Glancing over 20 Papers on Modeling Feature Interactions

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12/30/2017

Multi-View Learning

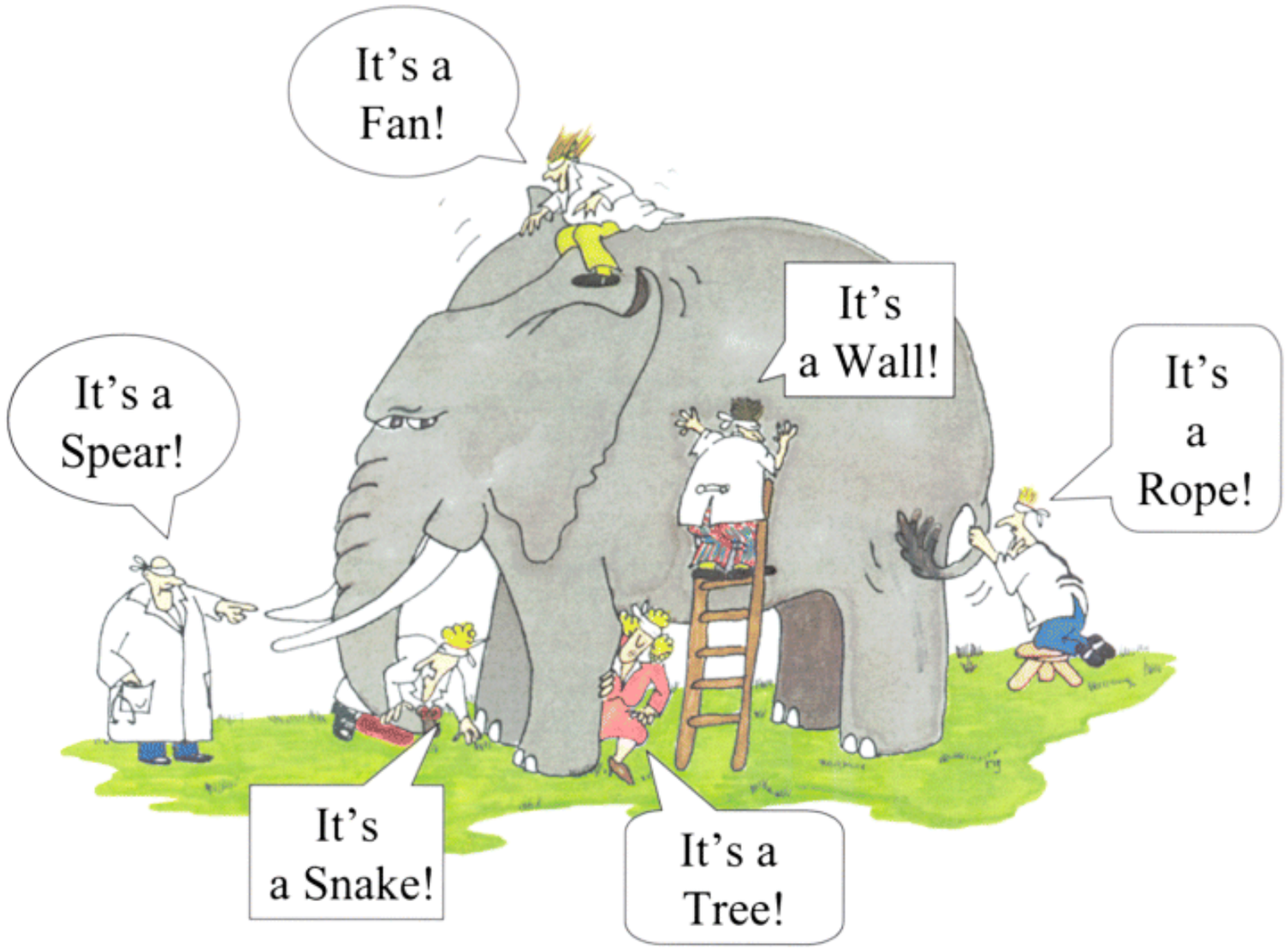
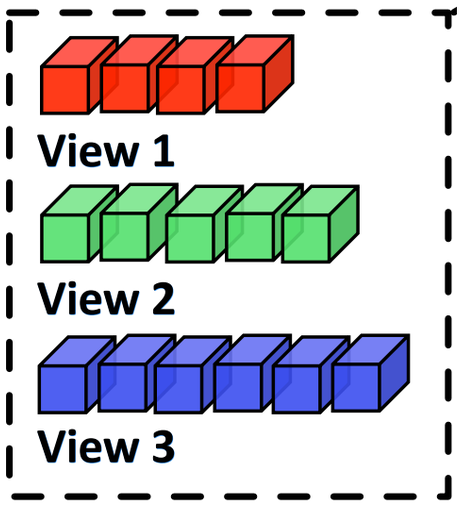


Image source: blind men and the elephant

Multi-View Learning

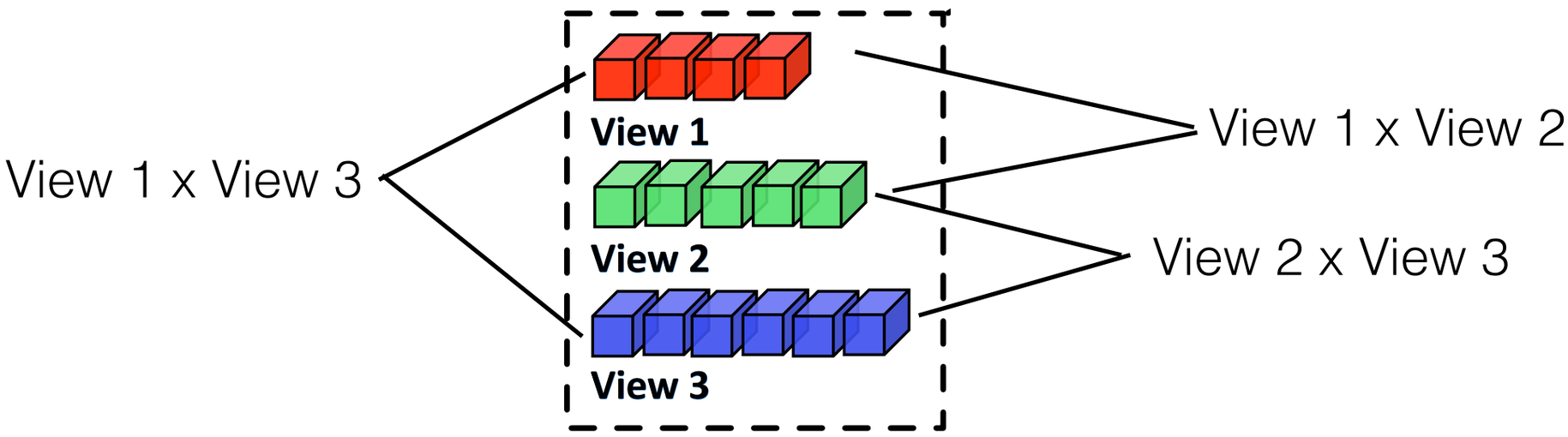
- (Definition) An instance is represented by multiple groups of features, and different feature groups are usually collected from different data sources, thereby having different physical meanings and statistical distributions.

An instance

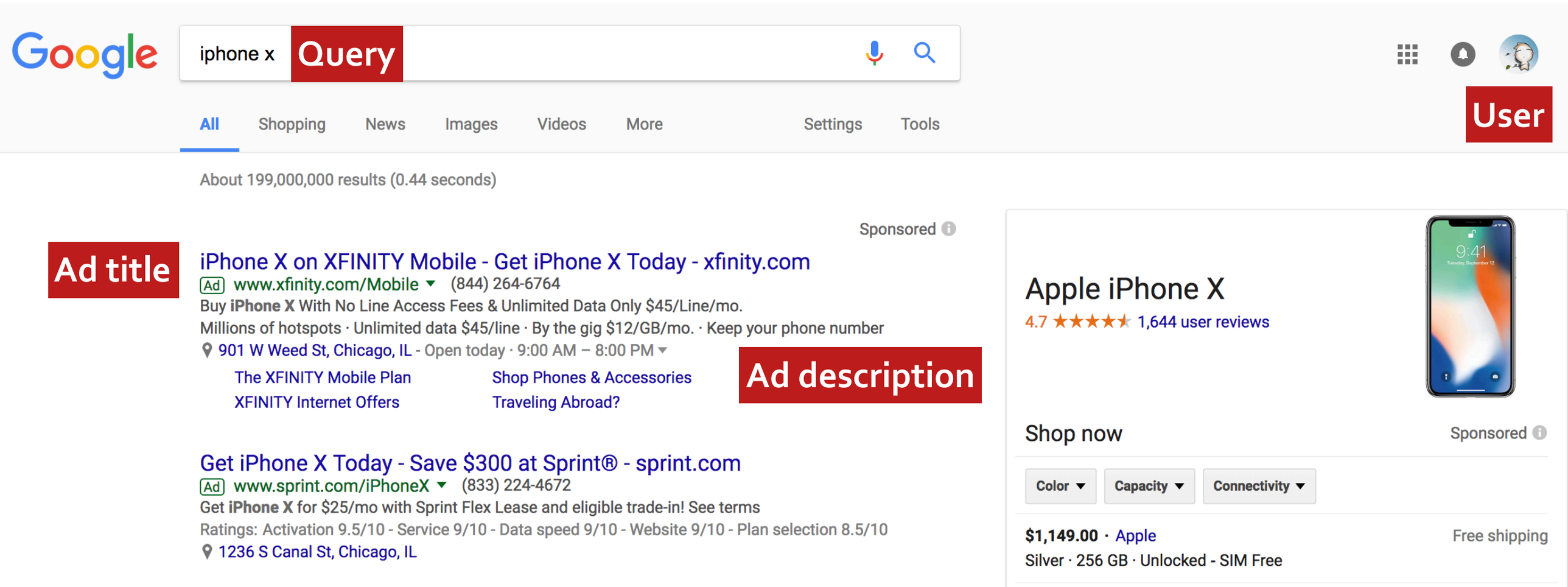


Multi-View Learning

- (Assumption) Features within the same view are usually correlated, while features from different views are complementary. Therefore, it is critical to consider inter-view feature interactions.



An Example



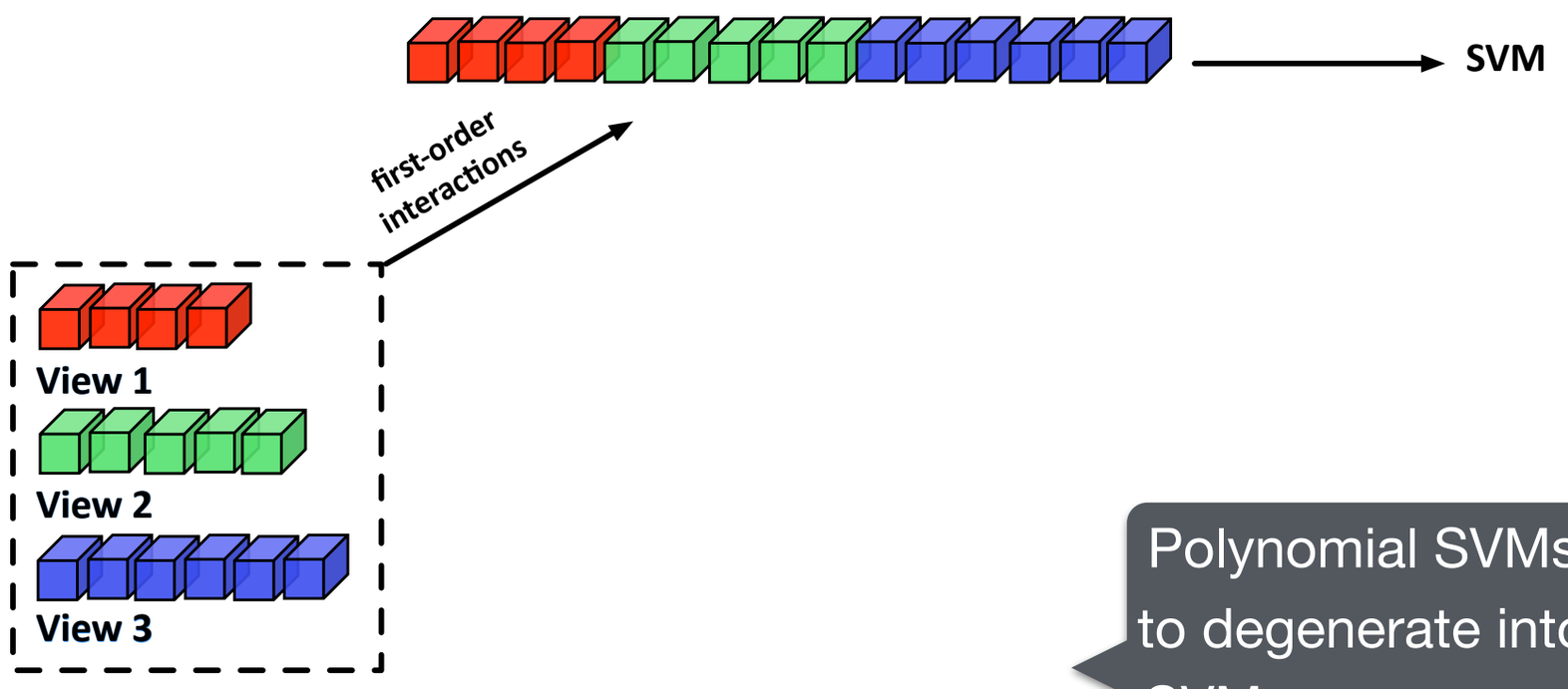
Given a query, how likely a user will click on an ad?

