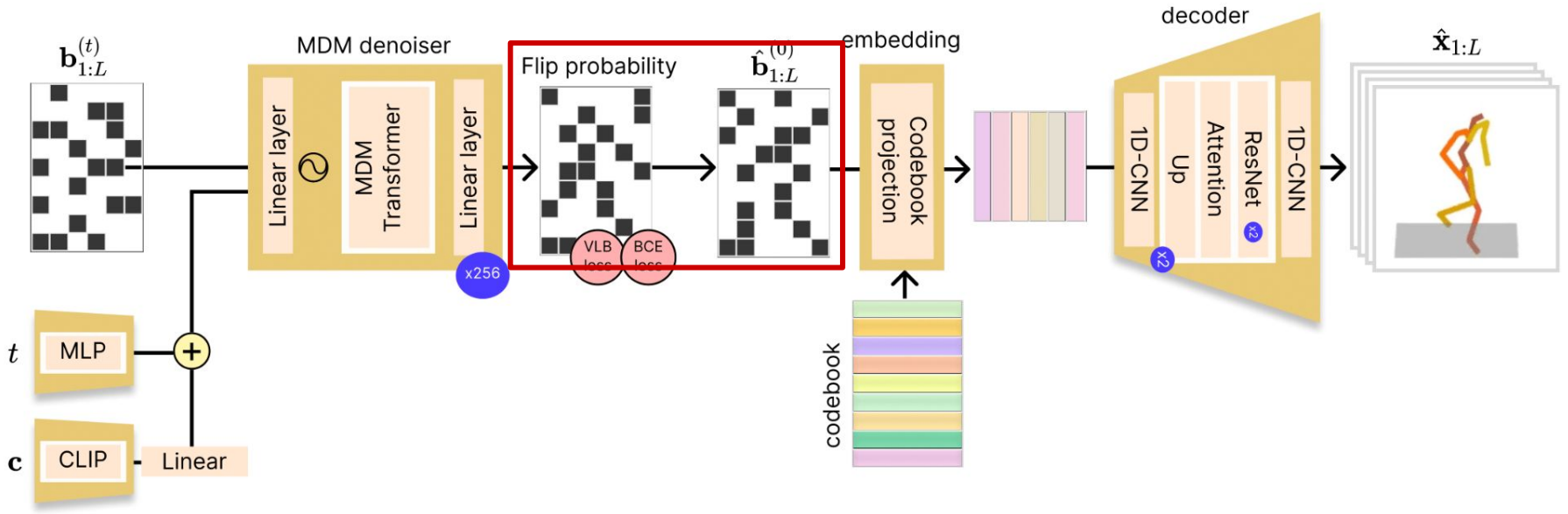


MBVAE | MBLD

Full-sequence



MBVAE | **MBLD**


$\mathbf{b}_{1:L}^{(t)}$
MDM denoiser
Linear layer
MDM Transformer
Linear layer
x256
Flip probability
$\hat{\mathbf{b}}_{1:L}^{(0)}$
VLB loss
BCE loss
embedding
Codebook projection
codebook
decoder
1D-CNN
Up
Attention
ResNet
x2
1D-CNN
$\hat{\mathbf{x}}_{1:L}$
t
MLP
$\mathbf{c}$
CLIP
Linear

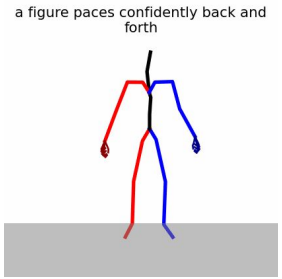
Experiments

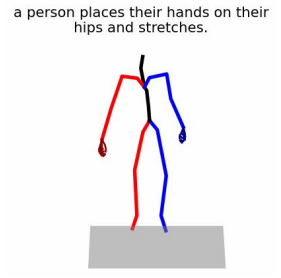
MBVAE	MBLD

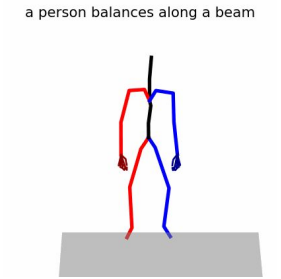
Dataset

Subset of HumanML3D:

