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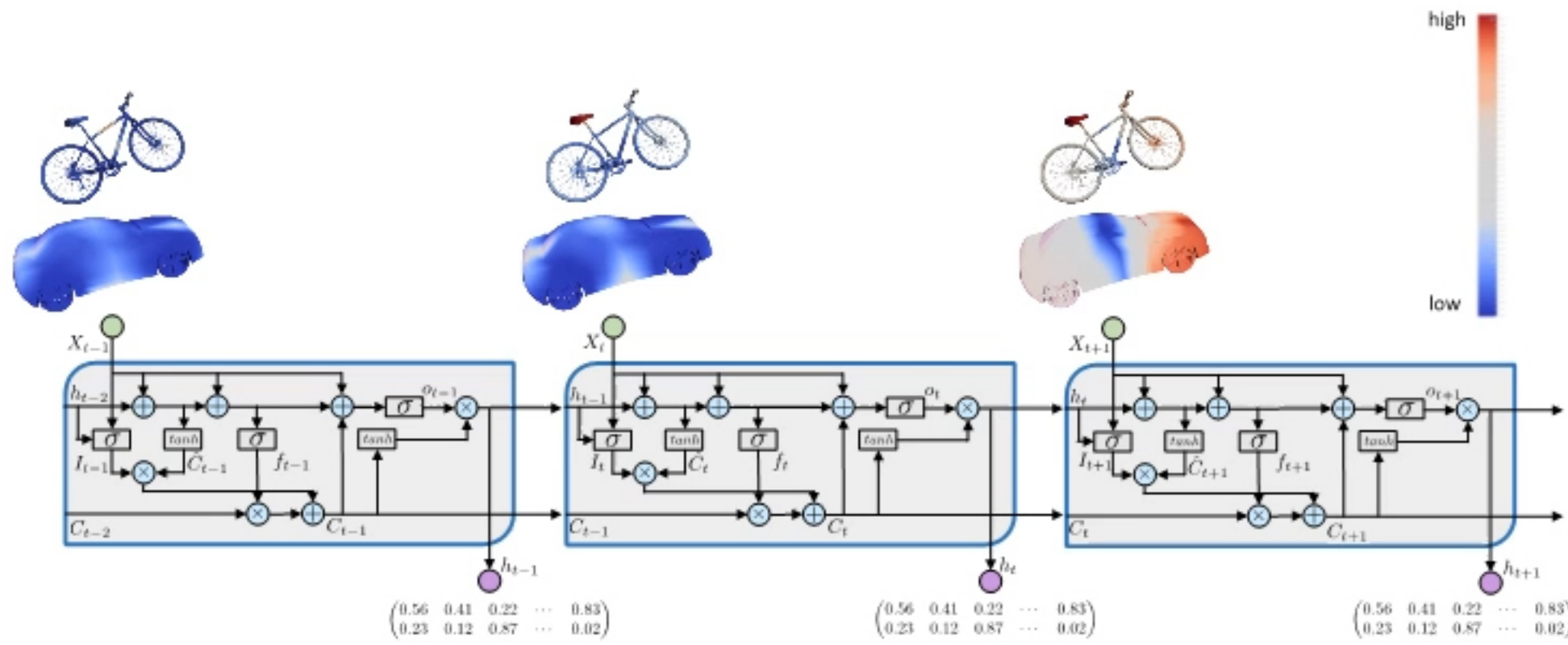
Heat Diffusion Long-Short Term Memory for 3D Shape Analysis