Feature Interactions

- Problem: How to model feature interactions?
- A common solution: Manually create combinatorial/ cross features and then feed them into downstream machine learning models.
  - Query X Ad title, Query X User, or Query X Ad description X User, …
  - Expensive to create, maintain, and improve.
  - Need domain knowledge.

Support Vector Machines (SVM)

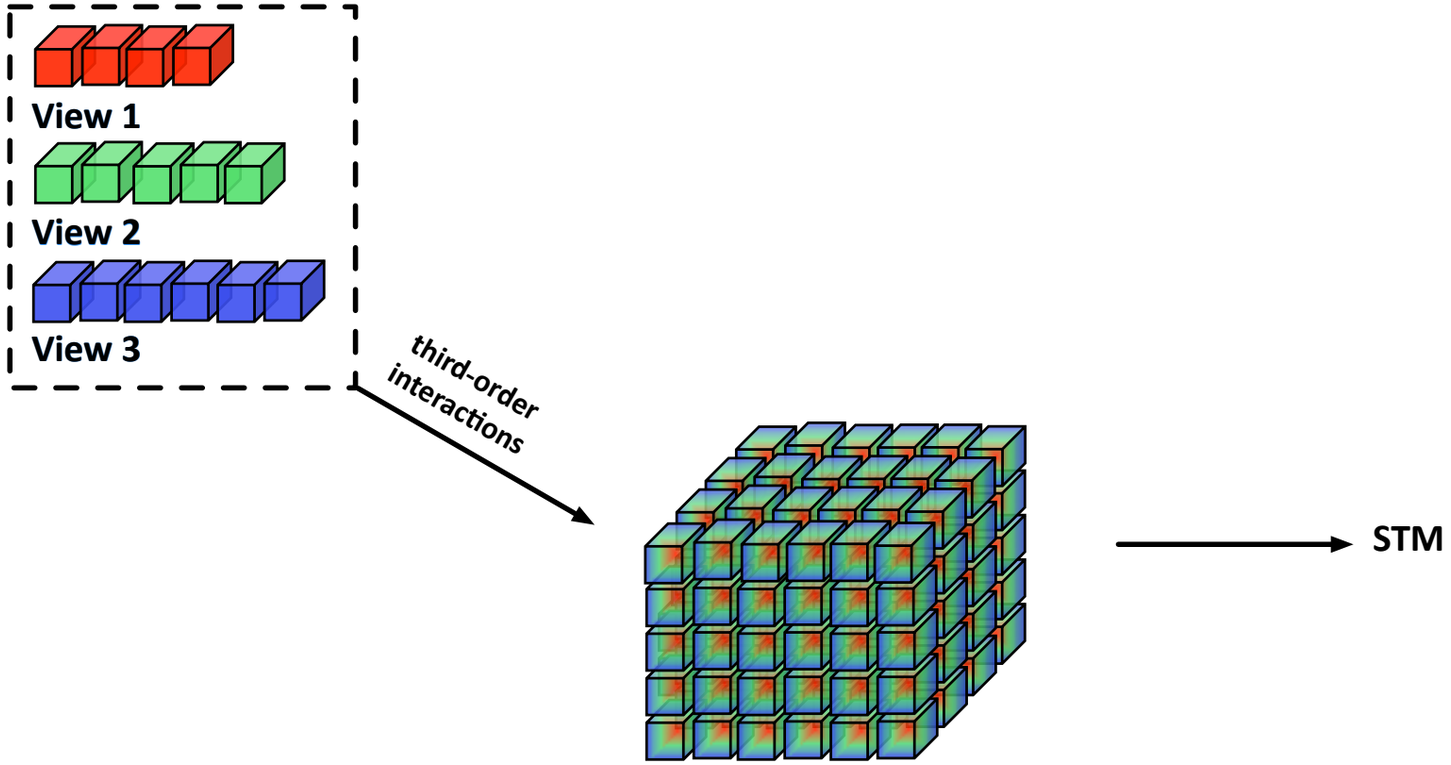
- The linear SVM model (and LR etc.) is limited to the first-order feature interactions.



Polynomial SVMs are likely to degenerate into linear SVMs on sparse datasets.

Support Tensor Machines (STM)

- Work with hinge loss only.
- Strong assumption: rank-1 weight tensor.

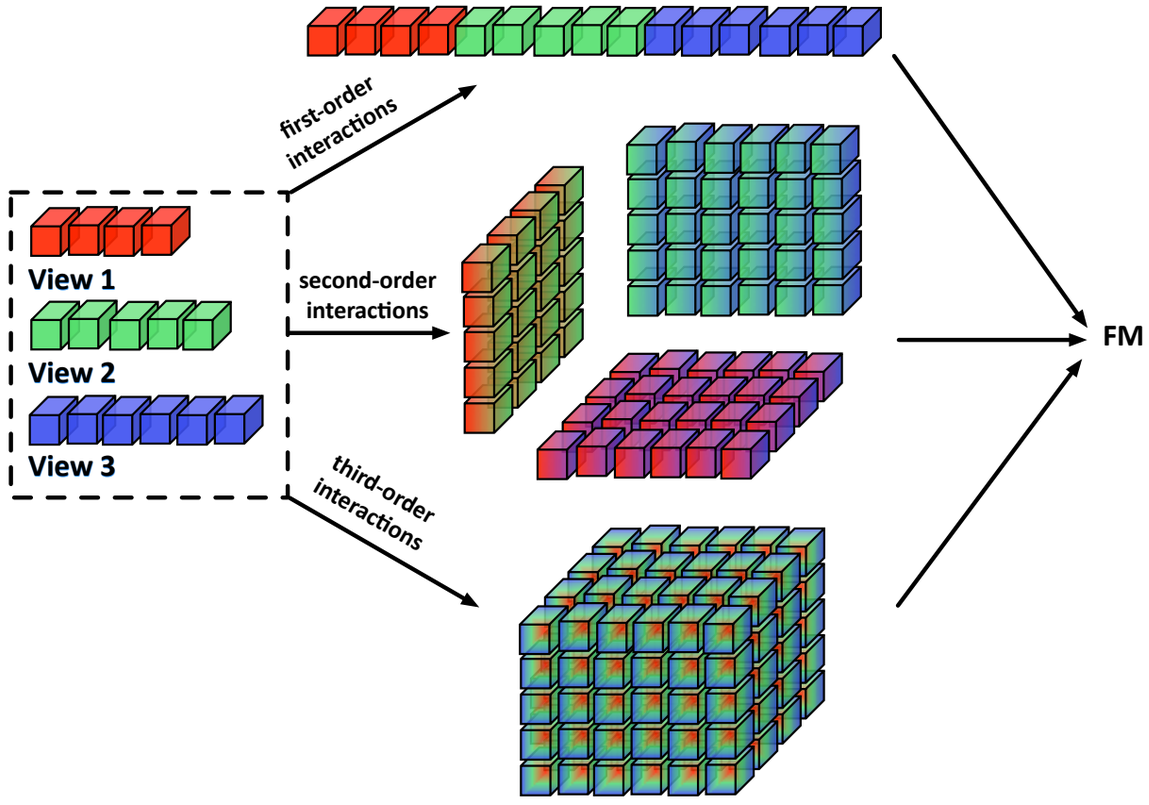


Factorization Machines (FM)

大阪大学
OSAKA UNIVERSITY

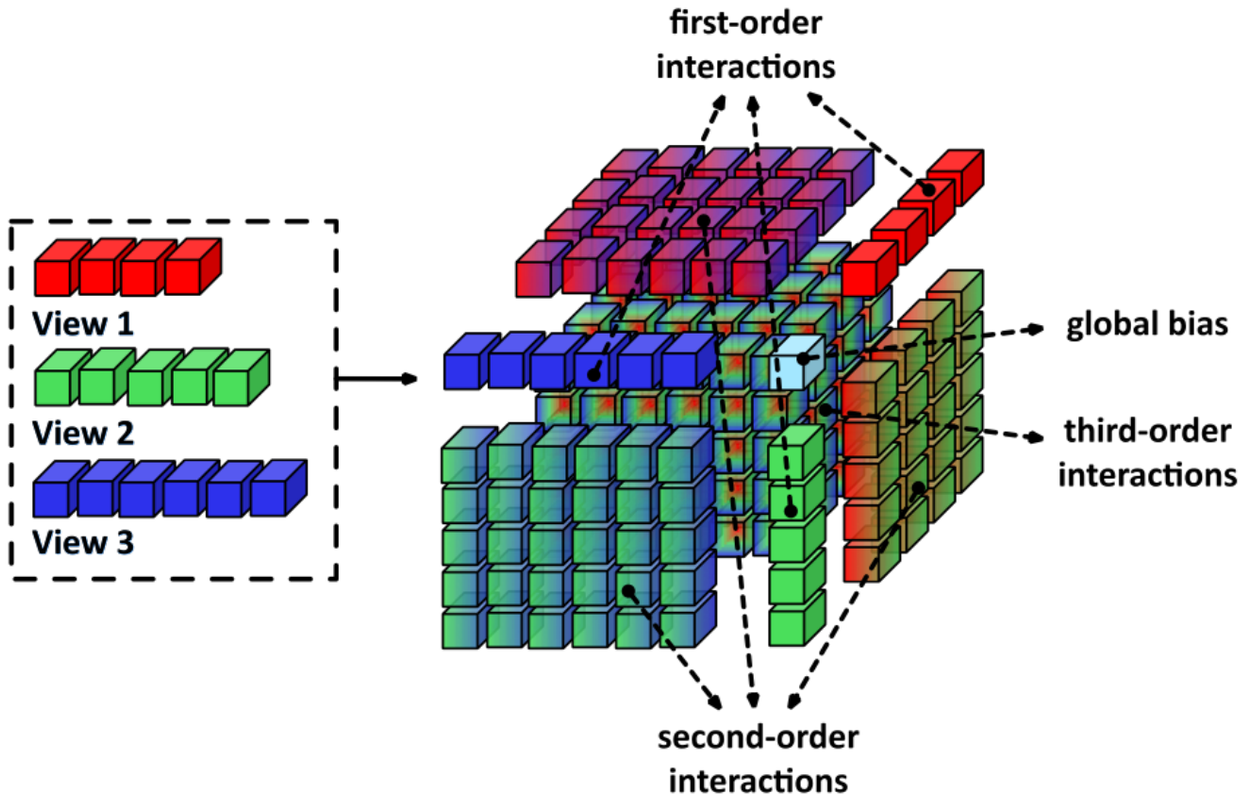
- Use separate parameters to approximate interactions in different orders.

- In practice, 2-way FM is usually used.



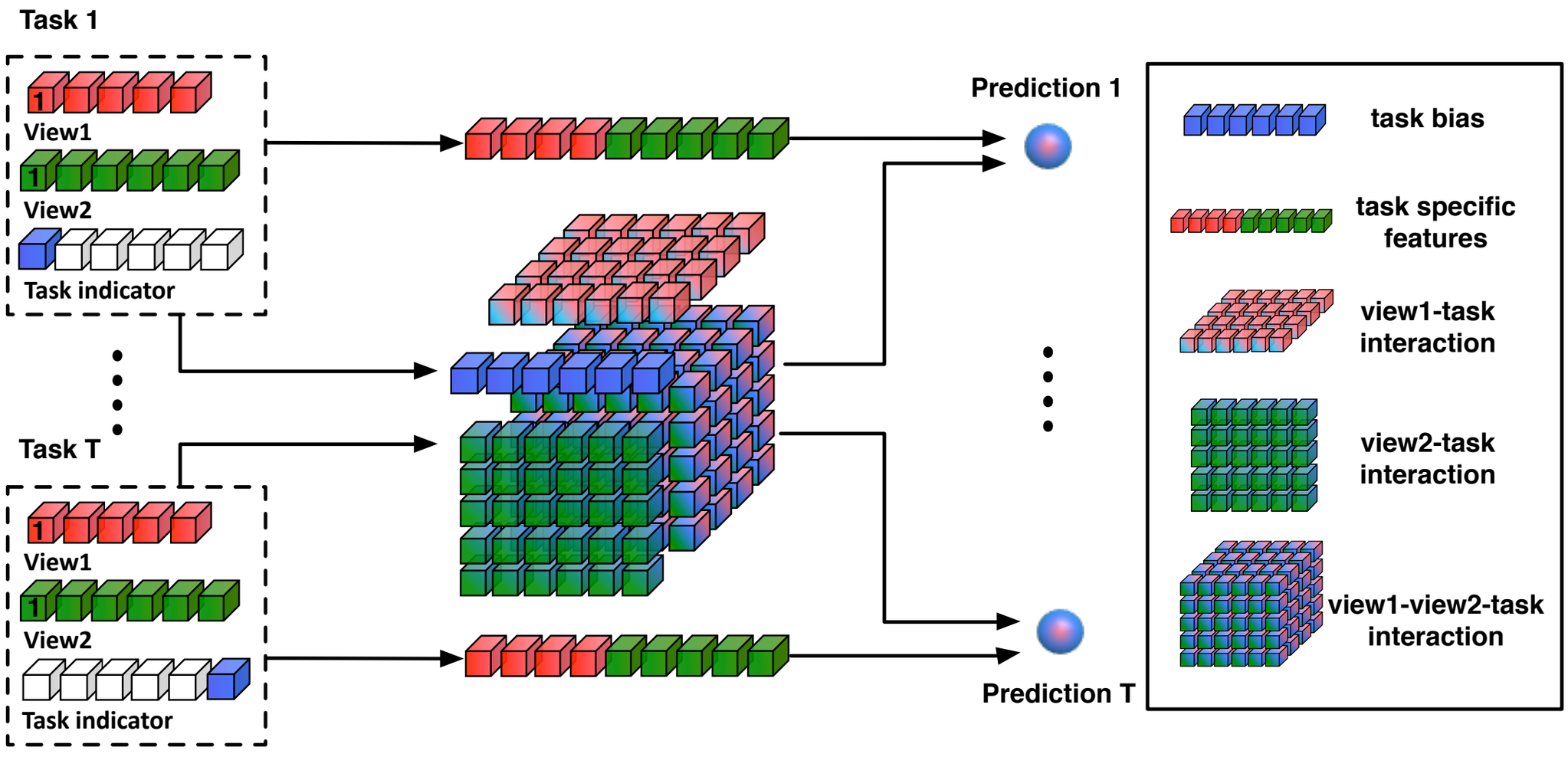
Multi-View Machines (MVM)

- Jointly model all interactions of every order.
- CP factorization on the weight tensor.



