ICLR Spotlight

NAISR: A 3D Neural Additive Model for Interpretable Shape Representation

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[3]The Ohio State University College of Medicine

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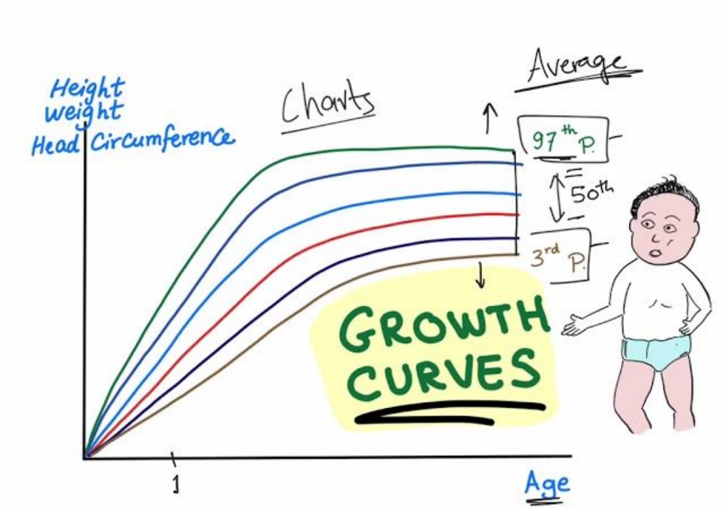
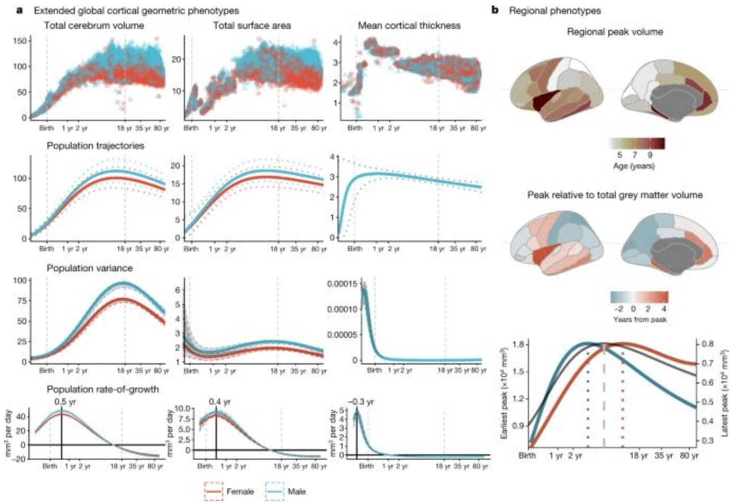
Shape Discovery

For scientific and medical discovery, it is very important to capture the individual dependencies of shapes on covariates.



Growth Chart[1]

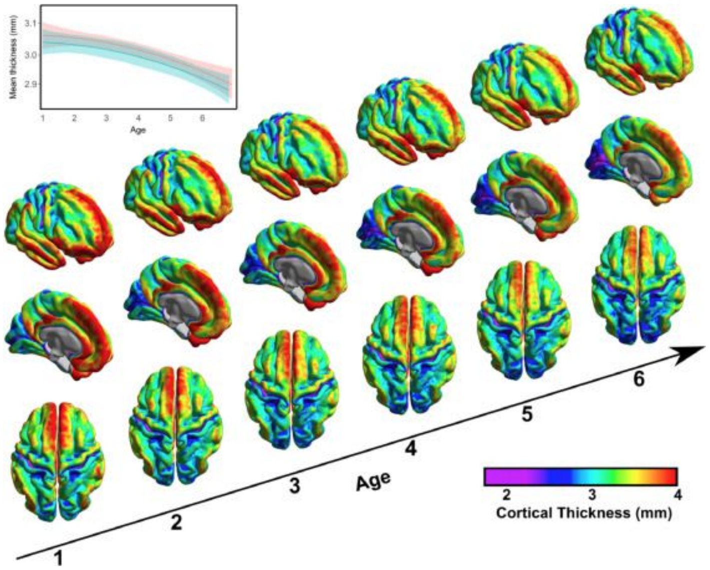


Brain Charts[2]

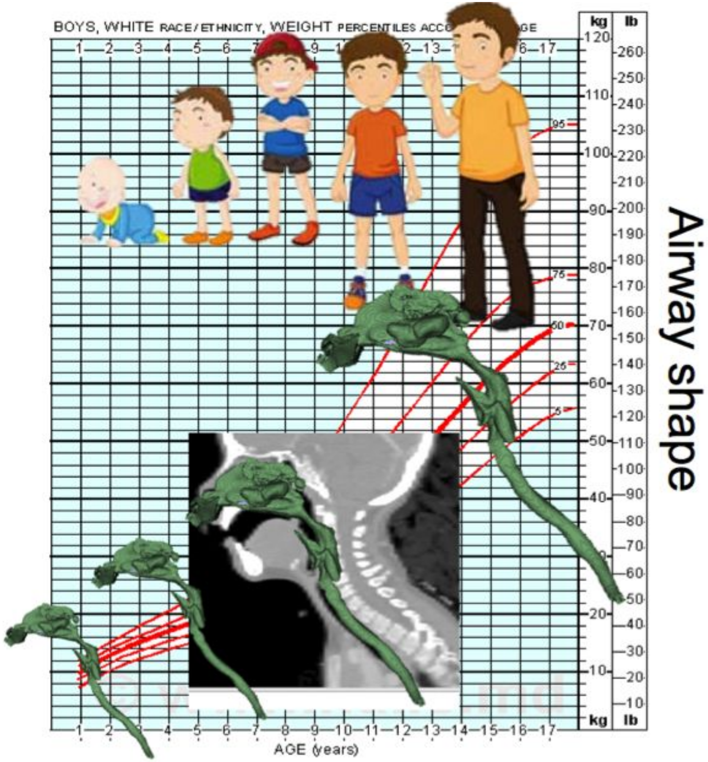
1. https://www.youtube.com/watch?app=desktop&v=jyxjXZ0vIz0
2. Bethlehem, Richard AI, et al. "Brain charts for the human lifespan." *Nature* 604.7906 (2022): 525-533.