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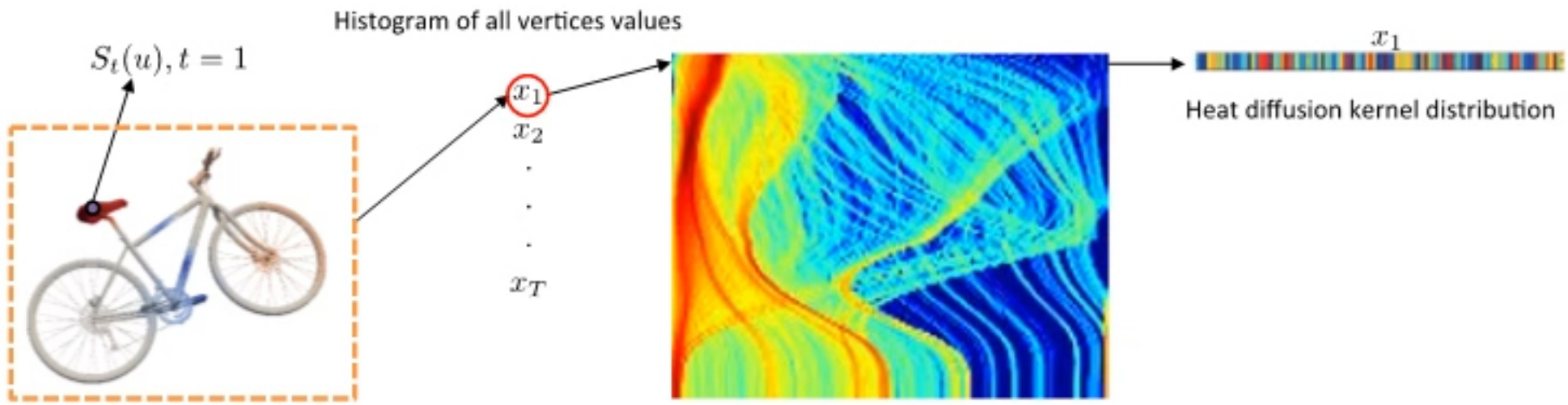

- Goals
  - We aim to develop a 3D shape representation by utilizing the heat flows on 3D surfaces and the corresponding temporal dynamics of the heat flows within the diffusion period.
  - We employ LSTM to capture the temporal dynamics of heat