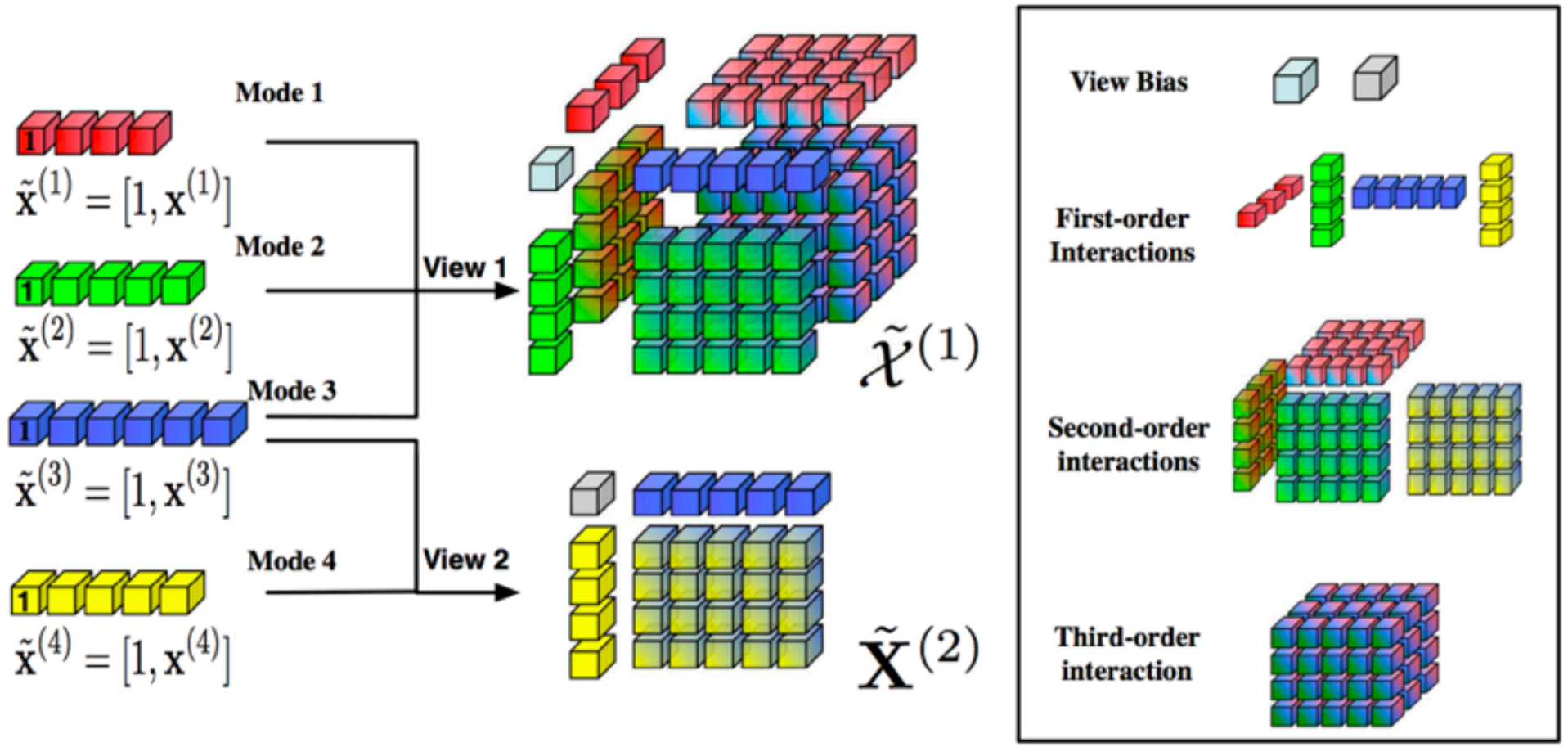
Multilinear Factorization Machines (MFM)

- Extend to multi-task learning.



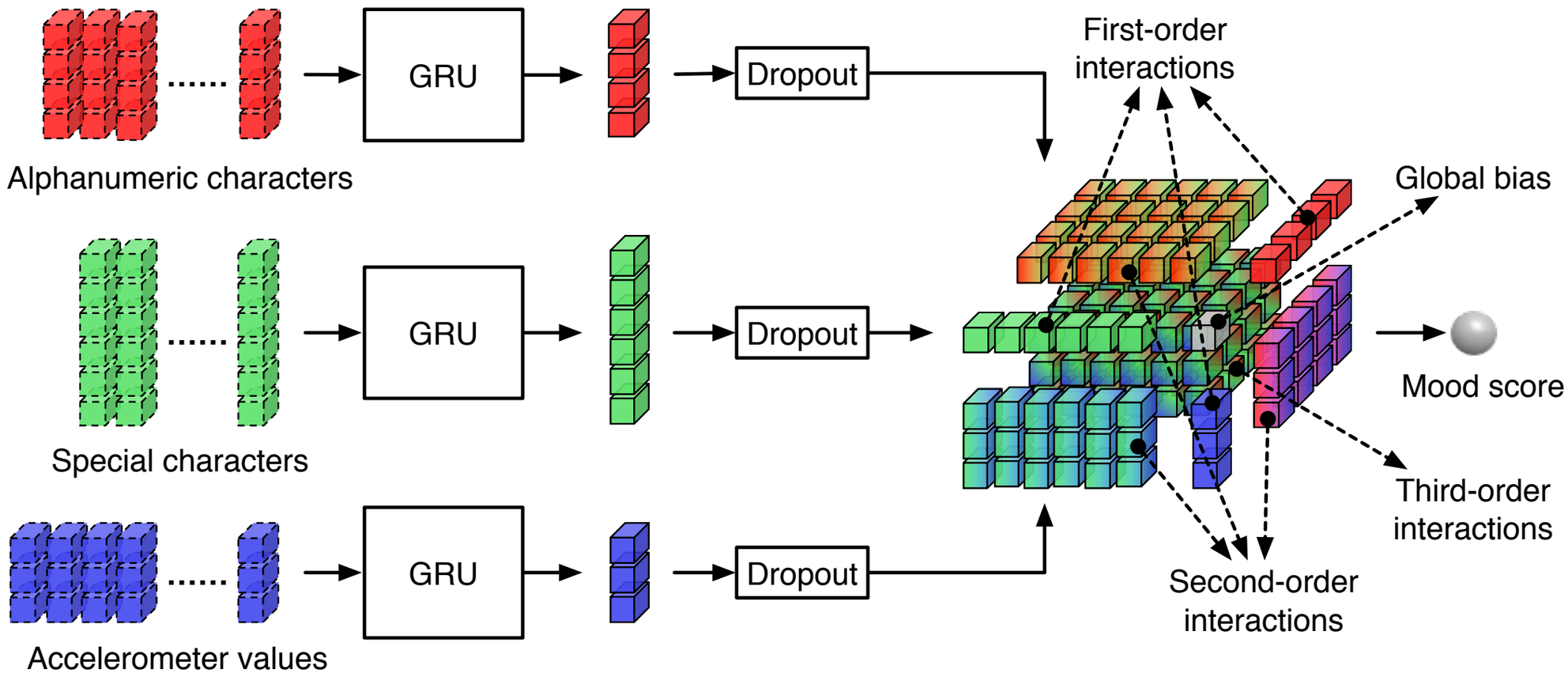
Structural Factorization Machines (SFM)

- Overlapping groups of views.



DeepMood

- Present a neural network view of FM and MVM.



Field-aware Factorization Machines (FFM)

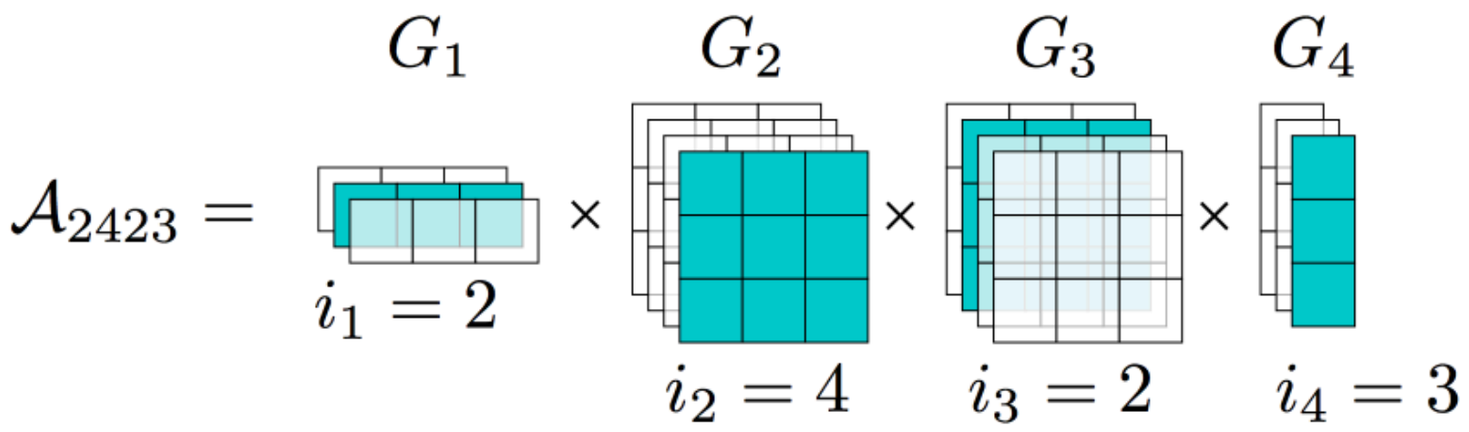
criteo

$$\phi_{\mathrm{FM}}(\boldsymbol{w}, \boldsymbol{x}) = \sum_{j_1=1}^{n} \sum_{j_2=j_1+1}^{n} (\boldsymbol{w}_{j_1} \cdot \boldsymbol{w}_{j_2}) x_{j_1} x_{j_2}$$

$$\phi_{\mathrm{FFM}}(\boldsymbol{w}, \boldsymbol{x}) = \sum_{j_1=1}^{n} \sum_{j_2=j_1+1}^{n} (\boldsymbol{w}_{j_1, f_2} \cdot \boldsymbol{w}_{j_2, f_1}) x_{j_1} x_{j_2}$$

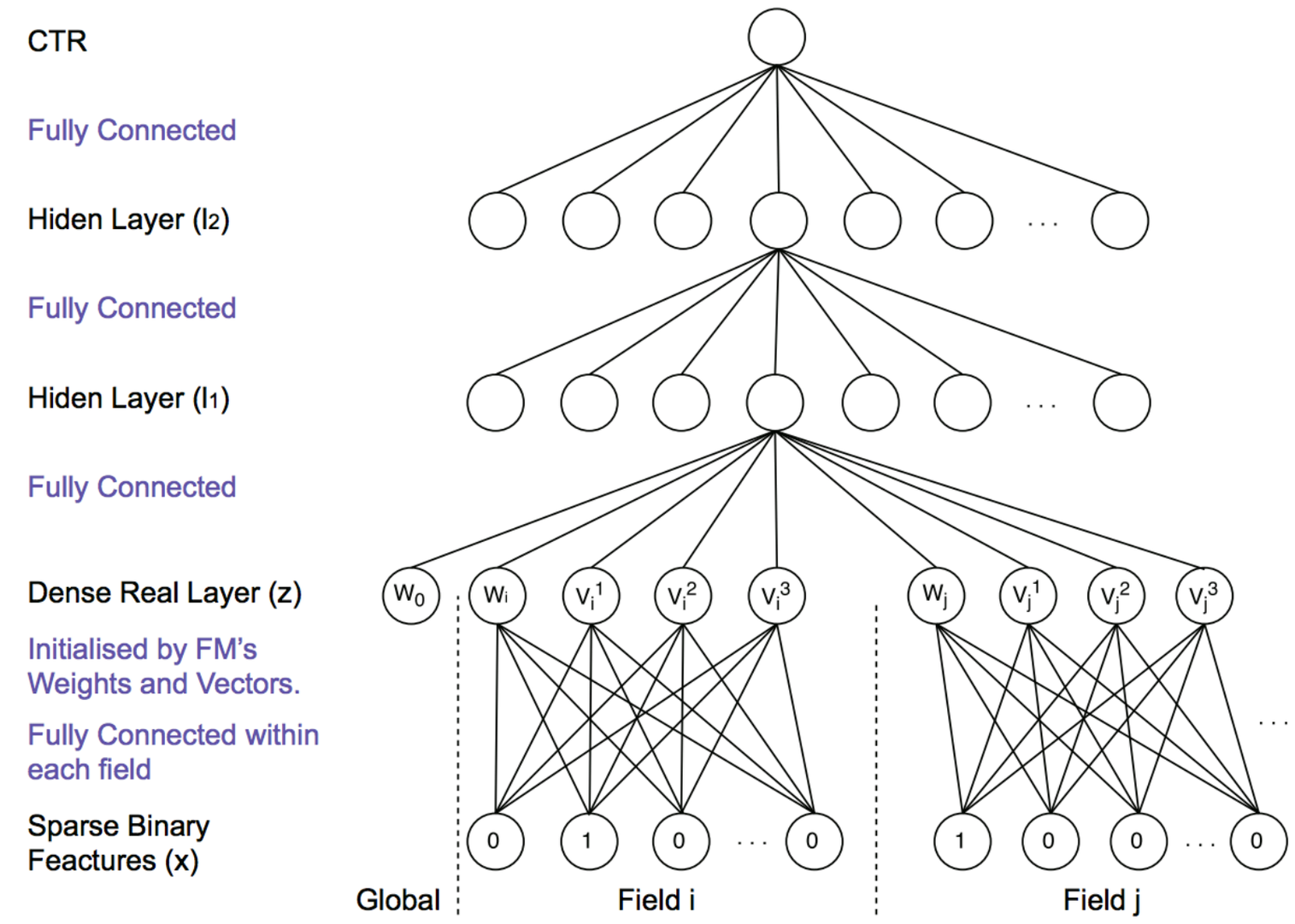
Exponential Machines (ExM)

- Model all interactions of every order.
- Represent the weight tensor in a factorized format called Tensor Train (TT).