- Number of samples: 1,528 motion clips
- Text prompts: 4 text description per clip
- Length range: [150, 196] frames per clip
- Pose representation: 263-dimensional vector of position and rotation







Evaluation

Fidelity:	**MSE:** *average of the squared differences between the prediction and the real motion.*	**FID:** *estimates the distance between the distribution of a feature space of the generated motion and the ground truth.*
Diversity:	**DIV:** *global diversity of the model.*	**MM:** *measures the diversity but conditioning to a set C of different text prompts.*
Condition Consistency:	**R-precision:** *measures the accuracy of the model to generate motions that satisfy a given condition.*	**Top-1** / **Top-2** / **Top-3**

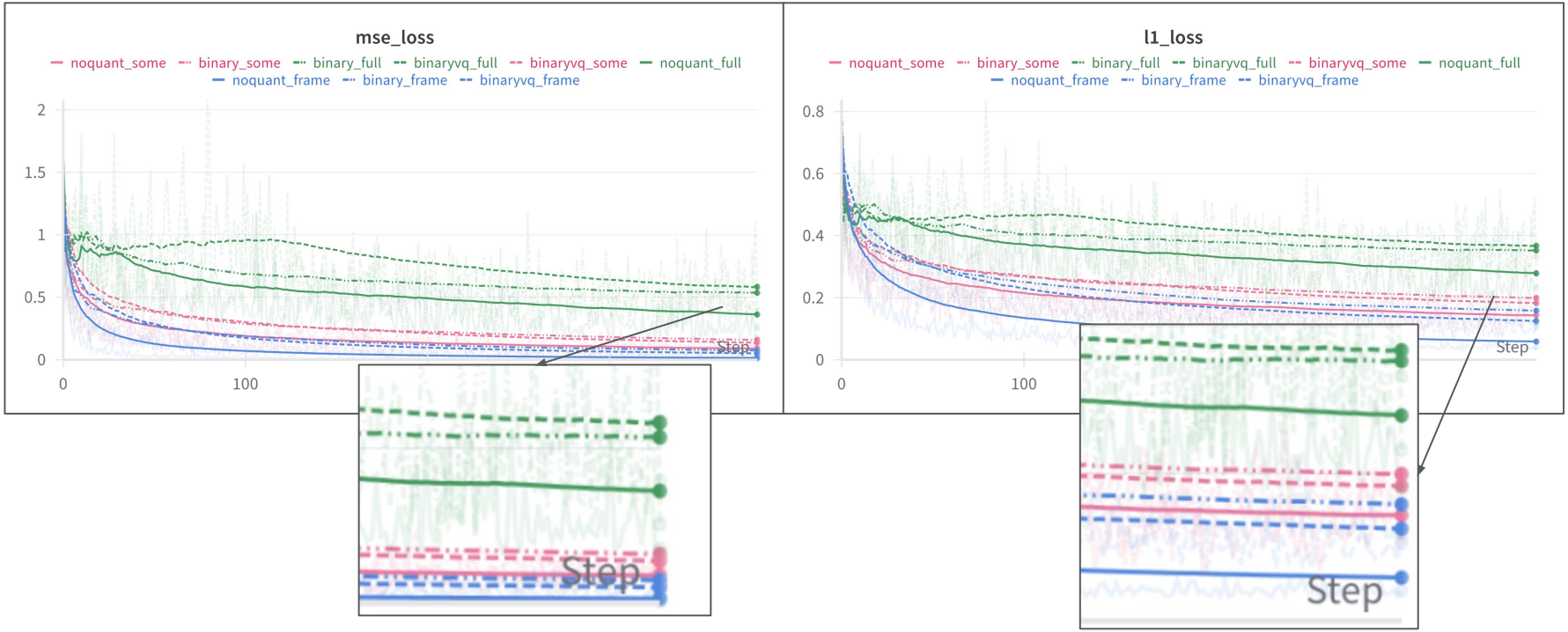
MBVAE | MBLD

1. Is the binary latent space able to encode motion data?
2. Which is the model that better performs?
3. Is it memory efficient?