flows and extract joint information between different time-steps that are either consecutive or with a large interval.
  - We incorporate a 3-layer fully-connected neural network with LSTM, and extend the proposed approach to a cross-domain scenario.

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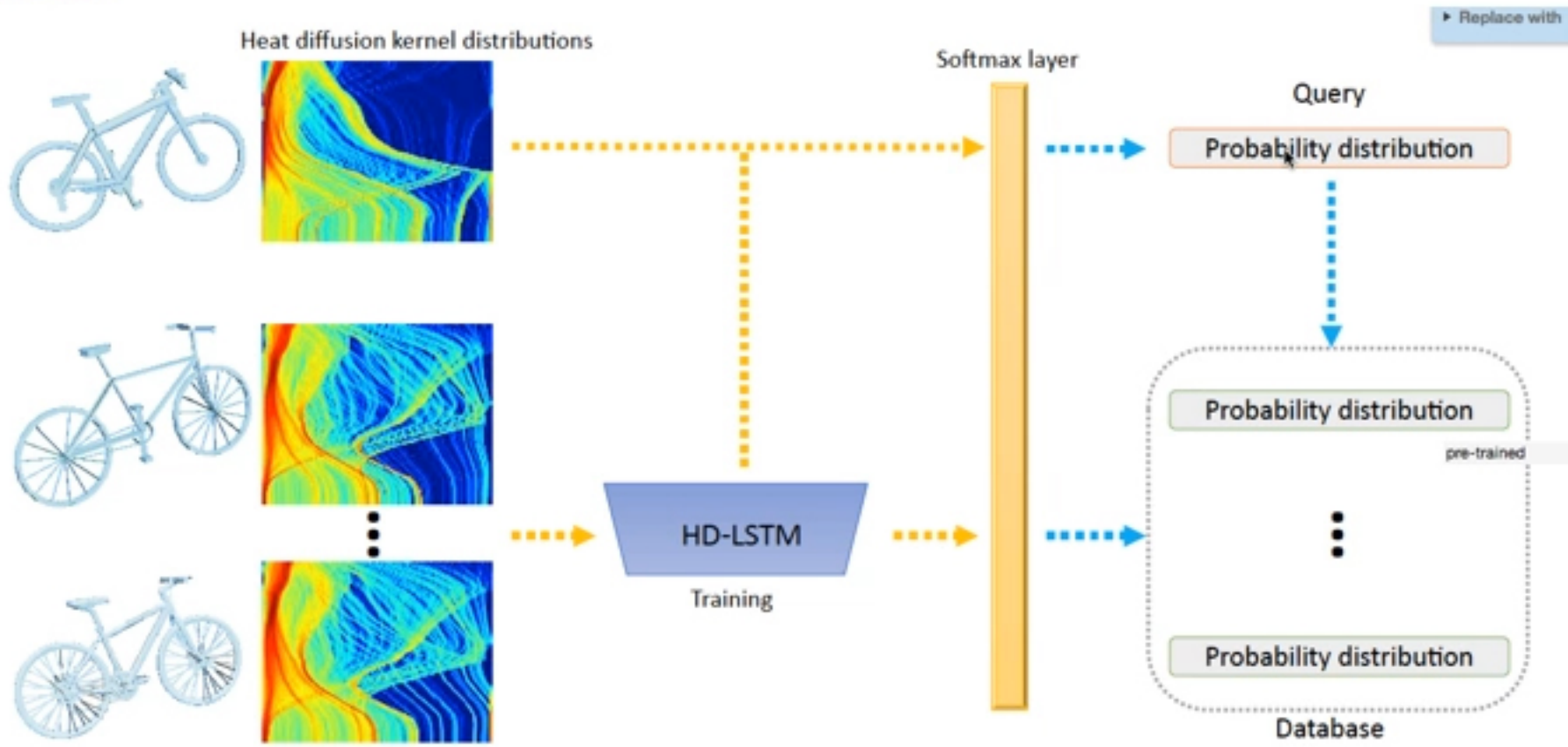