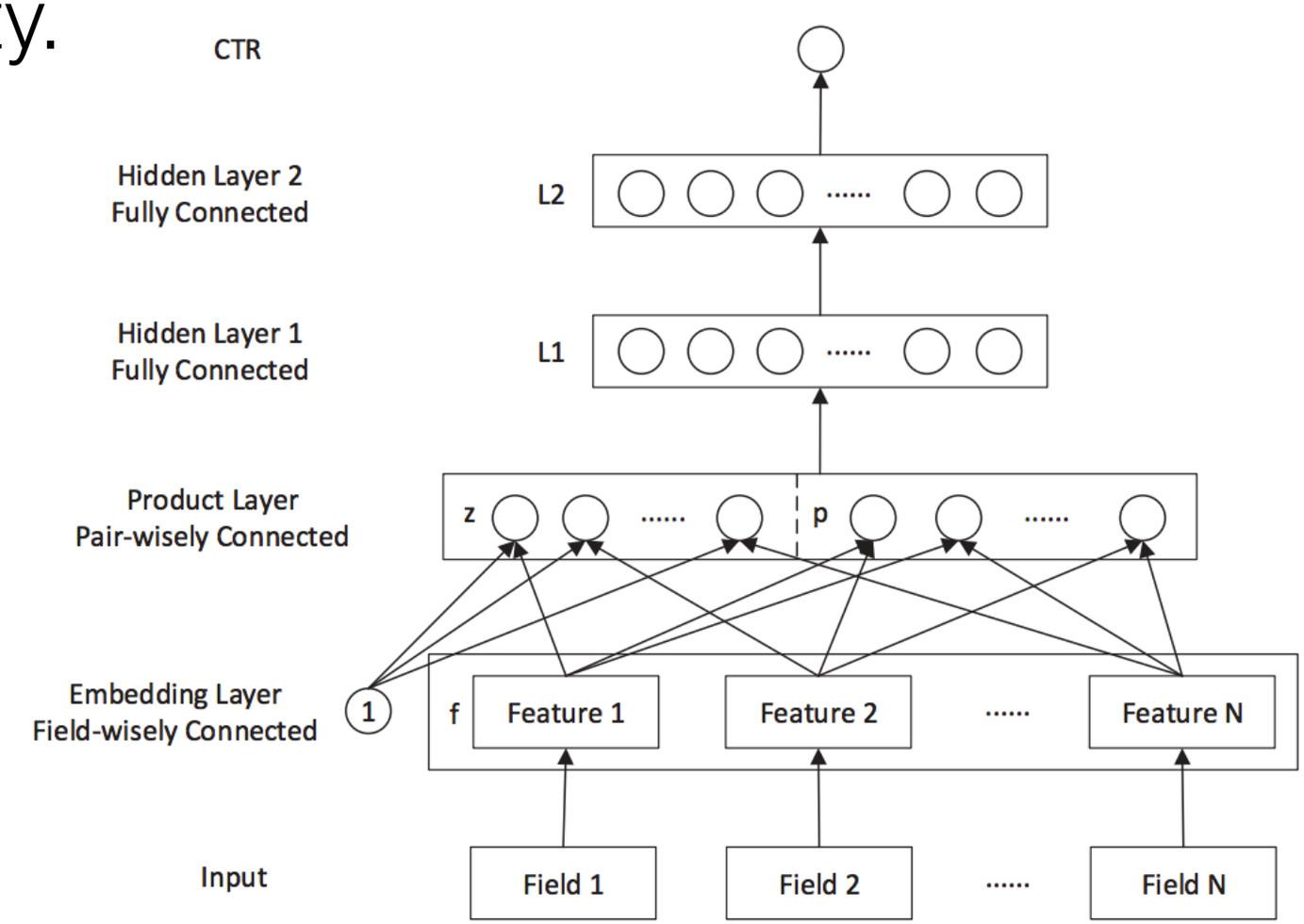
Factorization-Machine supported Neural Networks (FNN)

- Initialize the embedding layer by FM.



Product-based Neural Networks (PNN)

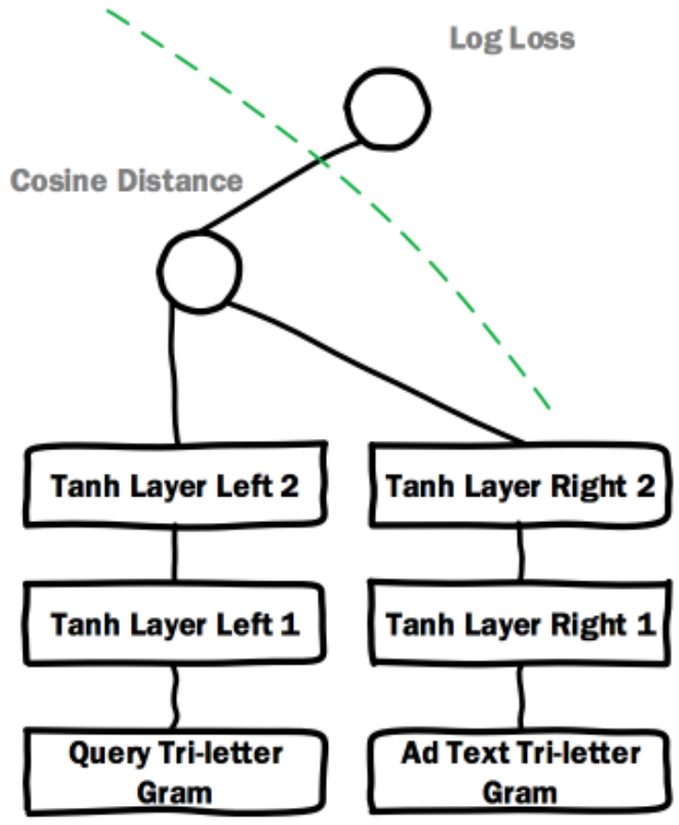
- Add a product layer to increase the model capacity.



Deep Semantic Similarity Model (DSSM)

Microsoft

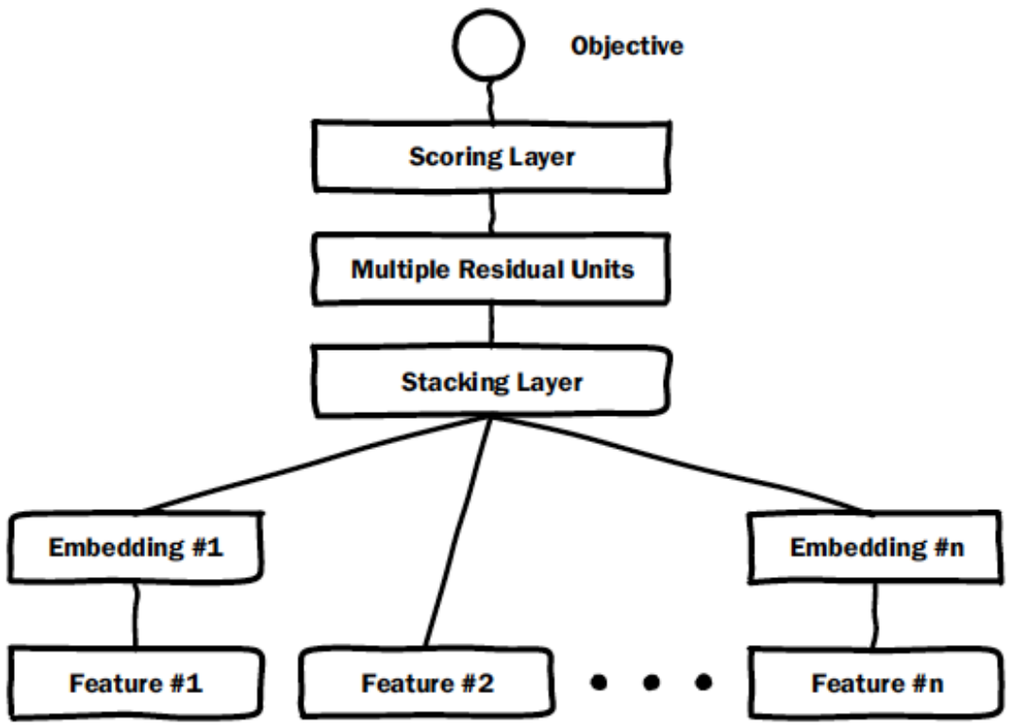
- Late crossing.



Deep Crossing

Microsoft

- Early crossing.

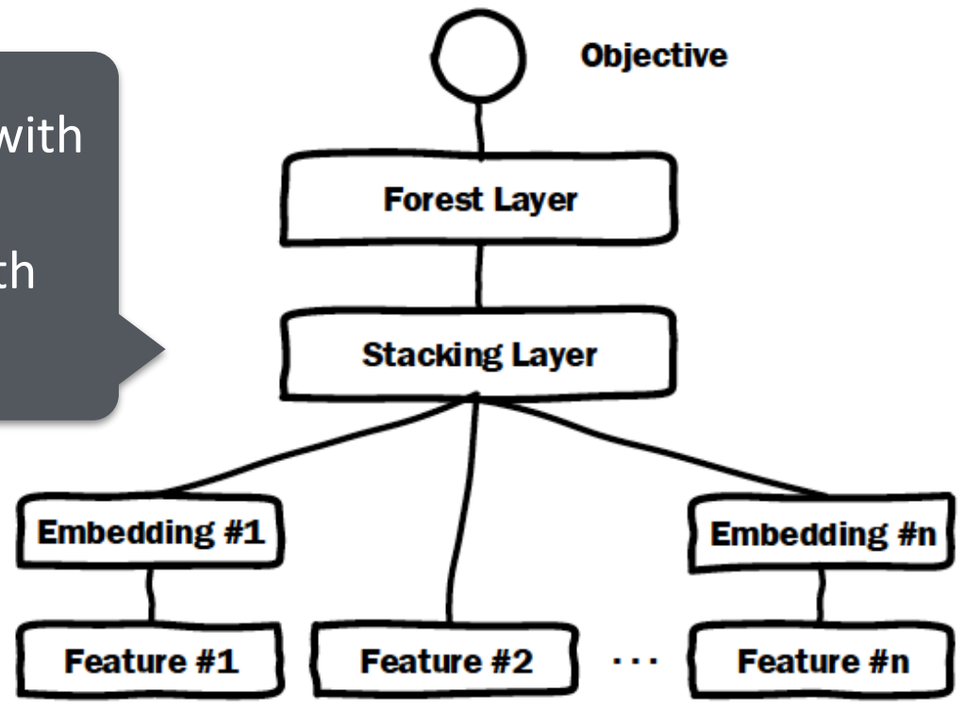


Deep Embedding Forest (DEF)

Microsoft

- Replace residual units in Deep Crossing with a forest/tree-like layer.

