

➤ **Regular Tensor data and decomposition:**  
multi-dim array for high-order structural data



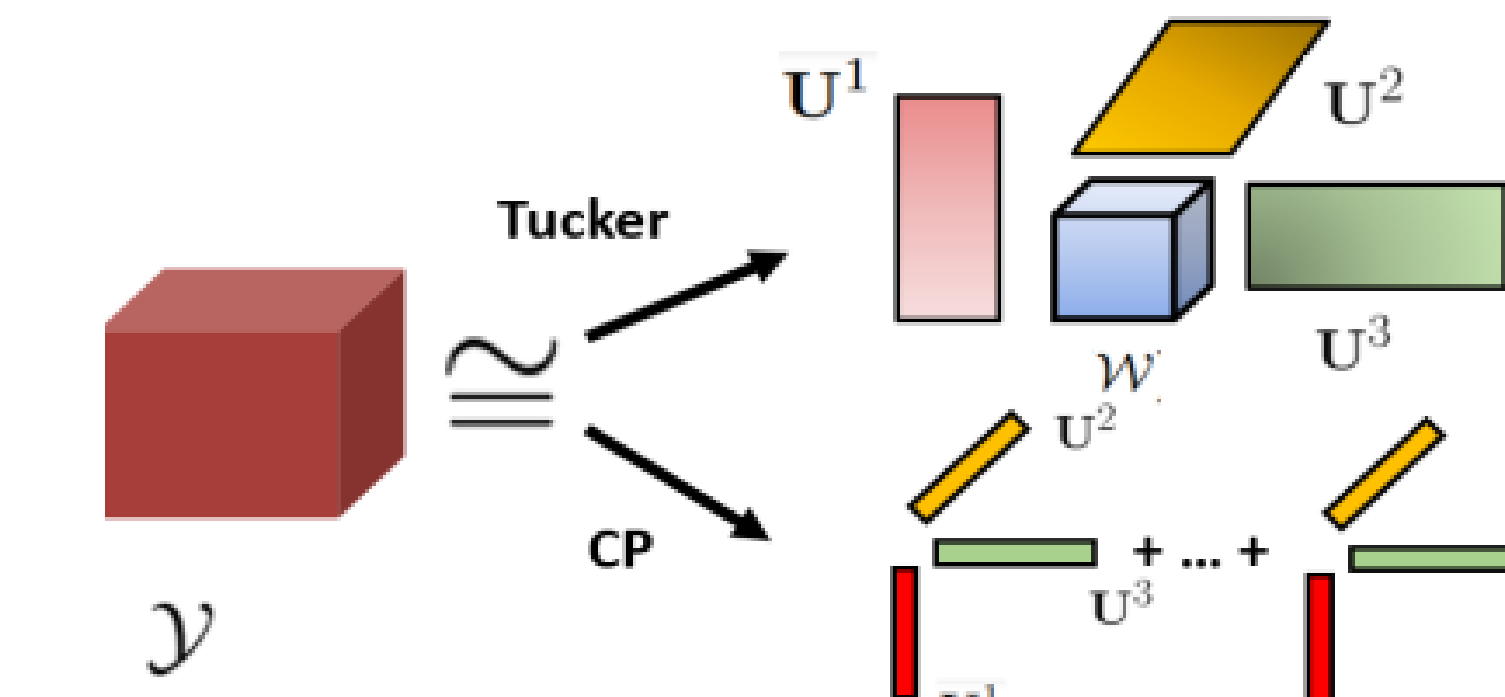
(user, user, message) (item, group, site, device) (city, road, section)

Each entry: (index1, index2, index3..) -> value

⇔ Interaction of multiple objects

$$y_i \approx \text{vec}(\mathcal{W})^\top (\mathbf{u}_{i_1}^1 \otimes \dots \otimes \mathbf{u}_{i_K}^K)$$