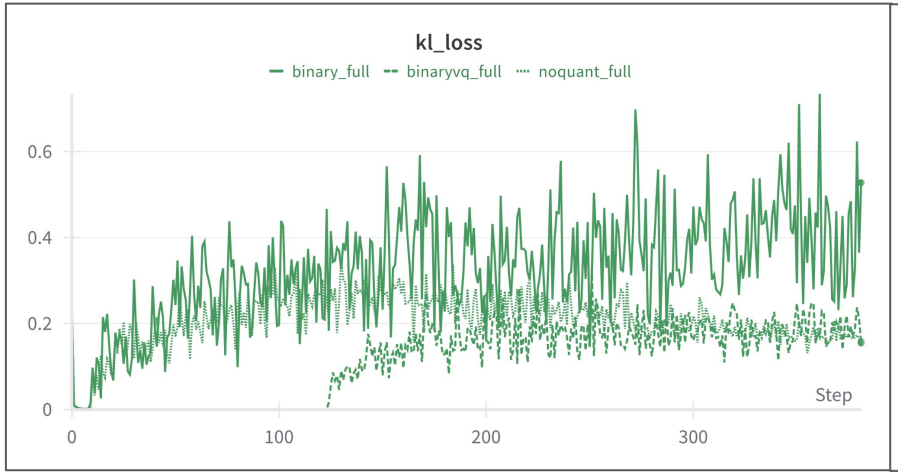
Model	Binary	Binary-VQ	No-Quant
Frame-wise	50,176bits $\simeq$ 6.3kB	100,352bits $\simeq$ 12.6kB	1,605,632bits $\simeq$ 200.7kB
Some-frames	784bits $\simeq$ 0.1kB	1,568bits $\simeq$ 0.2kB	25,088bits $\simeq$ 3.1kB
Full-sequence	256bits $\simeq$ 0.03kB	256bits $\simeq$ 0.03kB	8,192bits $\simeq$ 1.02kB

Memory footprint

MBVAE | MBLD

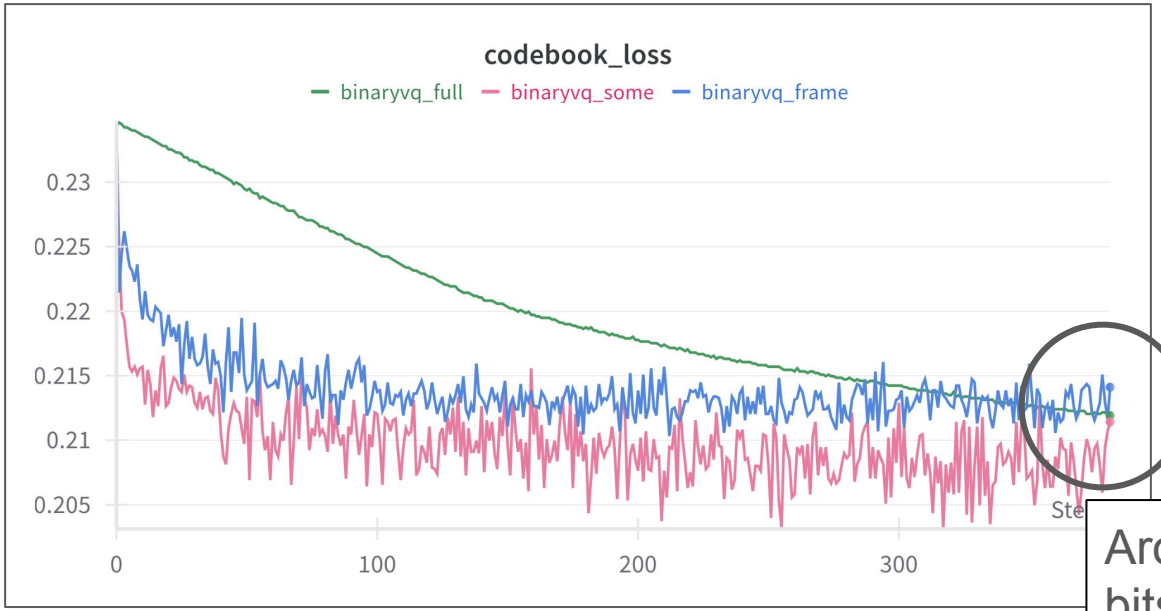

mse_loss
noquant_some
binary_some
binary_full
binaryvq_full
binaryvq_some
noquant_full
noquant_frame
binary_frame
binaryvq_frame
2
1.5
1
0.5
0
0
100
Step
Step
l1_loss
noquant_some
binary_some
binary_full
binaryvq_full
binaryvq_some
noquant_full
noquant_frame
binary_frame
binaryvq_frame
0.8
0.6
0.4
0.2
0
0
100
Step
Step