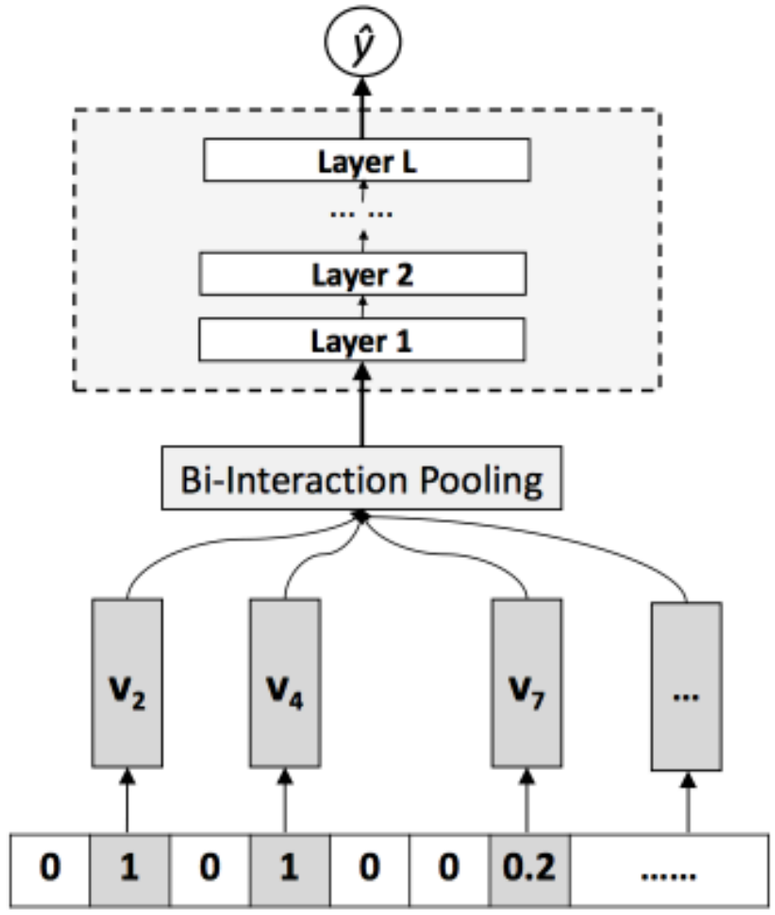
1.Initialize Embedding Layers with Deep Crossing.
2.Initialize the Forest Layer with XGBoost and LightGBM.



Neural Factorization Machines (NFM)

NUS National University of Singapore

- Replace the stacking layer in Deep Crossing with the Bi-Interaction pooling layer.



Prediction Score

Hidden Layers

B-Interaction Layer

Embedding Layer

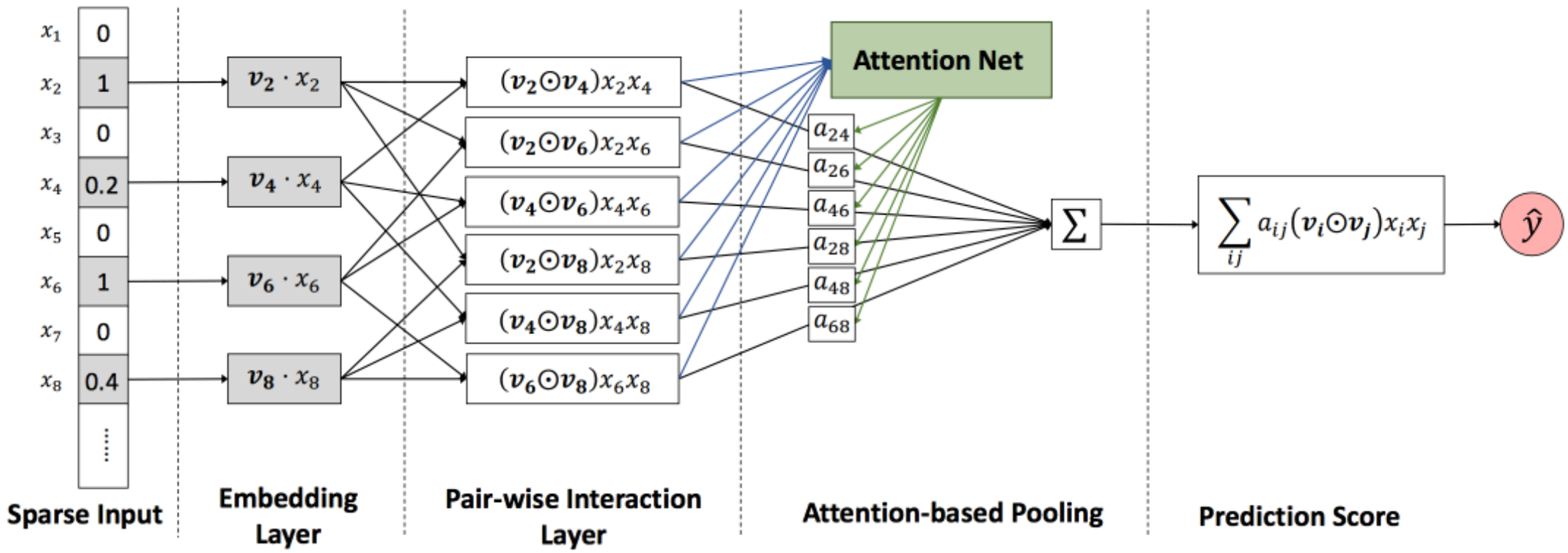
Input Feature Vector (sparse)

FM is a shallow and linear model, which can be seen as a special case of NFM with no hidden layer.

Attentional Factorization Machines (AFM)

- Apply the attention mechanism over the pair-wise interaction layer.

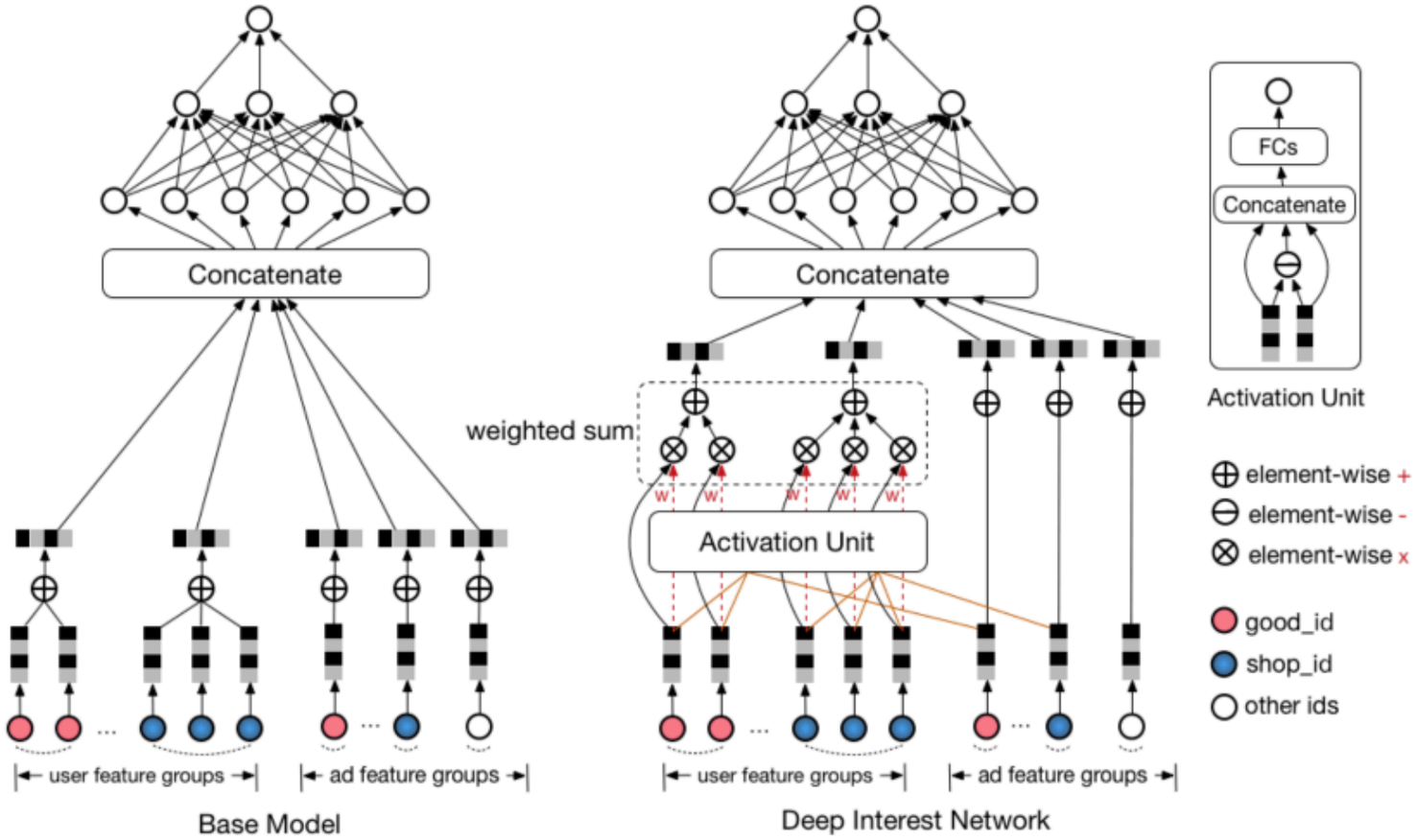
- The Bi-Interaction pooling layer can be seen as a sum pooling.



Deep Interest Network (DIN)

Alibaba Group

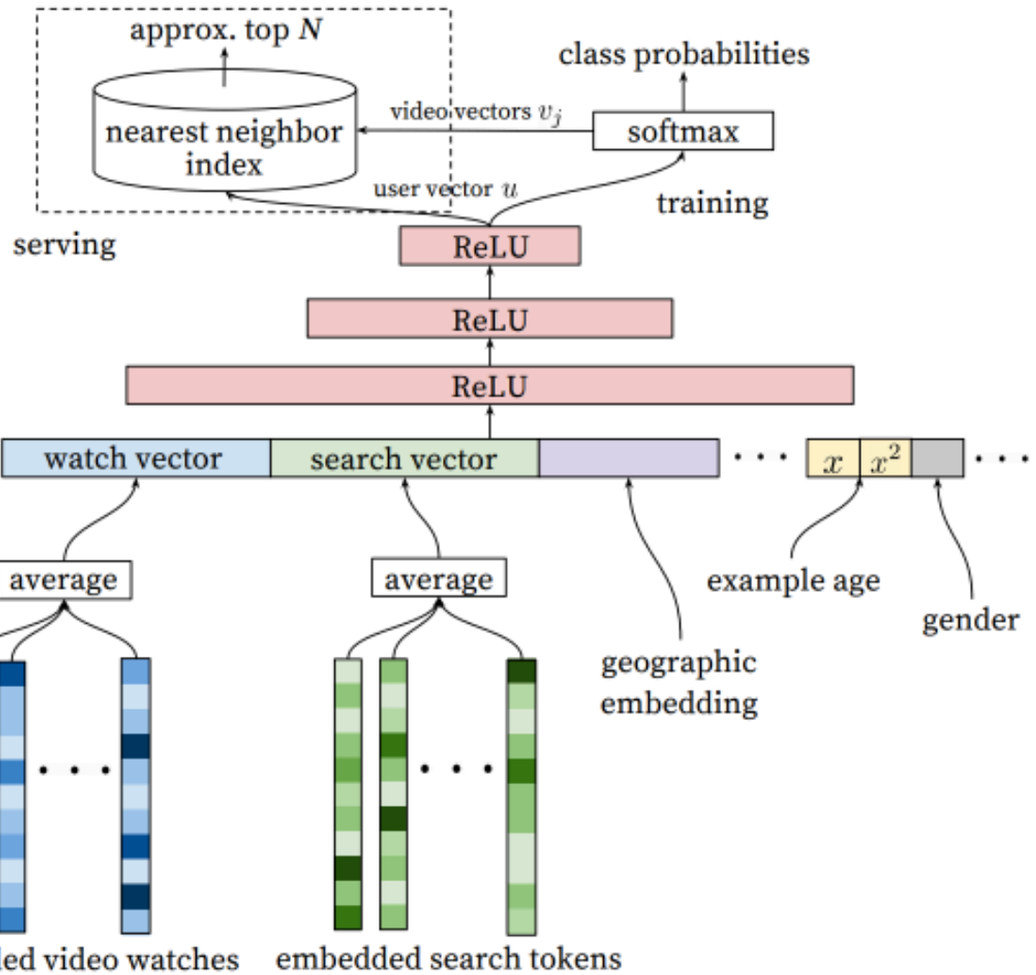
- The embedding vector of a user is a function of the embedding vector of an ad.



YouTube Recommendations

Google

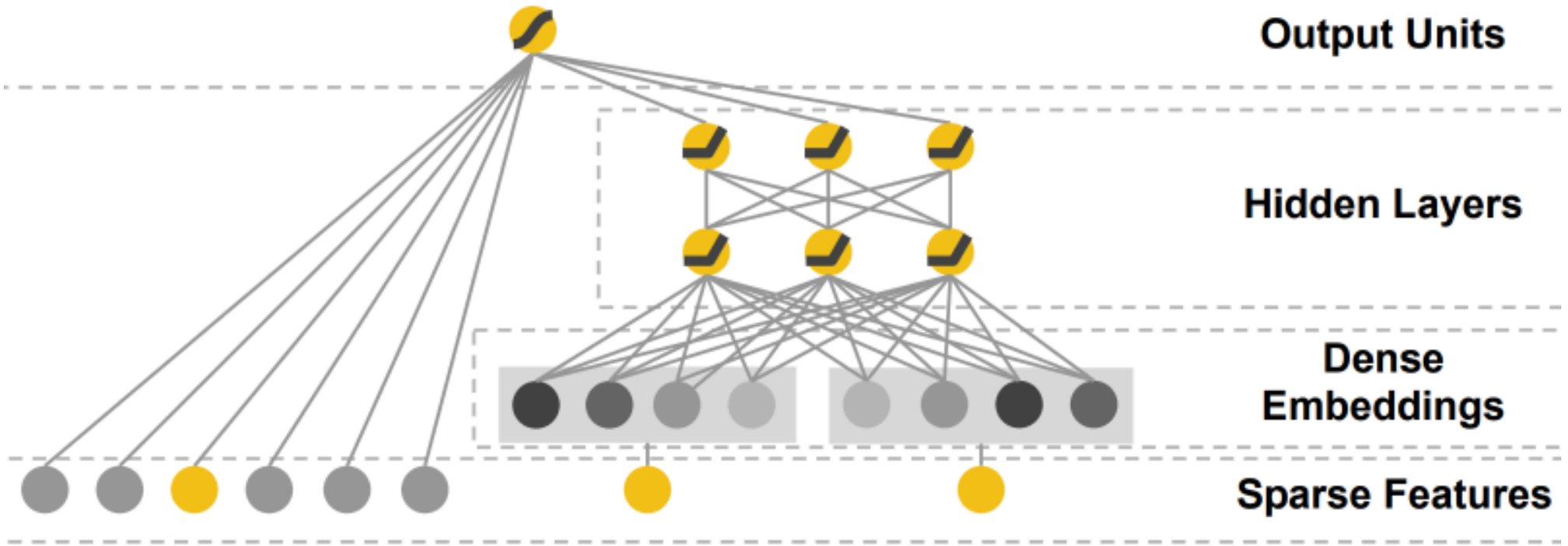
- Replace residual units in Deep Crossing with ReLu.