Shape Discovery

1D characteristrics ⇒ 3D shape representation



Brain Morphometry Chart [1]

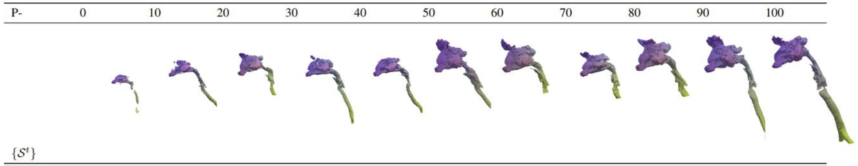


Airway Shape Chart [2]

1. Zhang, Hongxi, et al. "Growth charts of brain morphometry for preschool children." *NeuroImage* 255 (2022): 119178.
2. https://cismm.web.unc.edu/core-projects/biomedical-image-analysis/pediatric-airway-atlas/

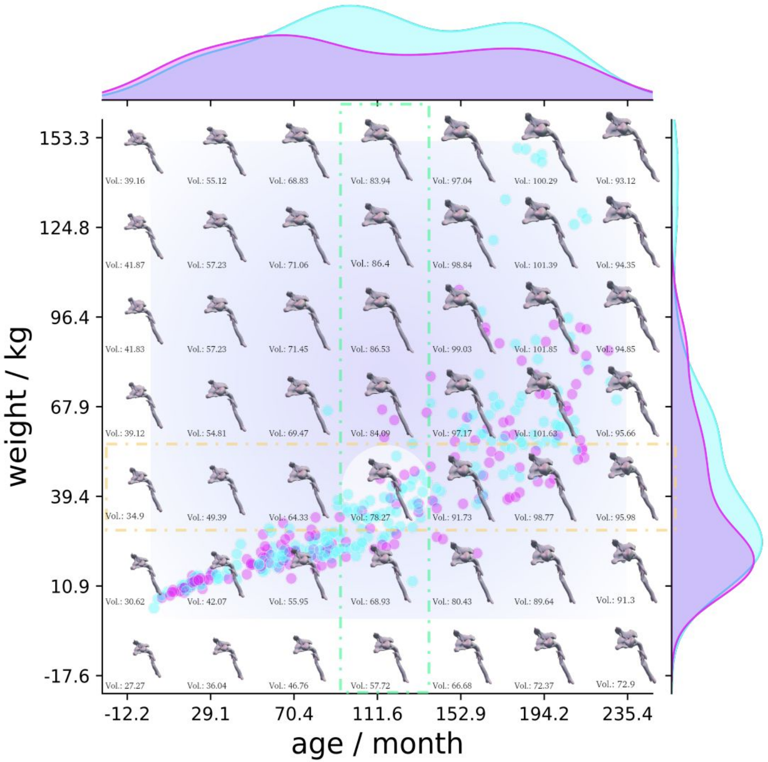
Motivation of **NAISR**

Incomplete, Entangled, and Individual Observations



P-	0	10	20	30	40	50	60	70	80	90	100
age	1.00	23.00	55.00	71.00	89.00	111.00	129.00	161.00	179.00	199.00	233.00
weight	3.90	14.20	20.10	21.80	19.70	32.85	44.80	21.30	59.00	93.90	75.60
sex	M	M	F	F	M	M	M	F	F	F	M
m-vol	4.56	16.84	29.53	28.91	27.31	70.90	71.23	43.34	78.63	102.35	113.84