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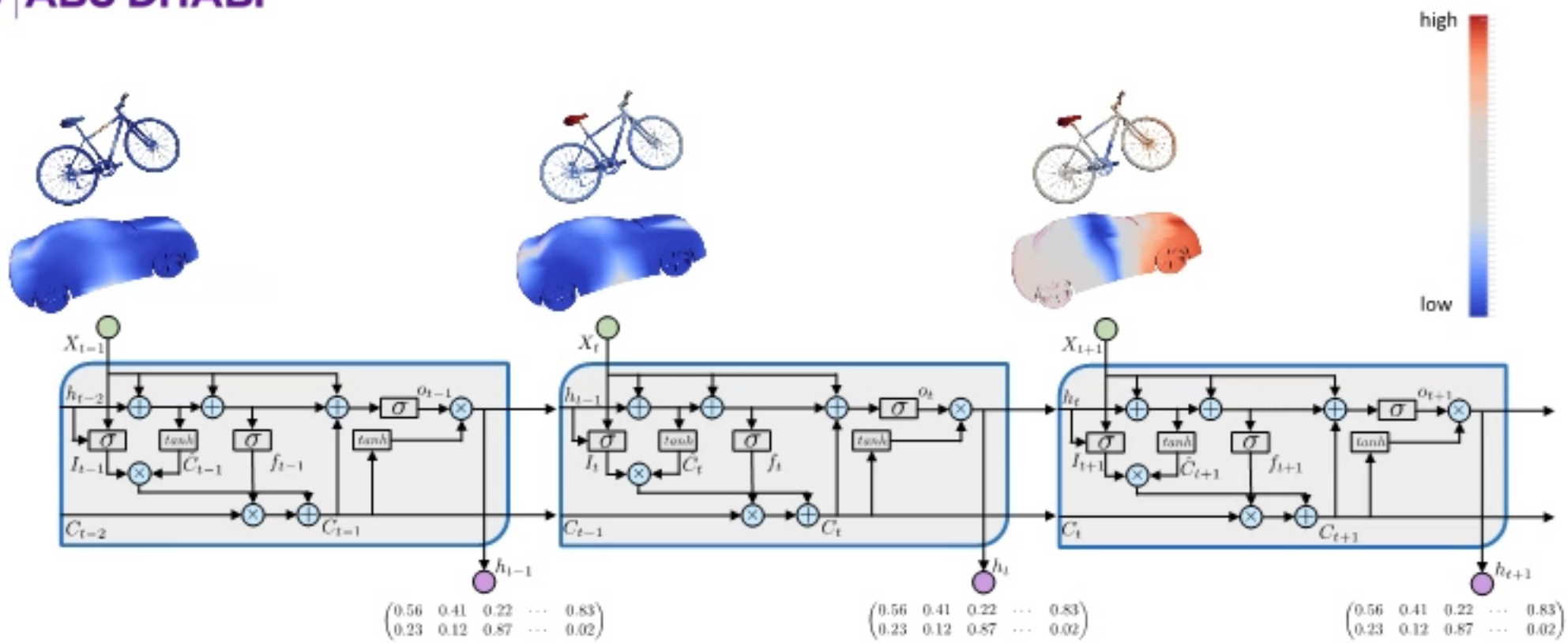