Wide & Deep Models

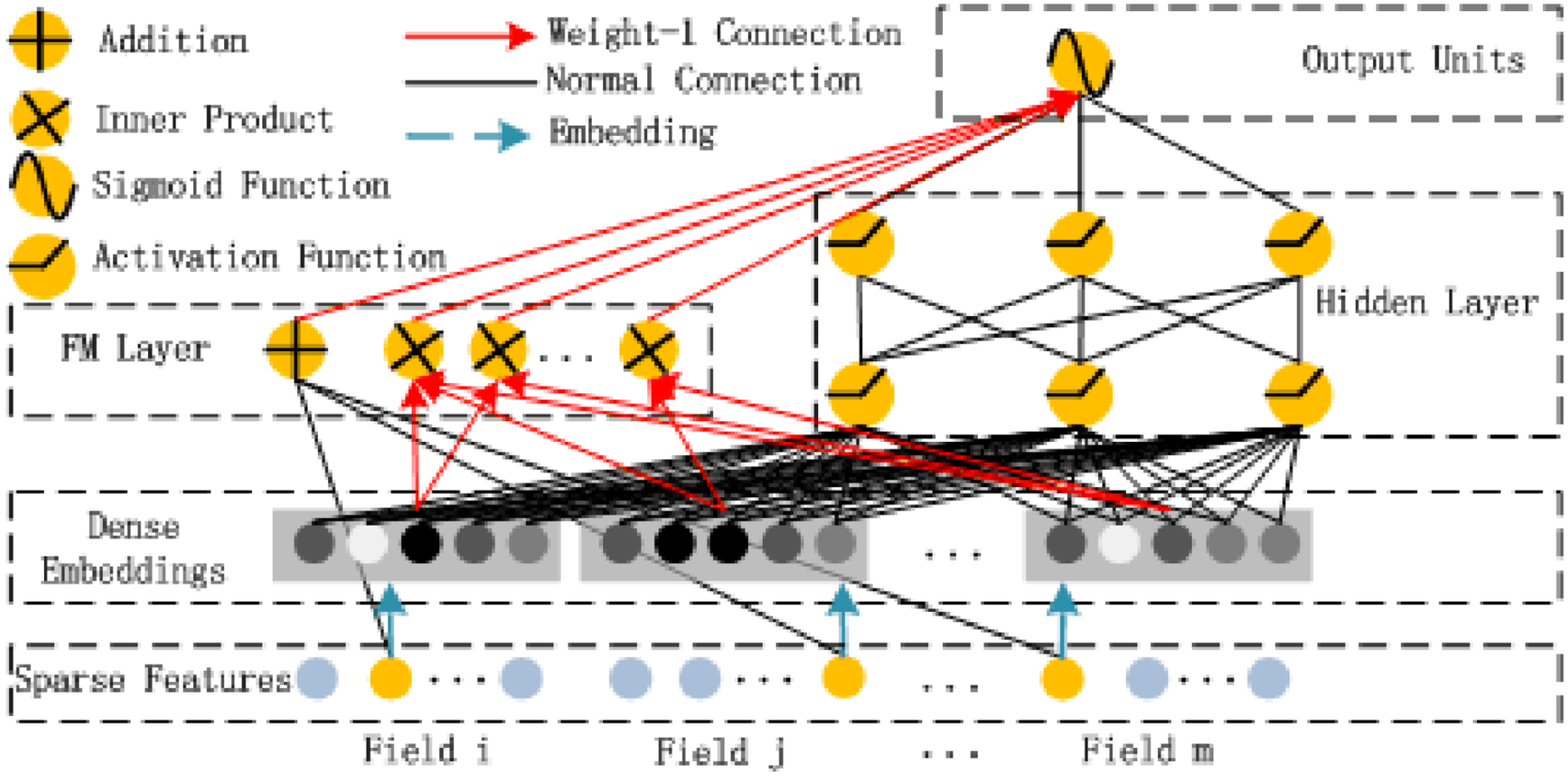
Google

- The wide part: cross features (memorization).
- The deep part: embedding layers (generalization).



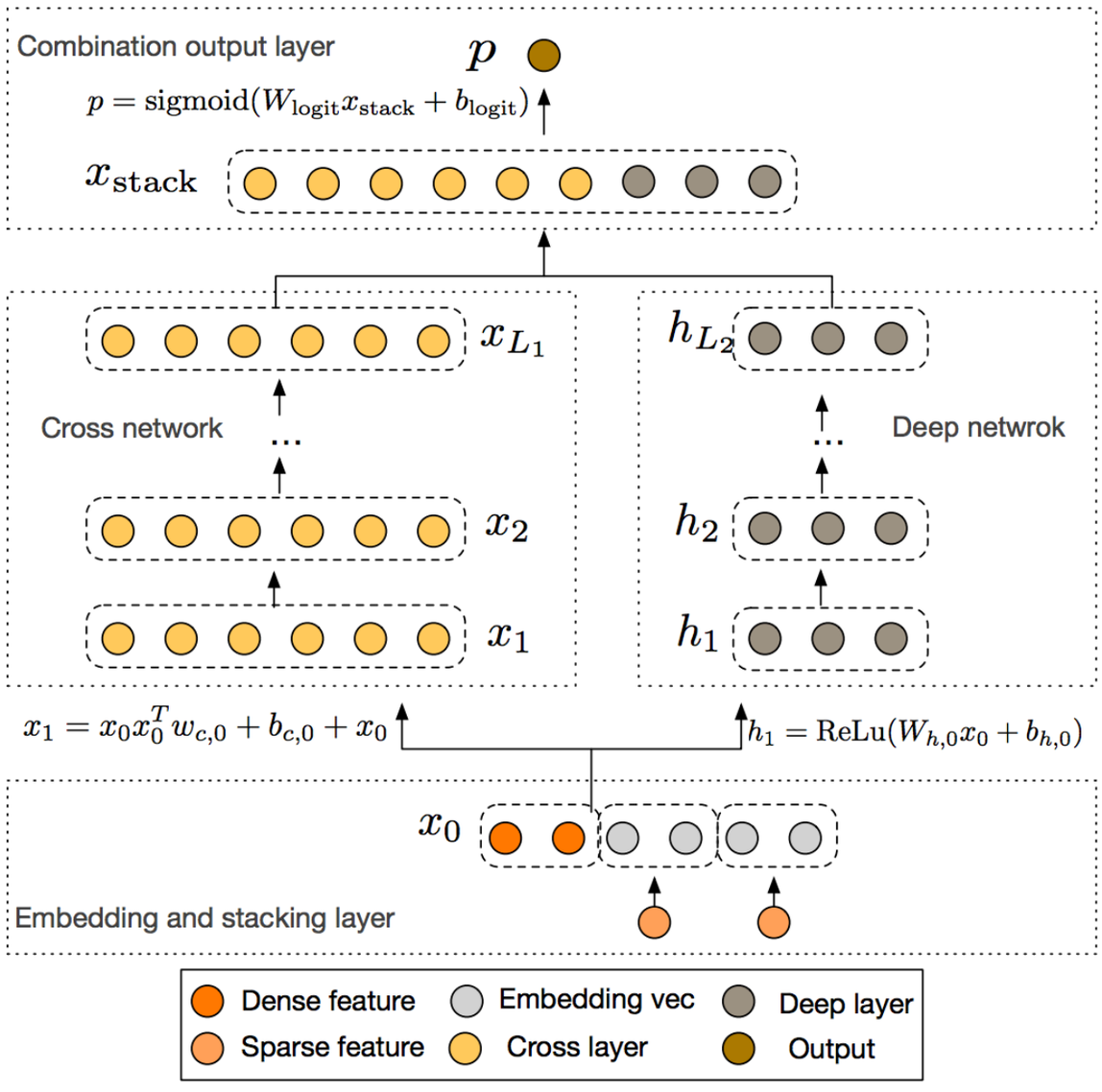
DeepFM

- Replace LR in Wide & Deep with FM.
- Share embeddings between the FM and deep part.



Deep & Cross Network (DCN)

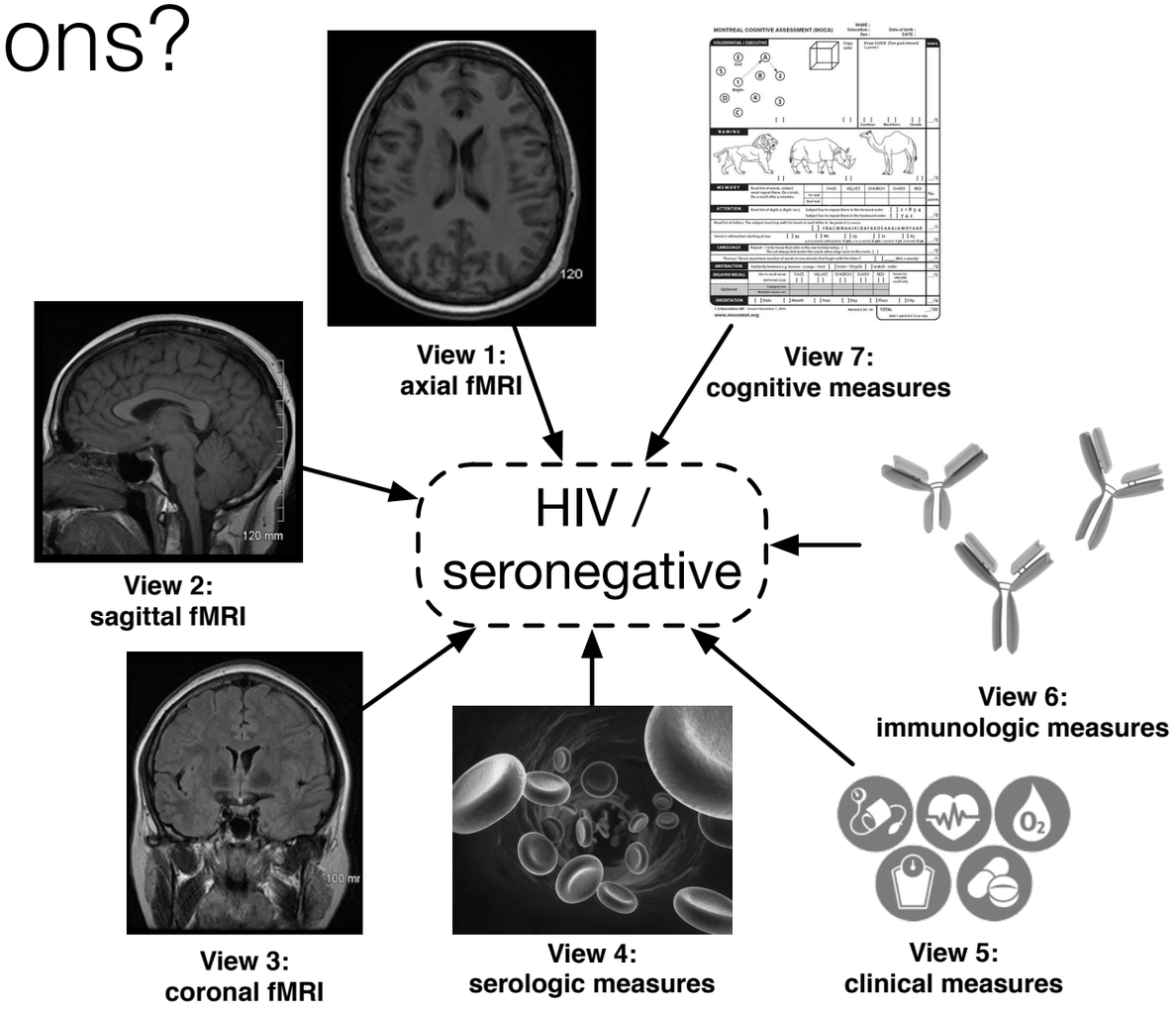
- Learn explicit cross features of bounded degree.