Complete, Disentangled, and Universal Shape Space

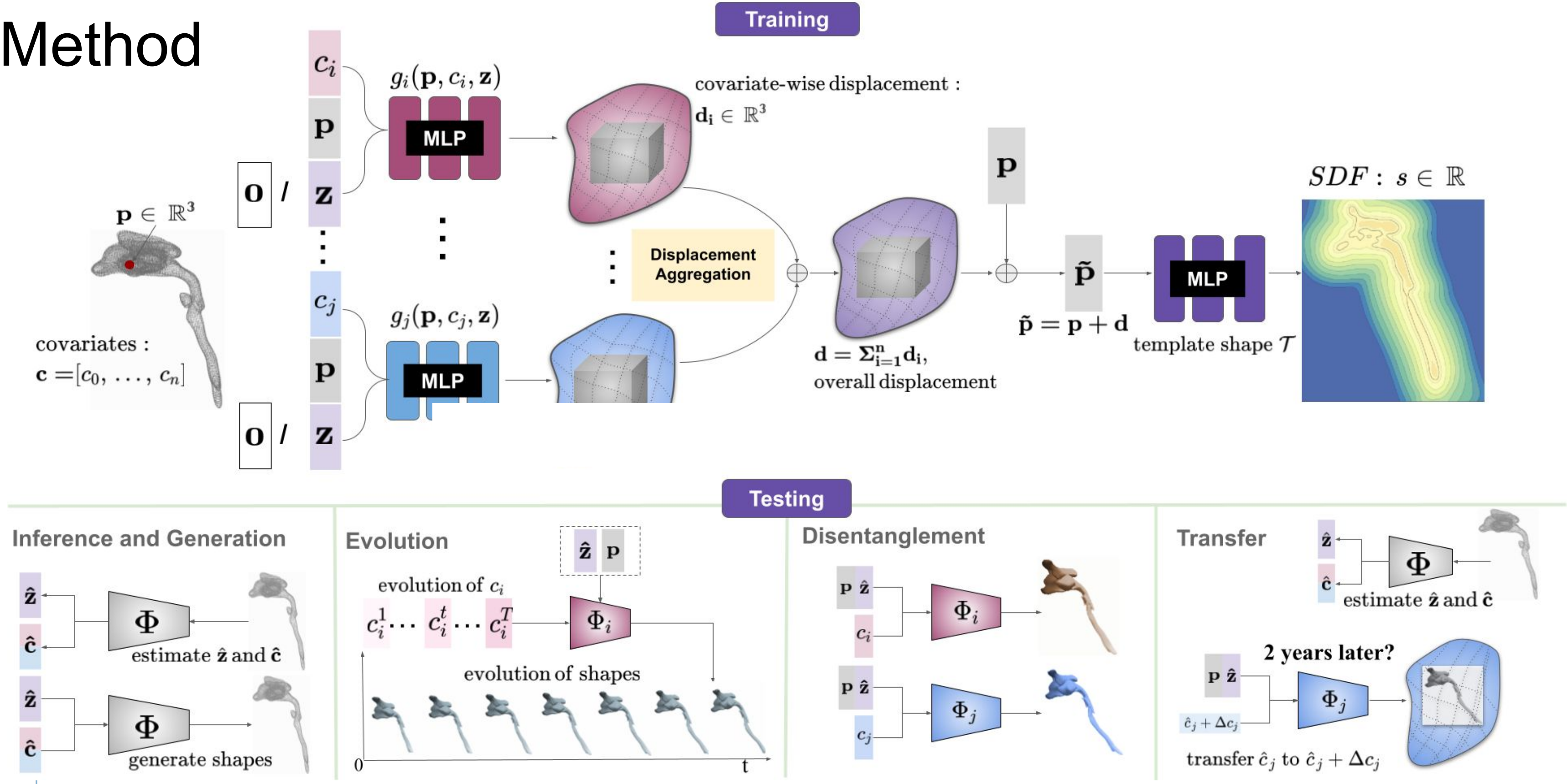


What is a good shape representation for Scientific Discovery?

- Given an atlas shape, how can one accurately represent individual shapes?
- Given a shape, how can one disentangle different covariate effects from each other?
- Given a covariate, e.g., age, how does the shape evolve based on this covariate?
- Given a random shape, how will this shape develop after a period of time?

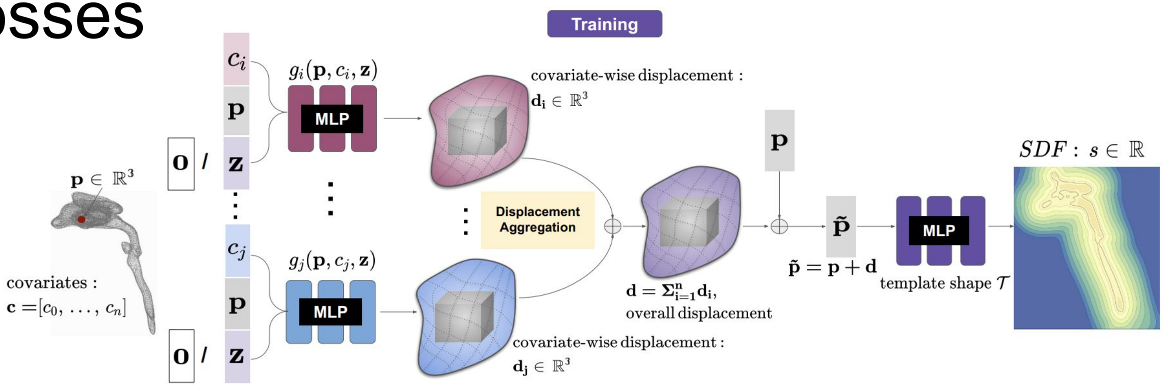
Method	Implicit	Deformable	Disentangleable	Evolvable	Transferable	Interpretable
ConditionalTemplate (Dalca et al., 2019)	✗	✓	✗	✓	✗	✗
3DAttriFlow (Wen et al., 2022)	✗	✓	✗	✓	✗	✗
DeepSDF (Park et al., 2019)	✓	✗	✗	✗	✗	✗
A-SDF (Mu et al., 2021)	✓	✗	✗	✓	✓	✗
DIT (Zheng et al., 2021), DIF (Deng et al., 2021), NDF (Sun et al., 2022a)	✓	✓	✗	✗	✗	✗
NASAM (Wei et al., 2022)	✓	✓	✗	✓	✗	✗
Ours (NAISR)	✓	✓	✓	✓	✓	✓