Integer index:  
object #

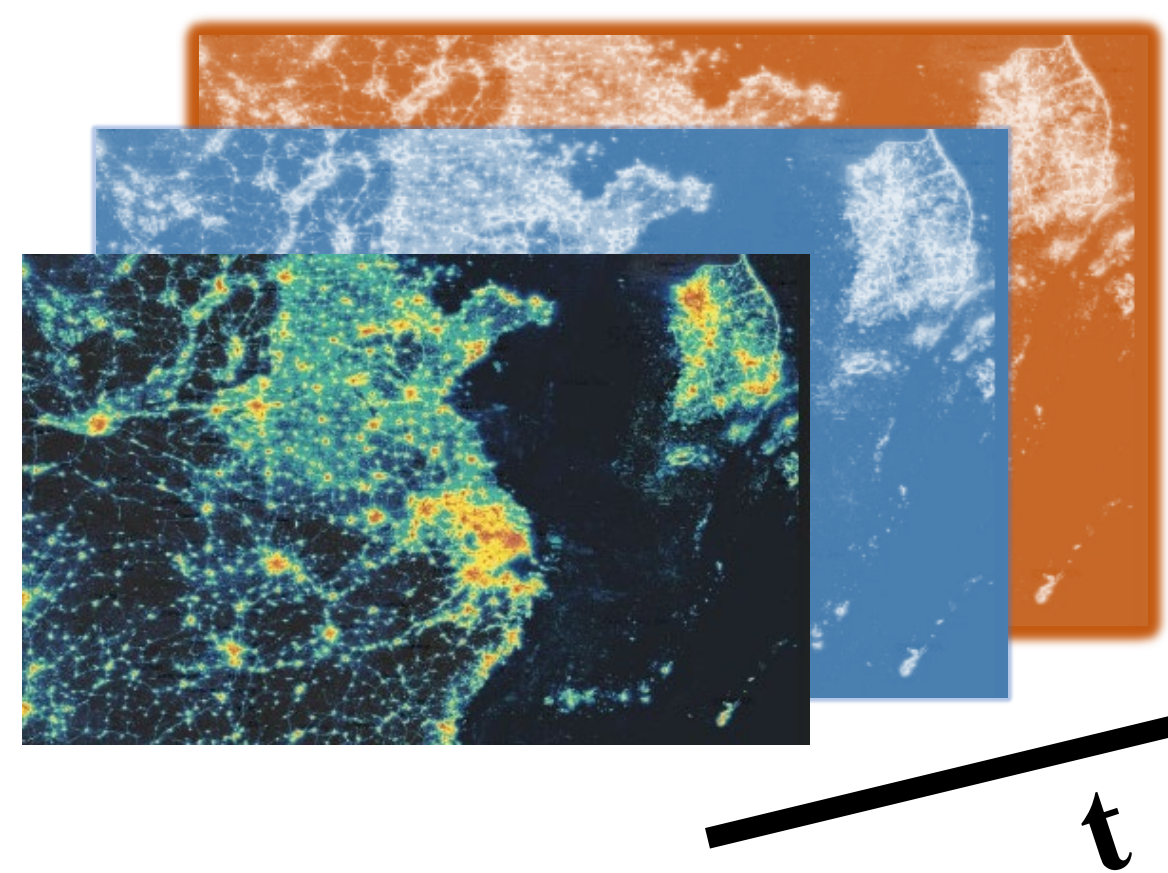


Object 2 Vector!