Figure. Heat diffusion kernel values on the 3D shape surfaces in consecutive 3 time-steps. The red points denote high values and blue points denote low values. The sequential inputs to HD-LSTM are histograms of heat diffusion kernel values at each time-step.

3D shape retrieval

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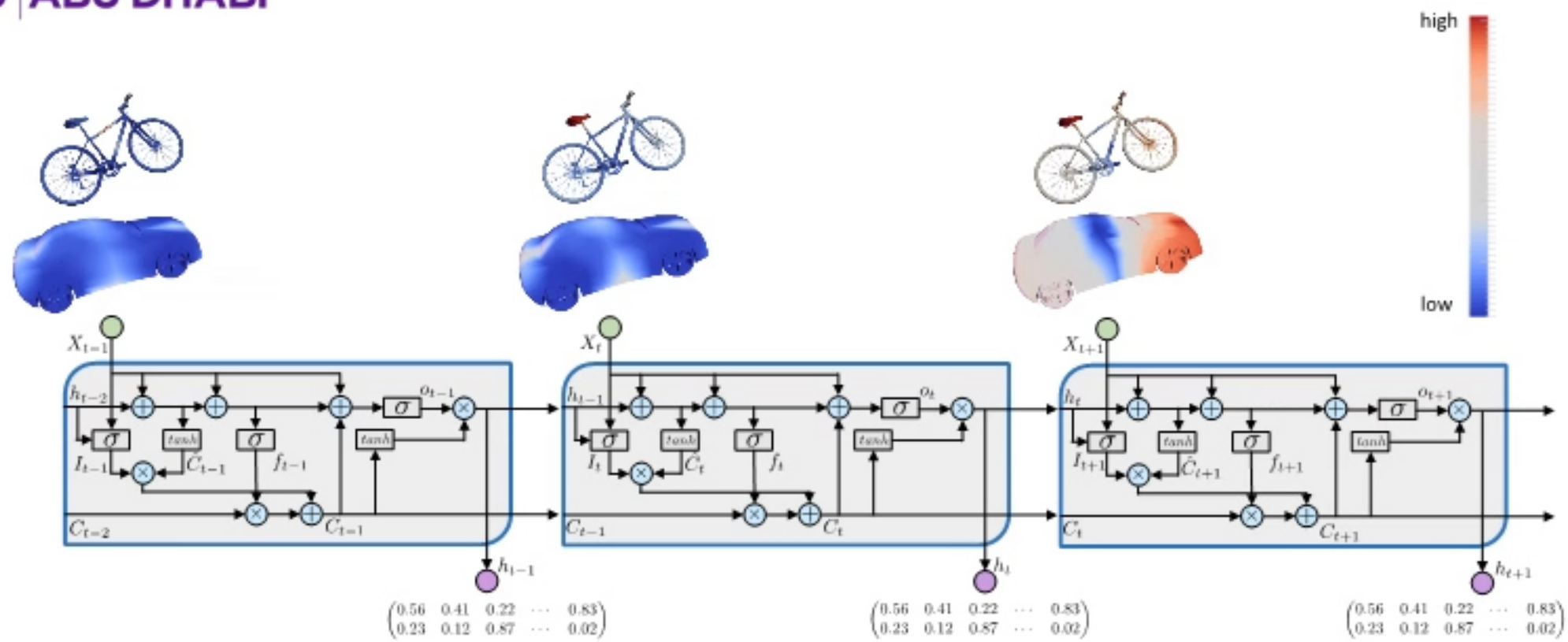