Method



Training
c_i
p
o / z
$g_i(\mathbf{p}, c_i, \mathbf{z})$
MLP
covariate-wise displacement :
$\mathbf{d_i} \in \mathbb{R}^3$
$\mathbf{p} \in \mathbb{R}^3$
covariates :
$\mathbf{c} = [c_0, \ldots, c_n]$
Displacement Aggregation
c_j
$g_j(\mathbf{p}, c_j, \mathbf{z})$
$\mathbf{d} = \Sigma_{i=1}^{n} \mathbf{d_i}$,
overall displacement
$\tilde{\mathbf{p}}$
$\tilde{\mathbf{p}} = \mathbf{p} + \mathbf{d}$
template shape $\mathcal{T}$
$SDF : s \in \mathbb{R}$
Testing
Inference and Generation
$\hat{\mathbf{z}}$
$\hat{\mathbf{c}}$
Φ
estimate $\hat{\mathbf{z}}$ and $\hat{\mathbf{c}}$
generate shapes
Evolution
evolution of c_i
$c_i^1 \cdots c_i^t \cdots c_i^T$
Φ_i
evolution of shapes
0
t
Disentanglement
Φ_j
Transfer
2 years later?
$\hat{c}_j + \Delta c_j$
transfer $\hat{c}_j$ to $\hat{c}_j + \Delta c_j$

Training Losses



$$\mathcal{L}(\Phi, \mathbf{c}, \mathbf{z}) = \underbrace{\mathcal{L}_{\text{lat}}(\mathbf{z})}_{\text{as regularizer}} + \underbrace{\mathcal{L}_{\text{on}}(\Phi, \mathbf{c}, \mathbf{z}) + \mathcal{L}_{\text{off}}(\Phi, \mathbf{c}, \mathbf{z})}_{\text{for reconstrution}},$$

As regularizer

$$\mathcal{L}_{\text{lat}}(\mathbf{z}) = \lambda_6 \frac{1}{\sigma^2} \|\boldsymbol{z}\|_2^2$$

For reconstruction

$$\mathcal{L}_{\text{on}}(\Phi, \mathbf{c}, \mathbf{z}) = \int_{\mathcal{S}} \lambda_1 \underbrace{\||\nabla_{\mathbf{p}} \Phi(\mathbf{p}, \mathbf{c}, \mathbf{z})| - 1\|}_{\mathcal{L}_{\text{Eikonal}}} + \lambda_2 \underbrace{\|\Phi(\mathbf{p}, \mathbf{c}, \mathbf{z})\|}_{\mathcal{L}_{\text{Dirichlet}}} + \lambda_3 \underbrace{(1 - \langle \nabla_{\mathbf{p}} \Phi(\mathbf{p}, \mathbf{c}, \mathbf{z}), \mathbf{n}(\mathbf{p}) \rangle)}_{\mathcal{L}_{\text{Neumann}}} d\mathbf{p}$$

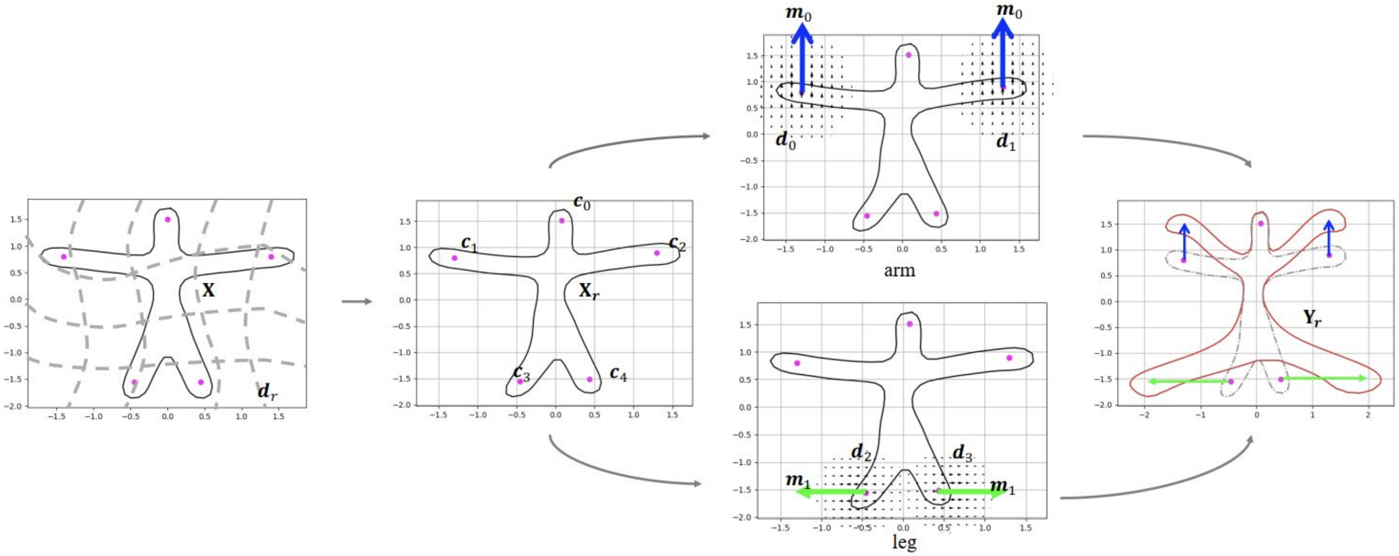
$$\mathcal{L}_{\text{off}}(\Phi, \mathbf{c}, \mathbf{z}) = \int_{\Omega \setminus \mathcal{S}} \lambda_4 \underbrace{|\Phi(\mathbf{p}, \mathbf{c}, \mathbf{z}) - s_{tgt}(\mathbf{p})|}_{\mathcal{L}_{\text{Dirichlet}}} + \lambda_5 \underbrace{\||\nabla_{\mathbf{p}} \Phi(\mathbf{p}, \mathbf{c}, \mathbf{z})| - 1\|}_{\mathcal{L}_{\text{Eikonal}}} d\mathbf{p}$$