Low-rank factors

$$\mathbf{U}^k = [\mathbf{u}_1^k \dots \mathbf{u}_{d_k}^k]$$

➤ **General case: "Continuous-index" tensor data**



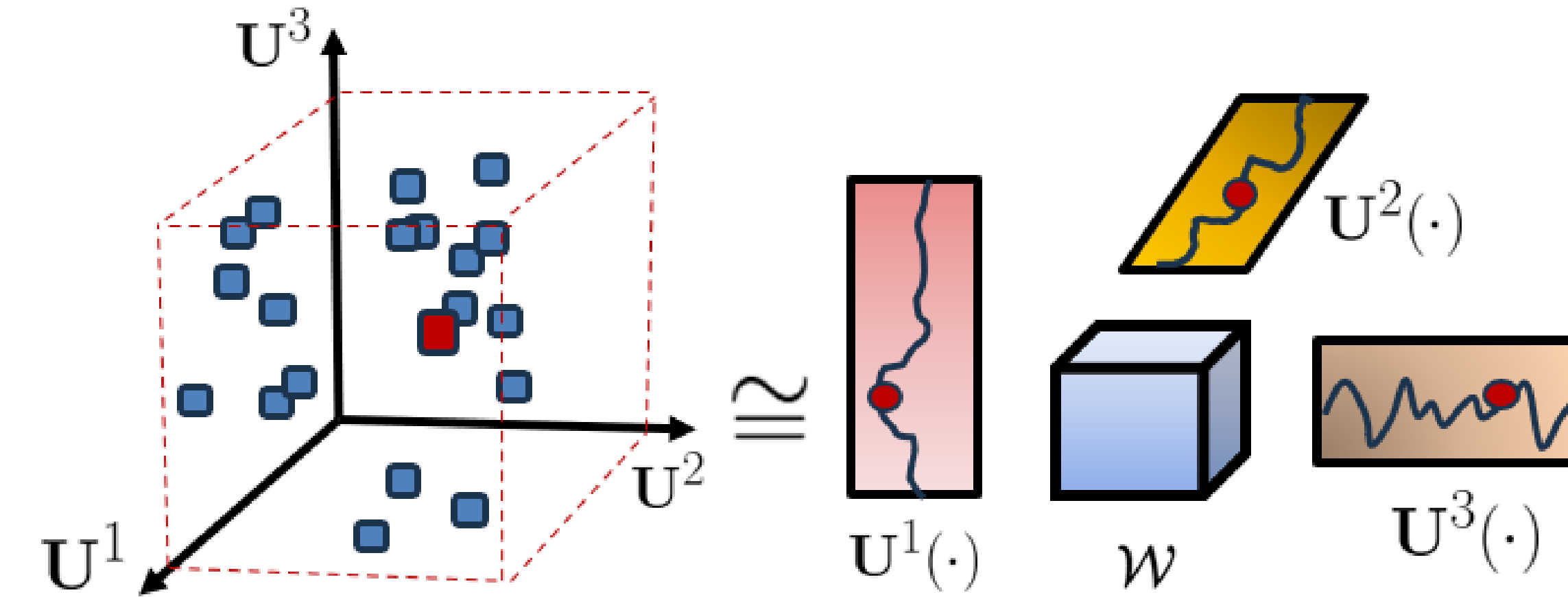
Each entry: (index1, index2, index3..) -> value

⇔ a multivariate functions

Real-valued index:  
input of function

(latitude, longitude, height, time)

➤ **FunBaT: Tucker-form functional decomposition**



$$f(\mathbf{i}) = f(i_1, \dots, i_K) \approx \text{vec}(\mathcal{W})^\top (\mathbf{U}^1(i_1) \otimes \dots \otimes \mathbf{U}^K(i_K))$$

continuous-index entry ⇔ interaction of **mode-wise latent functions**

➤ **Model of latent function: State-Space Gaussian Process (SSGP)**

$$\mathbf{U}^k(i_k) = [u_1^k(i_k), \dots, u_{r_k}^k(i_k)]^\top; u_j^k(i_k) \sim \mathcal{GP}(0, \kappa(i_k, i'_k)), j = 1 \dots r_k$$

$$p(\mathbf{U}^k) = p(\mathbf{Z}^k) = p(\mathbf{Z}^k(i_k^1), \dots, \mathbf{Z}^k(i_k^{N_k})) = p(\mathbf{Z}_1^k) \prod_{s=1}^{N_k-1} p(\mathbf{Z}_{s+1}^k | \mathbf{Z}_s^k),$$

$$\text{where } p(\mathbf{Z}_1^k) = \mathcal{N}(\mathbf{Z}_1^k(i_k^1) | \mathbf{0}, \tilde{\mathbf{P}}_\infty^k); p(\mathbf{Z}_{s+1}^k | \mathbf{Z}_s^k) = \mathcal{N}(\mathbf{Z}_{s+1}^k(i_k^{s+1}) | \tilde{\mathbf{A}}_s^k \mathbf{Z}_s^k(i_k^s), \tilde{\mathbf{Q}}_s^k).$$

➤ **Efficient and scalable Inference by:**

**moment-matching** + **message merging** + **Bayesian Filter/Smother**

$$\mathcal{N}(y_n | \text{vec}(\mathcal{W})^\top (\mathbf{U}^1(i_1^n) \otimes \dots \otimes \mathbf{U}^K(i_K^n)), \tau^{-1}) \approx Z_n f_n(\tau) f_n(\mathcal{W}) \prod_{k=1}^K f_n(\mathbf{Z}^k(i_k^n)),$$