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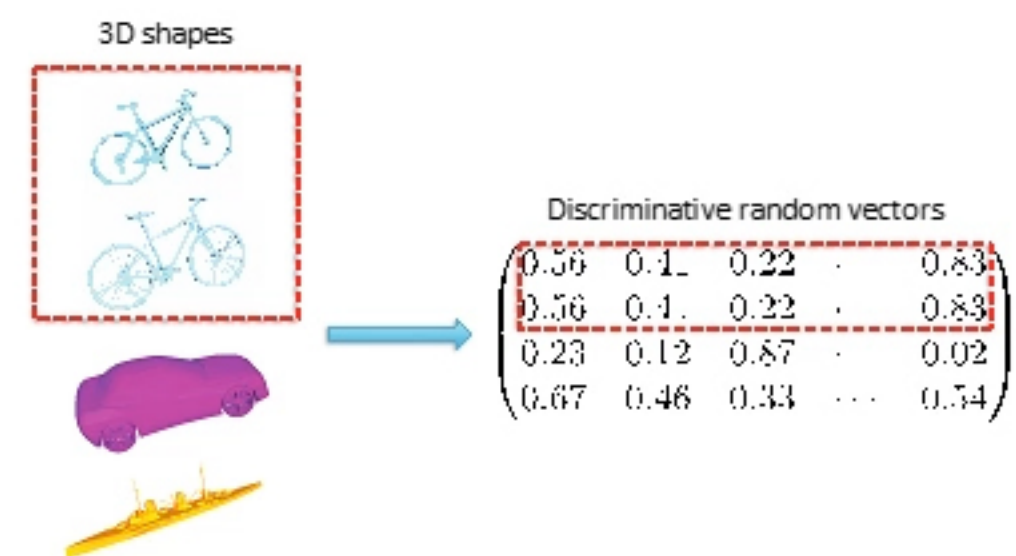
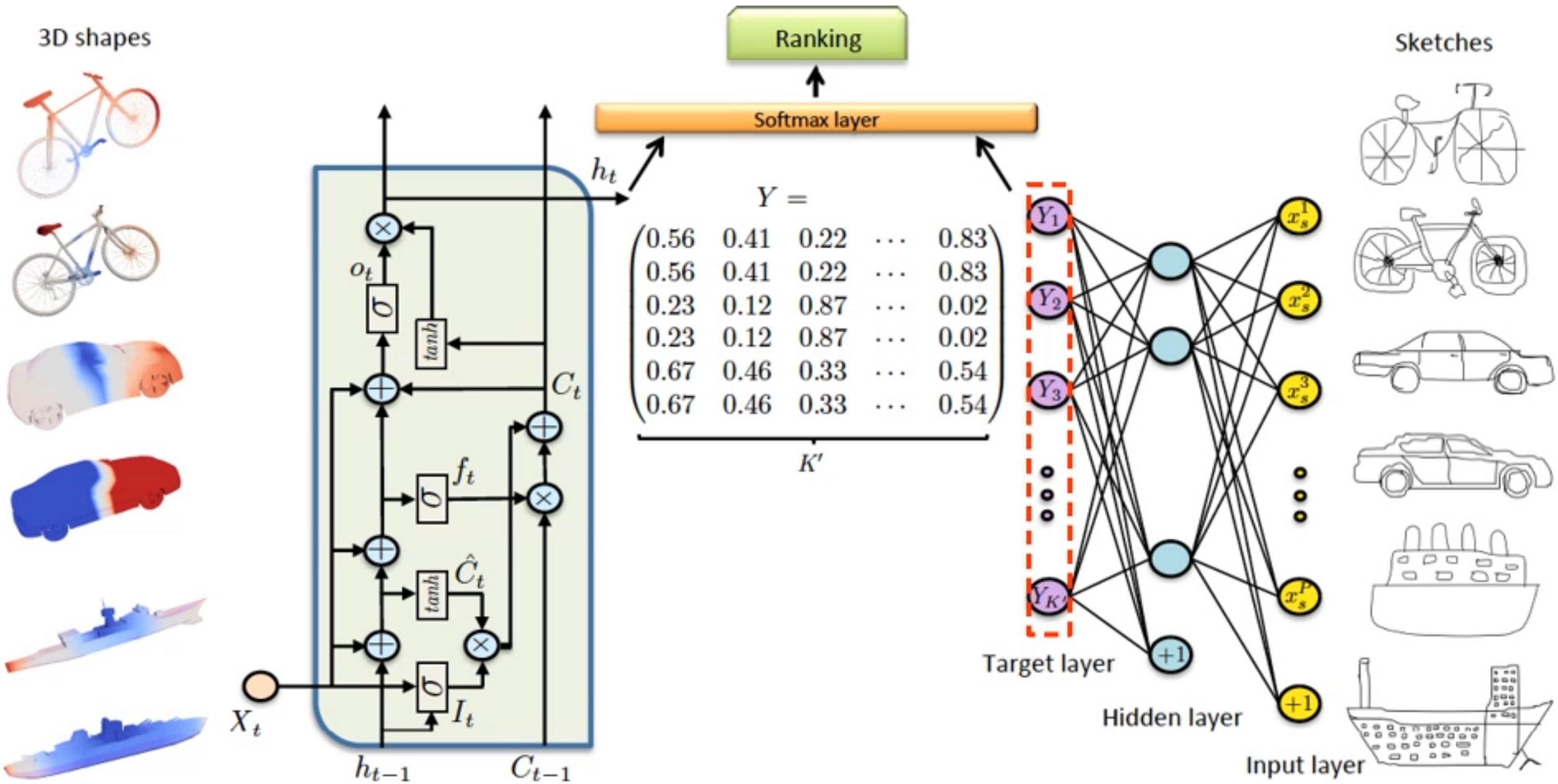