Experiment Setting - Datasets

Starman | ADNI Hippocampus | Pediatric Airway

Experiment Setting - Datasets

Starman ADNI Hippocampus Pediatric Airway



- Training set: 5041 shapes from 1000 different starmen;
- Testing set: 4966 shapes from another 1000 starmen;
- 2 covariates: arms & leg movements;
- Random number of observations are simulated for each individual.

Experiment Setting - Datasets

Starman **ADNI Hippocampus** Pediatric Airway

P-	0	10	20	30	40	50	60	70	80	90	100
$\{\mathcal{S}^t\}$											

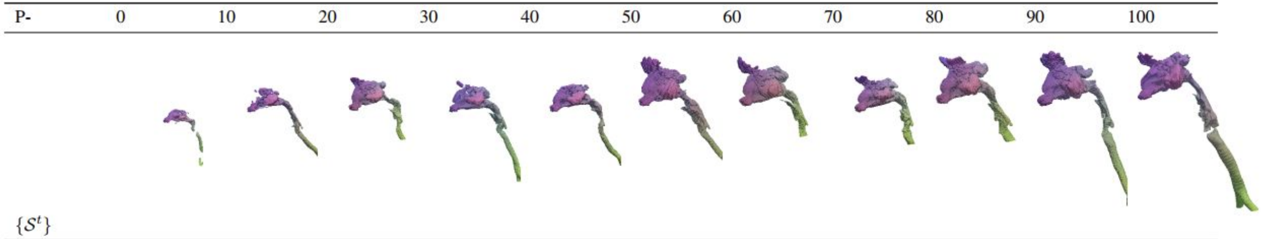
	0	1	2	3	4	5	6	7	8	9	10
age	55.2	68.4	71.2	72.6	74.2	76.2	77.9	79.8	82.0	85.2	90.8
AD	No	No	Yes	No	No	No	Yes	Yes	No	No	No
sex	F	F	F	F	M	F	F	M	M	F	F
edu	18.0	16.0	16.0	15.0	18.0	18.0	17.0	20.0	16.0	7.0	15.0
m-vol	1.91	1.58	1.3	1.48	2.08	2.2	1.66	1.63	2.0	1.64	2.21

# observations	1	2	3	4	5	6
# patients	3	10	410	5	7	54

- 1632 hippocampus shapes from MR images;
- 80%-20% split by patients;
- 4 covariates (age, sex, AD, education length).

Experiment Setting - Datasets

Starman ADNI Hippocampus **Pediatric Airway**

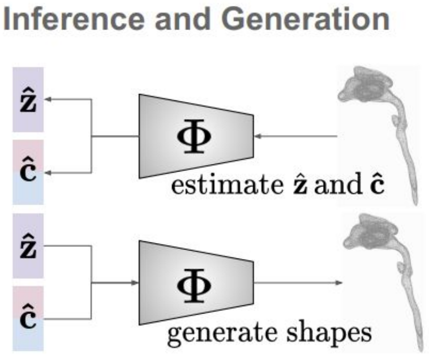


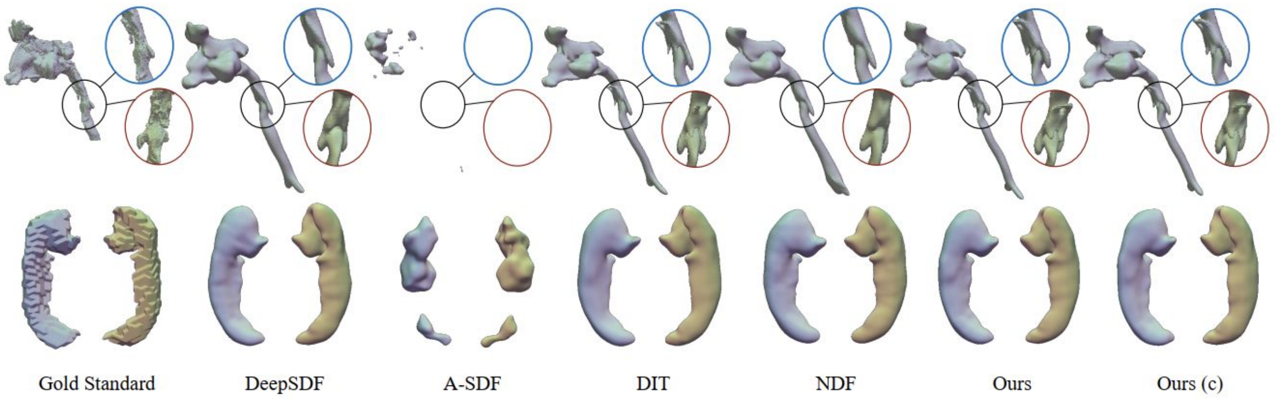
P-	0	10	20	30	40	50	60	70	80	90	100
age	1.00	23.00	55.00	71.00	89.00	111.00	129.00	161.00	179.00	199.00	233.00
weight	3.90	14.20	20.10	21.80	19.70	32.85	44.80	21.30	59.00	93.90	75.60
sex	M	M	F	F	M	M	M	F	F	F	M
m-vol	4.56	16.84	29.53	28.91	27.31	70.90	71.23	43.34	78.63	102.35	113.84