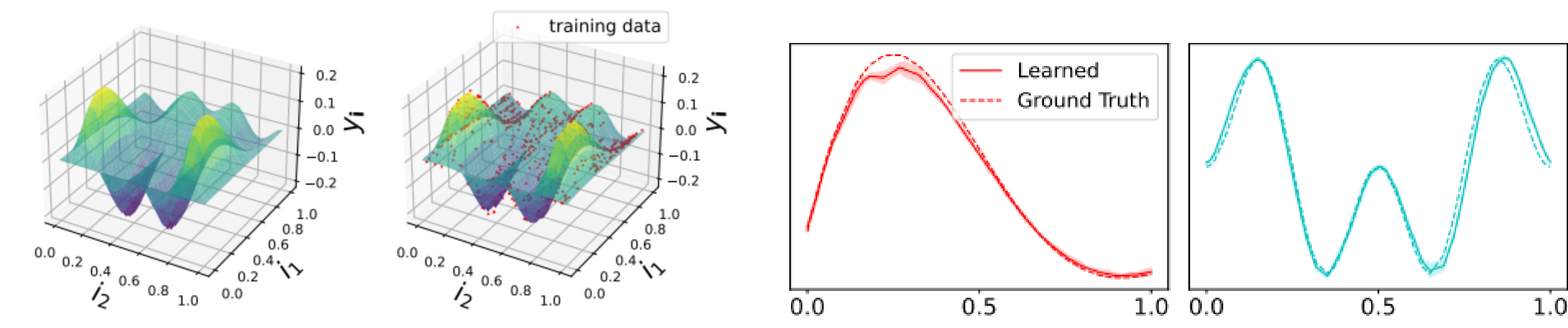
$$q(\mathcal{W}) = p(\mathcal{W}) \prod_{n=1}^N f_n(\mathcal{W}) = \mathcal{N}(\text{vec}(\mathcal{W}) | \mathbf{0}, \mathbf{I}) \prod_{n=1}^N \mathcal{N}(\text{vec}(\mathcal{W}) | \boldsymbol{\mu}_n, \mathbf{S}_n).$$

$$q(\mathbf{Z}_s^k) = q(\mathbf{Z}_{s-1}^k) p(\mathbf{Z}_s^k | \mathbf{Z}_{s-1}^k) \prod_{n \in \mathcal{D}_s^k} f_n(\mathbf{Z}_s^k)$$

Time cost:  $\mathcal{O}(NKR)$

**Linear** to mode, # entry, rank

➤ **Synthetic Data: reconstruction of tensor surface**



(a) Real tensor surface (b) Estimated tensor surface (c)  $\mathbf{U}^1(i_1)$  (d)  $\mathbf{U}^2(i_2)$

➤ **Real-world task results & learned latent functions**

BeijingAir:

(atmospheric-pressure, temperature, time)

Datasets	RMSE		
	PM2.5	PM10	SO2
Resolution: 428 × 501 × 1461 (original)			
P-Tucker	1.256 ± 0.084	1.397 ± 0.001	0.963 ± 0.169
Tucker-ALS	1.018 ± 0.034	1.012 ± 0.021	0.997 ± 0.024
Tucker-SVI	1.891 ± 0.231	1.527 ± 0.107	1.613 ± 0.091
Methods using continuous indexes			
FTT-ALS	1.020 ± 0.013	1.001 ± 0.013	1.001 ± 0.026
FTT-ANOVA	2.150 ± 0.033	2.007 ± 0.015	1.987 ± 0.036
FTT-cross	0.942 ± 0.025	0.933 ± 0.012	0.844 ± 0.026
RBF-SVM	0.995 ± 0.015	0.955 ± 0.02	0.794 ± 0.026
BLR	0.998 ± 0.013	0.977 ± 0.014	0.837 ± 0.021
FunBaT-CP	0.296 ± 0.018	0.343 ± 0.028	<b>0.386 ± 0.009</b>
FunBaT	<b>0.288 ± 0.008</b>	<b>0.328 ± 0.004</b>	<b>0.386 ± 0.01</b>

US-Temperature: (latitude, longitude, time)

Mode-Rank	RMSE		
	R=3	R=5	R=7
P-Tucker	1.306 ± 0.02	1.223 ± 0.022	1.172 ± 0.042
Tucker-ALS	> 10	> 10	> 10
Tucker-SVI	1.438 ± 0.025	1.442 ± 0.021	1.39 ± 0.09
FTT-ALS	1.613 ± 0.0478	1.610 ± 0.052	1.609 ± 0.055
FTT-ANOVA	5.486 ± 0.031	4.619 ± 0.054	3.856 ± 0.059
FTT-cross	1.415 ± 0.0287	1.312 ± 0.023	1.285 ± 0.052
RBF-SVM	2.374 ± 0.047	2.374 ± 0.047	2.374 ± 0.047
BLR	2.959 ± 0.041	2.959 ± 0.041	2.959 ± 0.041
FunBaT-CP	<b>0.805 ± 0.06</b>	<b>0.548 ± 0.03</b>	<b>0.551 ± 0.048</b>
FunBaT	1.255 ± 0.108	1.182 ± 0.117	1.116 ± 0.142