MBVAE | MBLD


kl_loss
binary_full
binaryvq_full
noquant_full
0.6
0.4
0.2
0
0
100
200
300
Step


mse_loss
noquant_full_nokl
binary_full_nokl
binary_full
noquant_full
1.5
1
0.5
0
0
100
200
300
Step

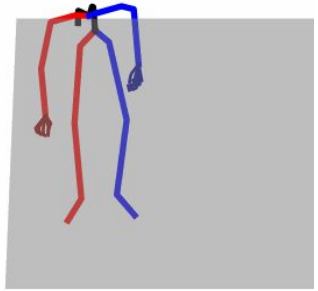
MBVAE | MBLD



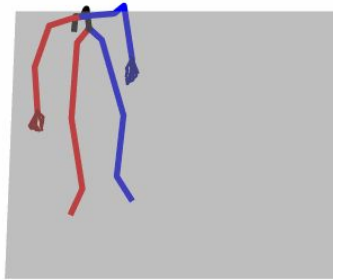
Around 21% of bits are 1 for every model!

MBVAE | MBLD

Input



Output



MBVAE | **MBLD**

Exp. 1

1. Is the Bernoulli diffusion able to generate plausible motion with **Frame-wise**?
2. Which is the best target for the denoising function?

Target:

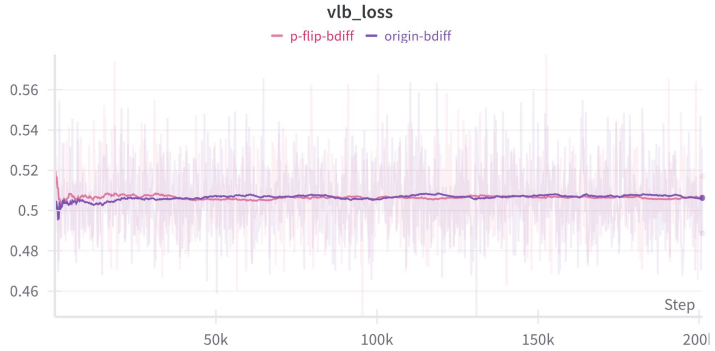
- **Original**
- **P-flip**

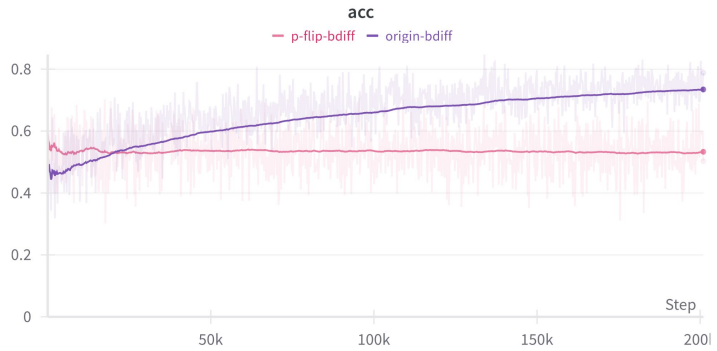
Exp. 2

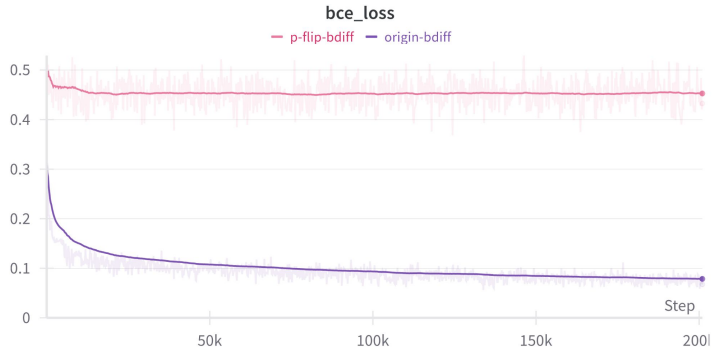
1. What about using **Full-sequence**?
2. Does the model properly fit the evaluation metrics?