# observations	1	2	3	4	5	6	7	9	11
# patients	229	12	6	8	3	2	1	1	1

- 357 upper airway shapes from CT images
- 80%-20% train-test split by patient (instead of shapes).
- Each shape has 3 covariates (age, weight, sex)

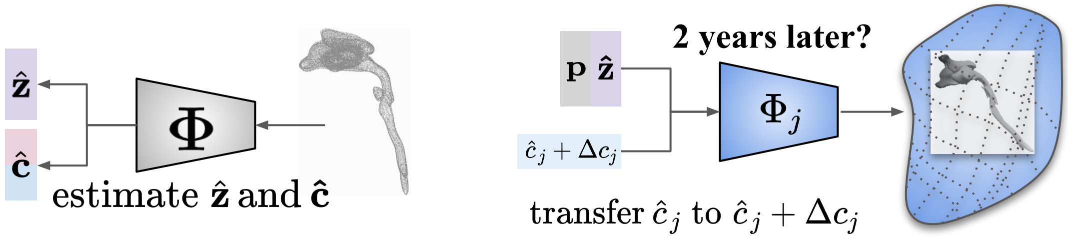
Results - Shape Reconstruction





	Starman						ADNI Hippocampus						Pediatric Airway					
	CD ↓		EMD ↓		HD ↓		CD ↓		EMD ↓		HD ↓		CD ↓		EMD ↓		HD ↓	
	μ	M	μ	M	μ	M	μ	M	μ	M	μ	M	μ	M	μ	M	μ	M
DeepSDF	0.117	0.105	1.941	1.887	6.482	6.271	0.157	**0.140**	2.098	**2.035**	9.762	9.276	**0.077**	0.052	1.401	1.266	10.765	9.446
A-SDF	0.173	0.092	2.01	1.668	8.806	6.949	1.094	1.162	7.156	7.667	25.092	25.938	2.647	1.178	10.302	9.068	47.172	37.835
A-SDF (c)	**0.049**	**0.043**	**1.298**	**1.261**	**5.388**	**4.964**	0.311	0.294	3.136	3.099	13.852	13.003	0.852	0.226	4.090	2.890	30.848	21.965
DIT	0.281	0.181	2.727	2.497	10.295	8.442	**0.156**	0.142	**2.096**	2.054	**9.465**	**9.123**	0.094	0.049	1.414	1.262	11.524	10.228
NDF	1.086	0.736	5.364	4.821	21.098	19.705	0.253	0.213	2.699	2.58	11.328	10.947	0.238	0.117	2.174	1.737	14.950	12.516
Ours	0.111	0.072	1.709	1.515	7.951	7.141	0.174	0.153	2.258	2.191	10.019	9.521	**0.067**	**0.039**	**1.233**	**1.132**	**10.333**	**8.404**
Ours (c)	**0.049**	**0.036**	**1.276**	**1.156**	**5.051**	**4.666**	**0.126**	**0.116**	**1.847**	**1.81**	**8.586**	**8.153**	0.084	**0.044**	**1.345**	**1.190**	**10.719**	**8.577**

Results - Shape Transfer

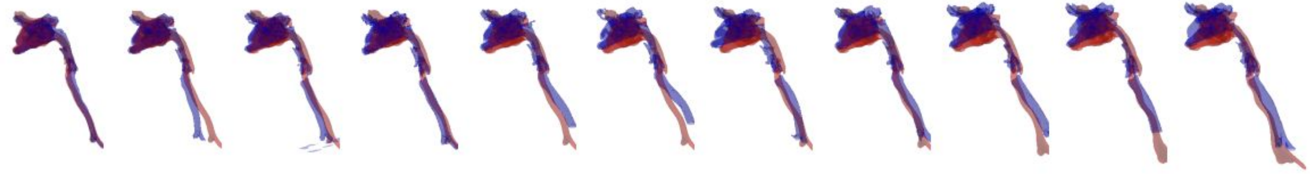


		Starman						ADNI Hippocampus		Pediatric Airway	
		CD ↓		EMD ↓		HD ↓		VD ↓		VD ↓	
	w.C.	μ	M	μ	M	μ	M	μ	M	μ	M
A-SDF	✗	**0**	**0**	**0.009**	**0.008**	**0.036**	**0.034**	0.518	0.488	81.07	82.92
A-SDF	✓	**0**	**0**	**0.009**	**0.009**	**0.036**	**0.035**	0.215	0.177	41.46	40.96
Ours	✗	0.003	0.002	0.025	0.023	0.094	0.077	**0.086**	**0.063**	**12.82**	**8.84**
Ours	✓	0.009	0.002	0.031	0.025	0.116	0.083	**0.089**	**0.071**	**11.23**	**9.65**

Results - Shape Transfer

Given a new airway shape  , we estimate $\hat{\mathbf{z}}$ at t_0, transfer shape to $t_1 \ldots t_{10}$