More on our works

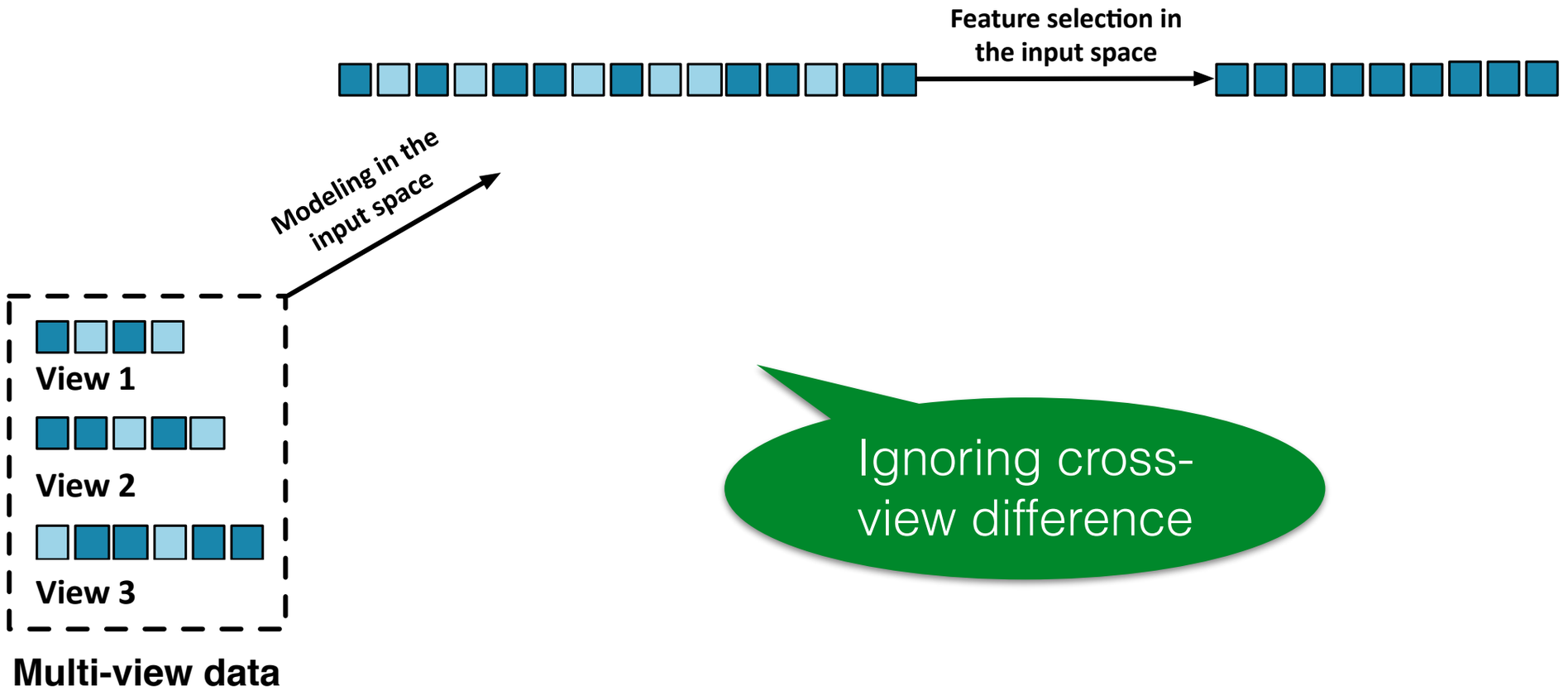
Problem Setting

- (P1) How can we select discriminative features from measures collected from different medical examinations?



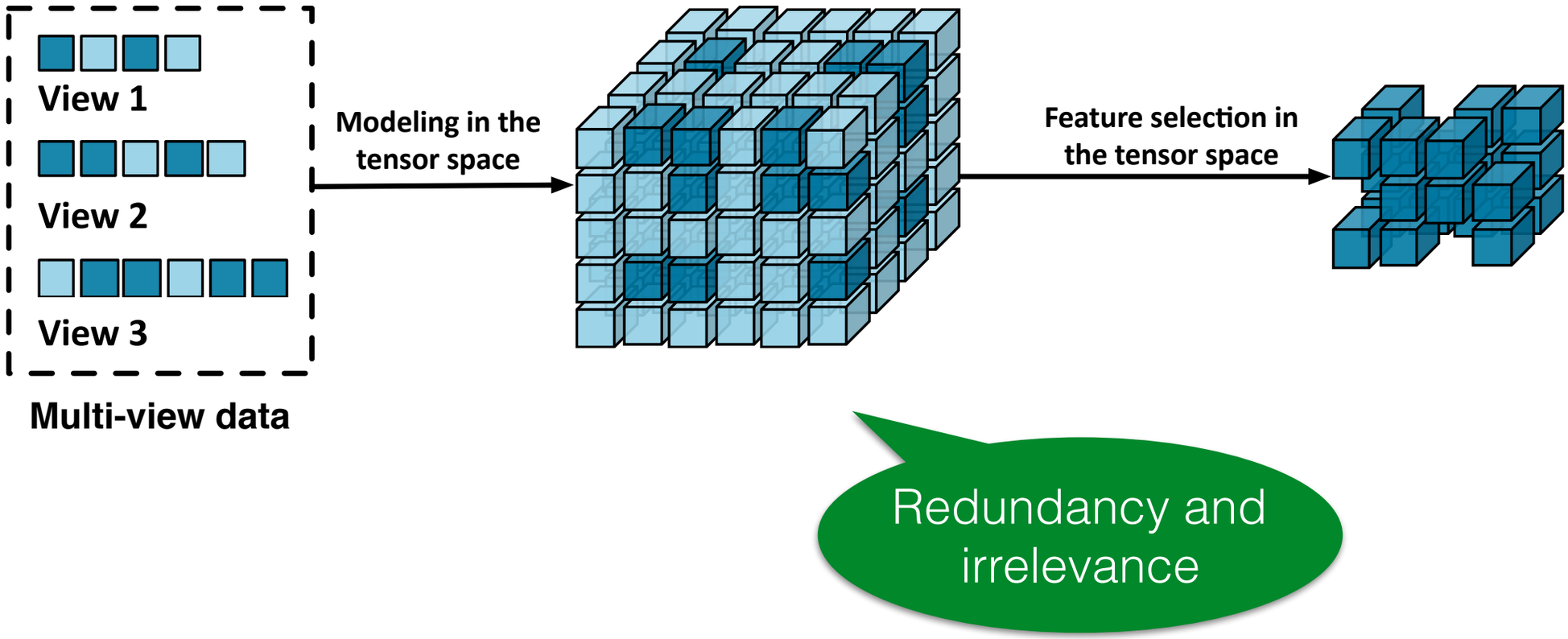
Modeling Multi-View Data

- Vector-based method.



Modeling Multi-View Data

- Tensor-based method.



Modeling Multi-View Data

- Input space.
  - Preserve the interpretability of original data.
  - Fail to explore feature interactions across different views.
- Tensor space.
  - Explore feature interactions across different views.
  - Introduce redundant and irrelevant features.

It motivates us to build a dual mapping between the ***input space*** and ***tensor space***.

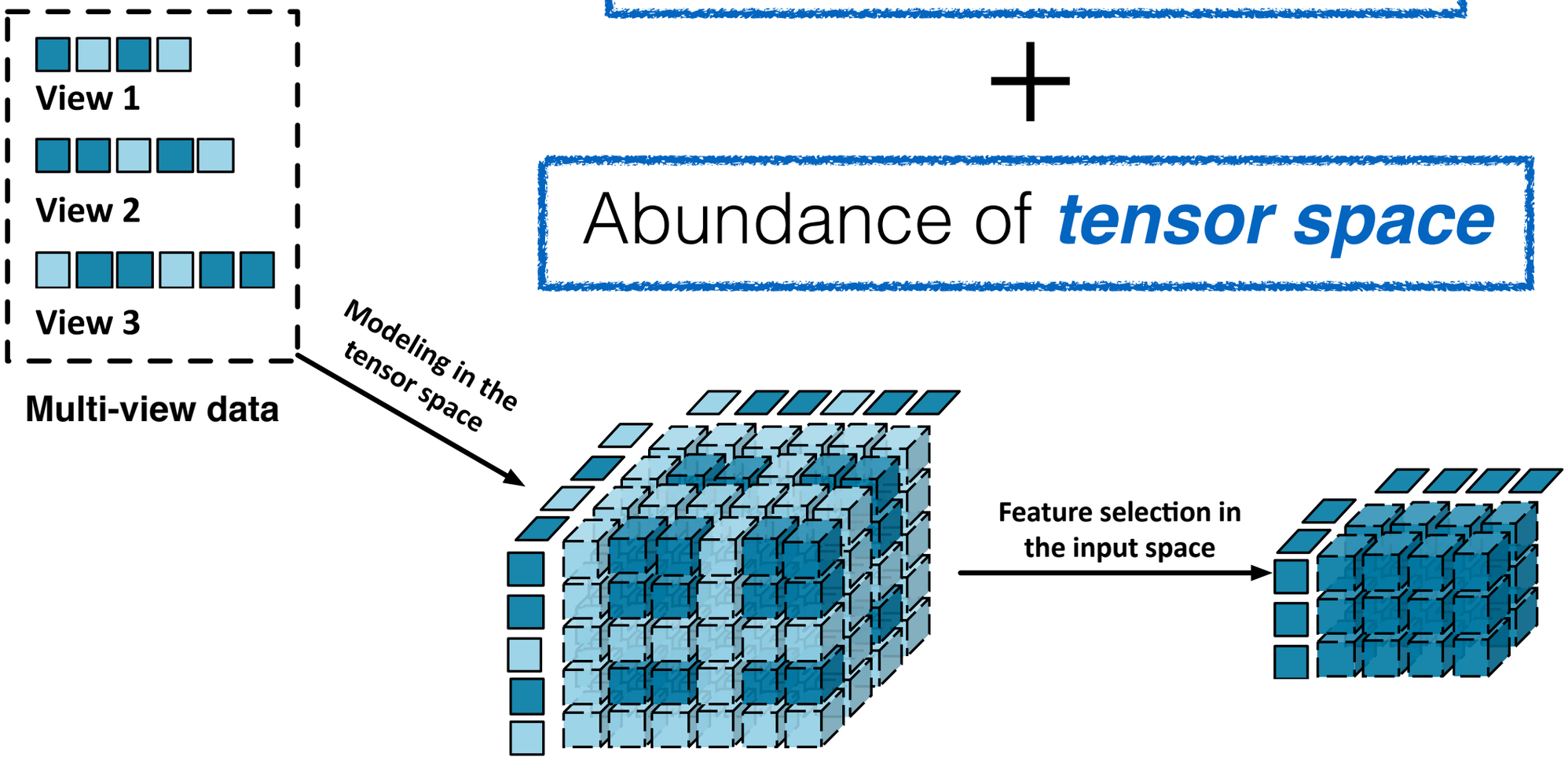
Modeling Multi-View Data

- Dual method.

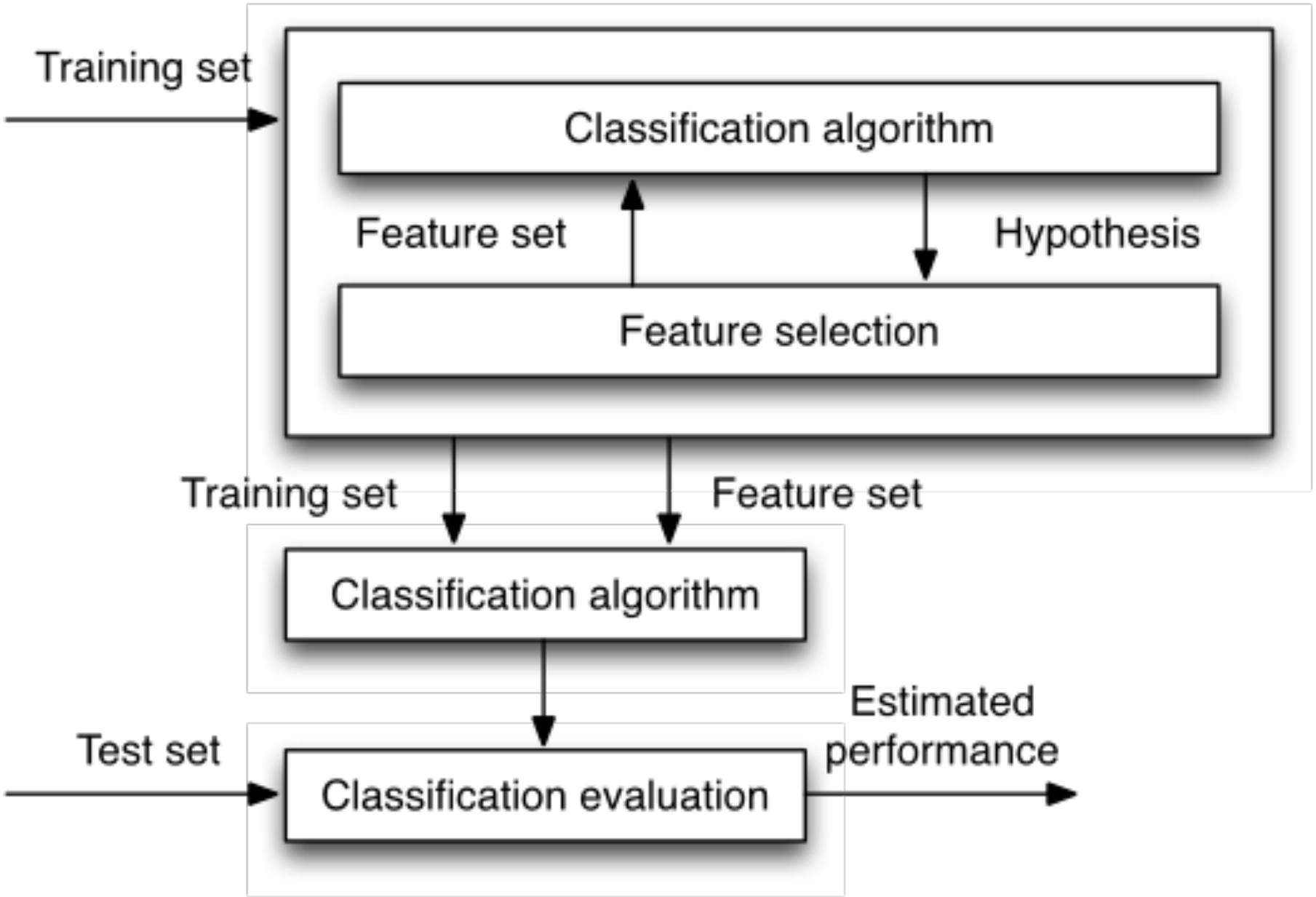
Simplicity of ***input space***

+

Abundance of ***tensor space***



Wrapper-based Feature Selection



Recursive Feature Elimination

- Feature ranking with ***Support Vector Machines***.