3D shape retrieval



Sketch-based 3D shape retrieval

Sketch CNN features are learned using a 3-layer neural network

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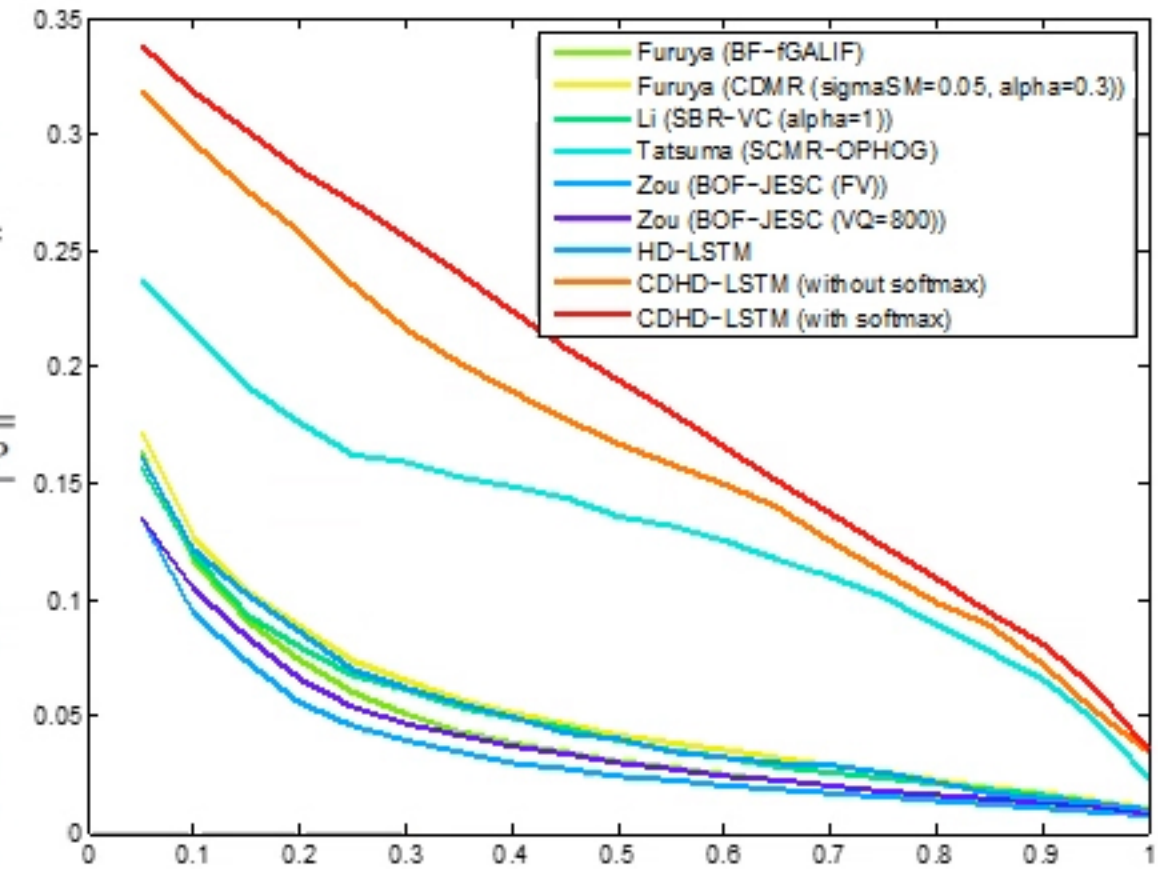
McGill dataset (query: 3D shapes)

Methods	NN	1-Tier	2-Tier	DCG	AP
Hybrid BoW [23]	0.95	0.63	0.79	0.88	–
Covariance method [35]	0.97	0.73	0.81	0.93	–
Graph-based method [1]	0.97	0.74	0.91	0.93	–
DeepShape [39]	**0.98**	0.78	0.83	–	–
BoW	0.80	0.40	0.54	0.70	0.46
HD-LSTM (without softmax)	0.97	0.88	0.83	0.88	0.90
HD-LSTM (with softmax)	**0.98**	**0.92**	**0.95**	**0.95**	**0.94**

SHREC14 dataset (query: sketches)

Method	NN	FT	ST	DCG	AP
		$1.0e-05*$			
BF-fGALIF	0.43	0.27	0.41	2.03	0.34
CDMR ($\sigma_{SM}=0.1$, $\alpha=0.6$)	0.18	0.14	0.22	0.12	0.15
CDMR ($\sigma_{SM}=0.1$, $\alpha=0.3$)	0.38	0.25	0.38	0.18	0.30
CDMR ($\sigma_{SM}=0.05$, $\alpha=0.6$)	0.33	0.27	0.40	0.18	0.31
CDMR ($\sigma_{SM}=0.05$, $\alpha=0.3$)	0.44	0.30	0.45	0.20	0.36
SBR-VC ($\alpha=1$)	0.25	0.14	0.26	1.86	0.19
SBR-VC ($\alpha=0.5$)	0.25	0.15	0.27	1.87	0.19
OPHOG	0.52	0.29	0.45	2.08	0.34
SCMR-OPHOG	0.52	0.39	0.61	2.17	0.49
BOF-JESC (VQ=800)	0.33	0.14	0.26	1.88	0.22
BOF-JESC (VQ=1000)	0.31	0.13	0.20	1.82	0.18
BOF-JESC (FV)	0.32	0.14	0.19	1.74	0.15
HD-LSTM	0.28	0.14	0.22	0.33	0.29
CDHD-LSTM (without softmax)	0.86	0.44	0.93	3.33	0.68
CDHD-LSTM (with softmax)	**0.91**	**0.54**	**1.03**	**3.37**	**0.75**



Source Code: github.com/blacksmithfan/HD_LSTM.git