#time	0	1	2	3	4	5	6	7	8	9	10

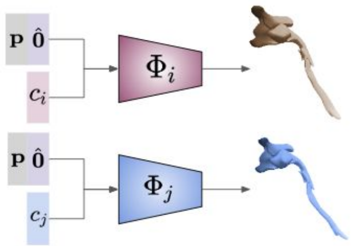


$\{\mathcal{S}^t\}$

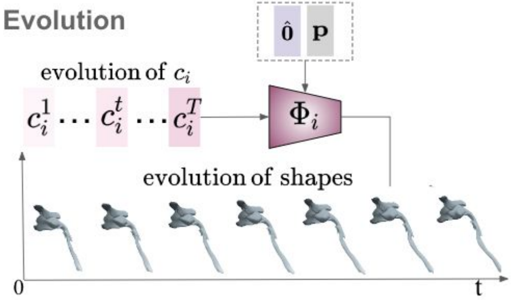
# time	0	1	2	3	4	5	6	7	8	9	10
age	154	155	157	159	163	164	167	170	194	227	233
weight	55.2	60.9	64.3	65.25	59.25	59.2	65.3	68	77.1	75.6	75.6
sex	M	M	M	M	M	M	M	M	M	M	M
p-vol	92.5	93.59	94.64	95.45	96.33	96.69	98.4	99.72	109.47	118.41	118.76
m-vol	86.33	82.66	63.23	90.65	98.11	84.35	94.14	127.45	98.81	100.17	113.84

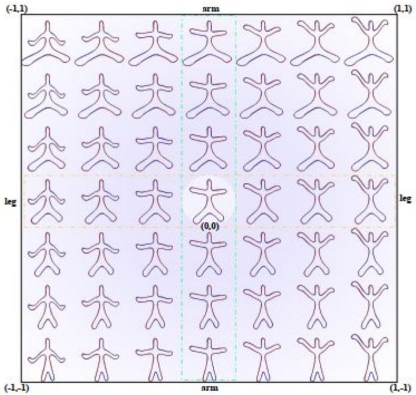
Results -
Shape Evolution & Disentanglement In Template Space