Exp. 1

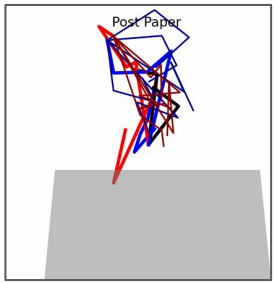
MBLD



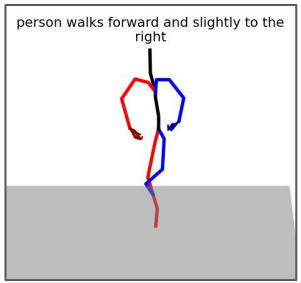




P-flip:

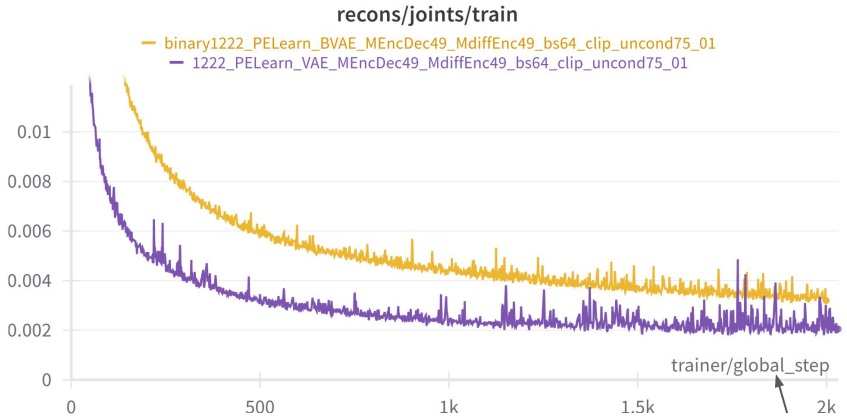


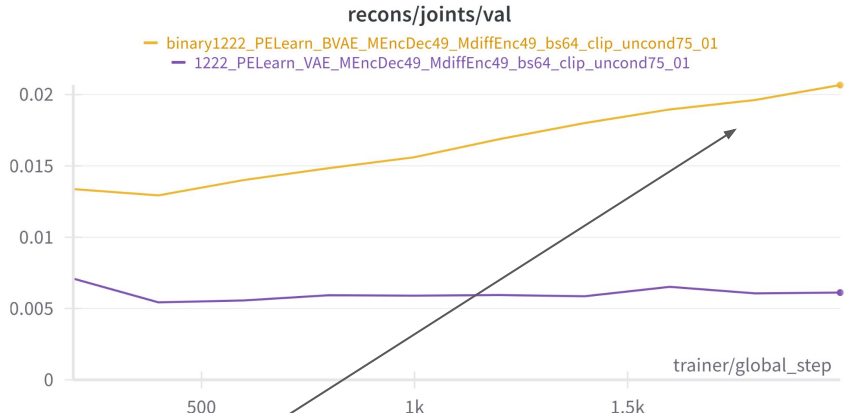
Original:



Exp. 2

MBLD





Model	FID	MM	DIV	Top-1	Top-2	Top-3
GT	-	-	9.5	0.514	0.705	0.797
MLD	17.504	4.744	5.284	0.03	0.062	0.093
MBLD	31.49	4.041	4.292	0.034	0.067	0.1

Conclusions and Future work

Conclusions

- ✖ Requires further regularization → to avoid shaky movement
- ✖ Requires more data → overfits rapidly
- ✓ Binary latent space successfully **encode pose data**
- ✓ Can be **memory efficient**
- ✓ Setting Original as target better that P-flip, as in MDM!
- ✓ Comparable to MLD in terms of Diversity and Condition Consistency

Future work

- Add extra regularization:
  - Adversarial loss
  - Perceptual losses (use joints, rotations, velocities)

- Train on larger dataset:
  - Bigger subset of HumanML3D
  - MotionX

References

[1] Oord, Aaron van den, Oriol Vinyals, and Koray Kavukcuoglu (2018). Neural Discrete Representation Learning.

[2] Wang, Ze et al. (2023). Binary Latent Diffusion.

Thank you for your attention