Disentanglement

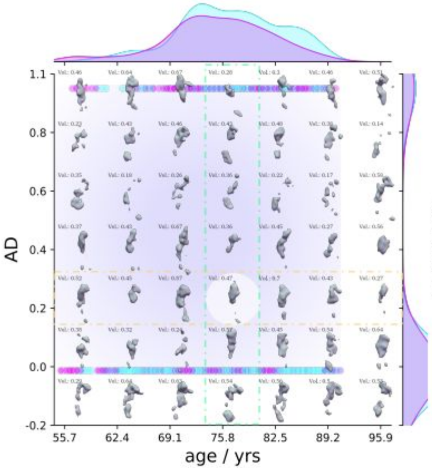


Evolution

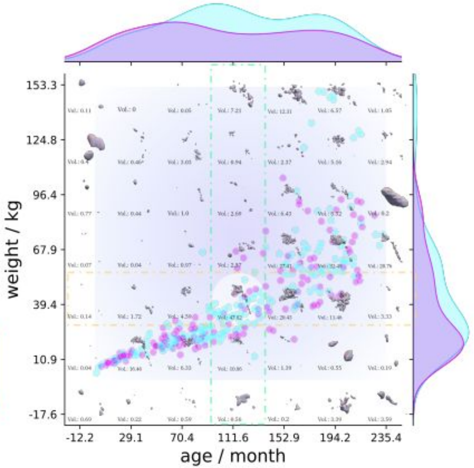




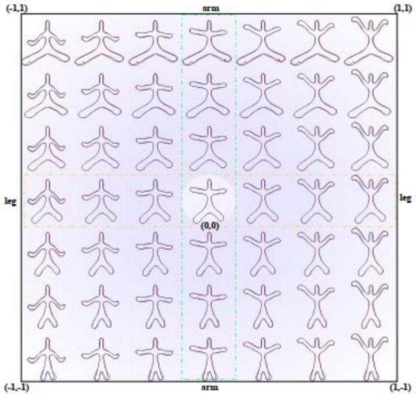
A-SDF, *Starman*



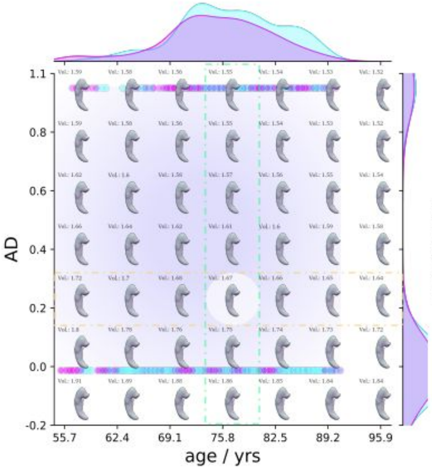
A-SDF, ADNI Hippocampus



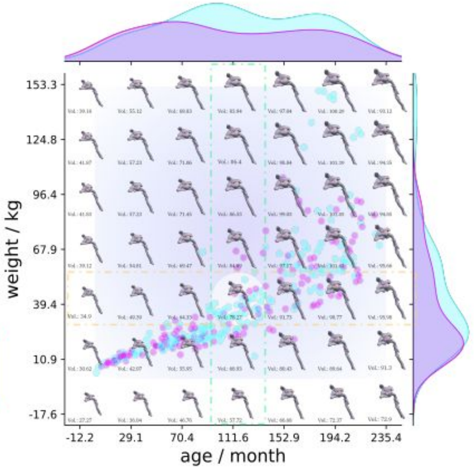
A-SDF, Pediatric Airway



Ours, *Starman*



Ours, ADNI Hippocampus



Ours, Pediatric Airway

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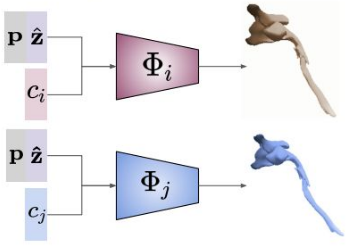
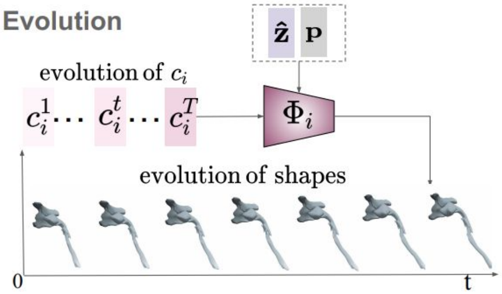
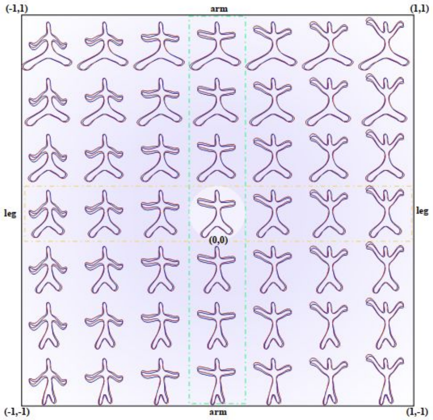
Results - Shape Evolution & Disentanglement For a Specific Patient

Disentanglement

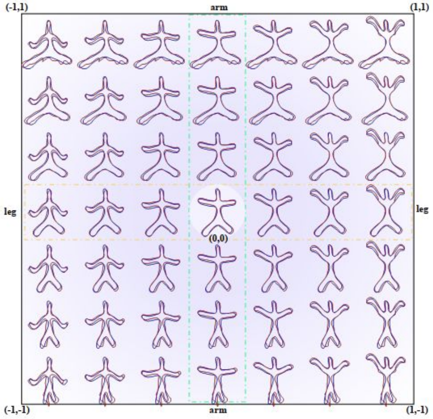


Evolution

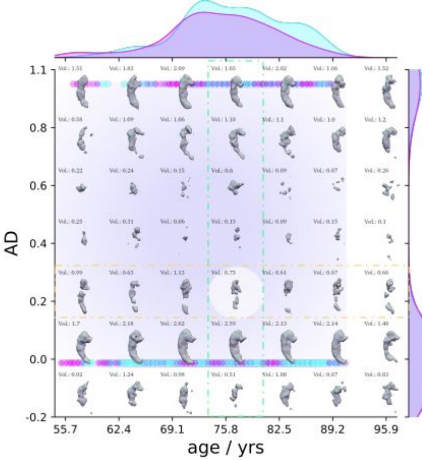




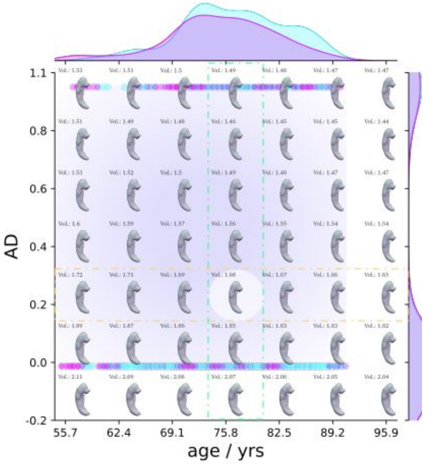
A-SDF, *Starman*



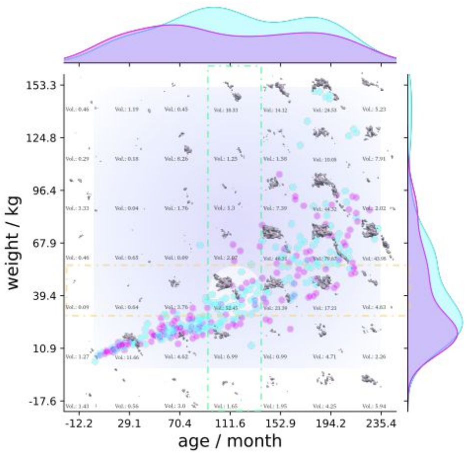
Ours, *Starman*



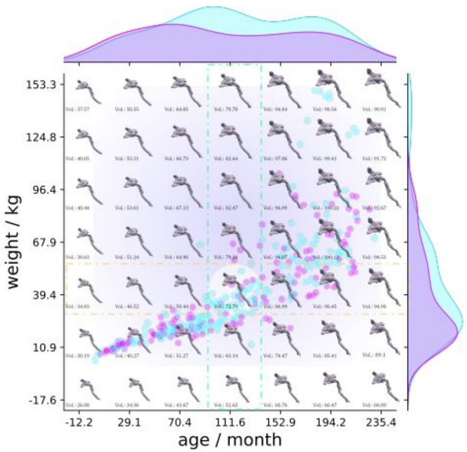
A-SDF, ADNI Hippocampus



Ours, ADNI Hippocampus



A-SDF, Pediatric Airway



Ours, Pediatric Airway

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[1]University of North Carolina at Chapel Hill, [2]Wake Forest School of Medicine, [3]The Ohio State University College of Medicine

🌸 First author 🌲 Corresponding author

THANK YOU!

Code

Project Page

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