Train a SVM classifier

Weight vector $\mathbf{w} = \sum_i \alpha_i y_i \mathbf{x}_i$

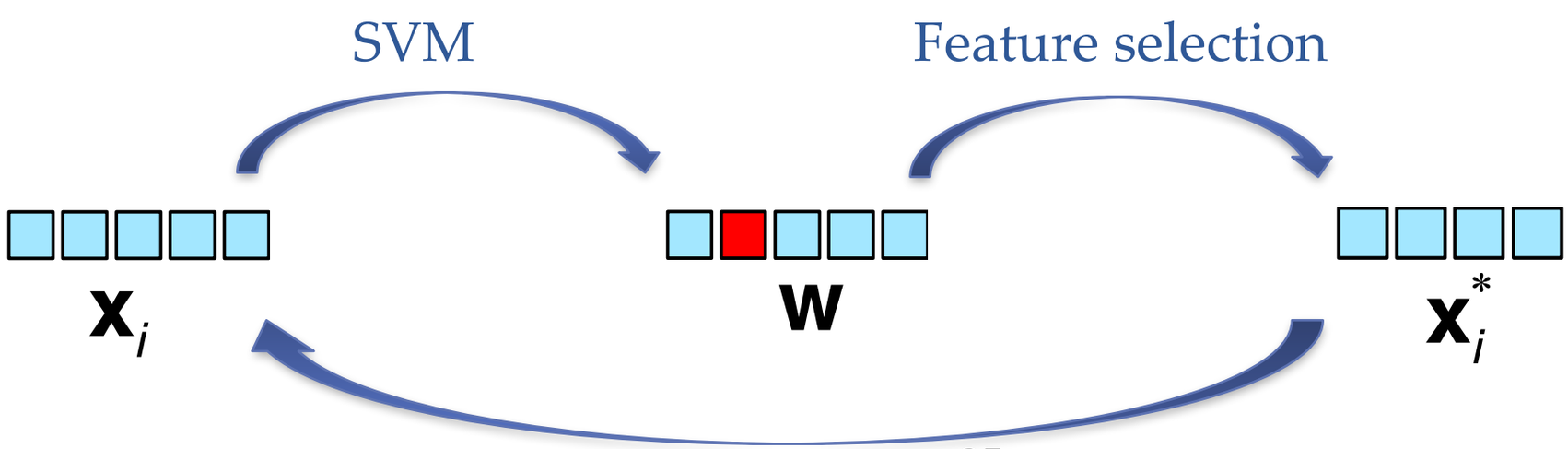
Ranking criteria $r_i = (w_i)^2$

Eliminate feature $\arg\min(\mathbf{r})$

Iteration

Guyon, Isabelle, et al. "Gene selection for cancer classification using support vector machines." Machine learning 46.1-3 (2002): 389-422.

SVM-RFE



Recursive Feature Elimination

- Feature ranking with ***Support Tensor Machines***.

Train a STM classifier $\mathcal{X} = \prod_{v=1}^{m} \circ \mathbf{x}^{(v)}$

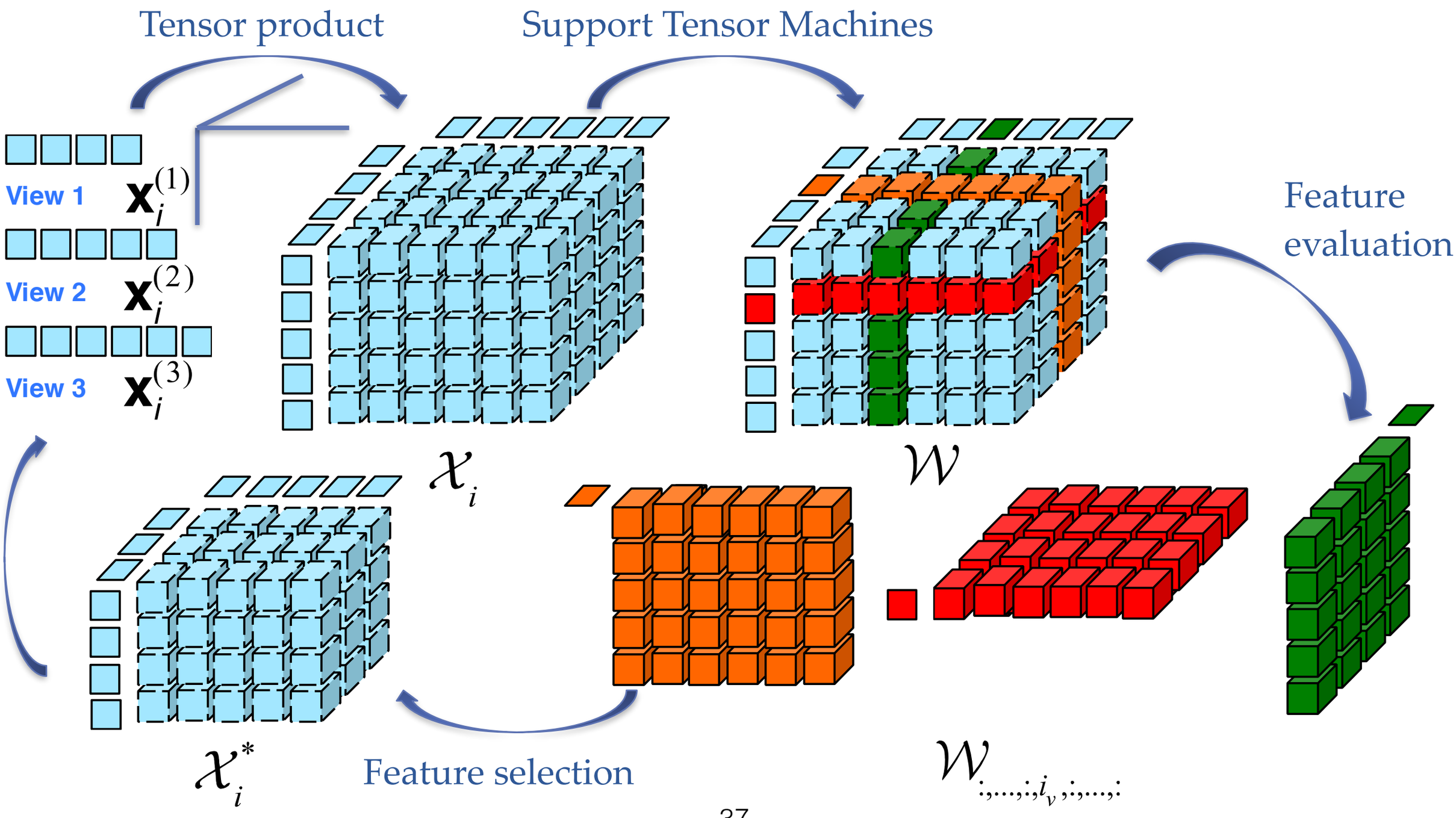
Weight tensor $\mathcal{W} = \sum_{i} \alpha_i y_i \mathcal{X}_i$

Ranking criteria $r_{i_v}^{(v)} = \sum_{i_1} \cdots \sum_{i_{v-1}} \sum_{i_{v+1}} \cdots \sum_{i_m} (w_{i_1,\cdots,i_m})^2$

Eliminate feature $\arg\min(\mathbf{r}^{(v)})$

Iteration

Tensor-based Multi-View Recursive Feature Elimination



Linear Kernel

Optimization objective

$$\min_{\mathbf{w}^{(v)},b,\xi} \frac{1}{2}\prod_{v=1}^{m}\left\|\mathbf{w}^{(v)}\right\|_F^2 + C\sum_{i=1}^{n}\xi_i$$

$$\text{s.t. } y_i\left(\prod_{v=1}^{m}\left\langle \mathbf{w}^{(v)}, \mathbf{x}_i^{(v)}\right\rangle + b\right) \geq 1-\xi_i$$

$$\xi_i \geq 0, \forall i = 1, \cdots, n.$$

$$f(\mathcal{X}) = \text{sign}\left(\prod_{v=1}^{m}\left\langle \mathbf{w}^{(v)}, \mathbf{x}^{(v)}\right\rangle + b\right)$$

$$\mathcal{W} = \prod_{v=1}^{m} \circ \mathbf{w}^{(v)}$$

Feature selection

$$\underset{i_v}{\text{argmin}}\left(r_{i_v}^{(v)}\right) \qquad r_{i_v}^{(v)} = \left(w_{i_v}^{(v)}\right)^2$$

$$r_{i_v}^{(v)} = \sum_{i_1}\cdots\sum_{i_{v-1}}\sum_{i_{v+1}}\cdots\sum_{i_m}\left(w_{i_1,\cdots,i_m}\right)^2$$

$$= \sum_{i_1}\cdots\sum_{i_{v-1}}\sum_{i_{v+1}}\cdots\sum_{i_m}\left(w_{i_1}^{(1)}\cdots w_{i_m}^{(m)}\right)^2$$

$$= \left(w_{i_v}^{(v)}\right)^2 \prod_{1\leq j\leq m}^{j\neq v}\left\|\mathbf{w}^{(j)}\right\|_F^2$$

$$= P^{(-v)}\left(w_{i_v}^{(v)}\right)^2$$

Extension to Nonlinear Kernels

Optimization objective

$$\min_{\alpha} \frac{1}{2}\alpha^{(v)T}\mathbf{H}\alpha^{(v)} - \alpha^{(v)T}\mathbf{1}$$

$$\text{s.t.} \sum_{i=1}^{n} \alpha_i^{(v)} y_i = 0$$

$$0 \le \alpha_i^{(v)} \le C, \forall i = 1, \cdots, n.$$

where $\mathbf{H}_{p,q} = y_p y_q \kappa(\mathbf{x}_p^{(v)'}, \mathbf{x}_q^{(v)'})$

$$P^{(-v)} = \prod_{1 \le j \le m}^{j \ne v} \|\mathbf{w}^{(j)}\|_F^2$$

$$Q_i^{(-v)} = \prod_{1 \le j \le m}^{j \ne v} \langle \mathbf{w}^{(j)}, \mathbf{x}_i^{(j)} \rangle$$

Feature selection

$$\underset{i_v}{\text{argmin}} \left(r_{i_v}^{(v)} \right)$$

$$r_{i_v}^{(v)} = \frac{1}{2}(\alpha^{(v)T}\mathbf{H}\alpha^{(v)} - \alpha^{(v)T}\mathbf{H}(-i_v)\alpha^{(v)})$$

where

$$\mathbf{H}_{p,q}(-i_v) = y_p y_q \kappa(\mathbf{x}_p^{(v)'}(-i_v), \mathbf{x}_q^{(v)'}(-i_v))$$

$$\mathbf{x}_i^{(v)'} = (Q_i^{(-v)}/\sqrt{P^{(-v)}})\mathbf{x}_i^{(v)}$$

Input:

- Training examples in multiple views:
  $\mathfrak{X}^{(v)} = \{\mathbf{x}_1^{(v)}, \cdots, \mathbf{x}_n^{(v)}\}, v = 1, 2, \cdots, m$
- Class labels: $\mathfrak{Y} = \{y_1, \cdots, y_n\}$
- Number of features selected in each view: p_v

Initialize:

- Subset of surviving features: $\mathbf{s}^{(v)} = [1, 2, \cdots, I_v]$

Iterate through each view v**:**

Repeat until length($\mathbf{s}^{(v)}$) $\leq p_v$

- Restrict training examples to good feature indices:
  $\mathfrak{X}^{(v)*} = \mathfrak{X}^{(v)}(\mathbf{s}^{(v)}, :)$
- Train the classifier: $\alpha = \text{SVM-TRAIN}(\mathfrak{X}^{(v)*}, \mathfrak{Y})$
- Compute the weight vector $\mathbf{w}^{(v)}$ according to Eq. (26)
- Compute the ranking criteria $\mathbf{r}^{(v)}$ according to Eq. (18)
- Find the feature with smallest ranking criterion:
  $f = \arg\min(\mathbf{r}^{(v)})$
- Eliminate the feature with smallest ranking criterion:
  $\mathbf{s}^{(v)} = \mathbf{s}^{(v)}(1{:}f\text{-}1, f{+}1{:}\text{length}(\mathbf{s}^{(v)}))$

Output:

- Subset of selected features in each view:
  $\mathbf{s}^{(v)}, v = 1, 2, \cdots, m$

The Next

- To use other loss functions.
- To include lower-order feature interactions.
- To extend to higher rank weight decomposition.

$$\mathcal{W} = \prod_{v=1}^{m} \circ \mathbf{w}^{(v)} \rightarrow \mathcal{W} = \sum_{r=1}^{R} \prod_{v=1}^{m} \circ \mathbf{w}^{(v)}$$

$$\hat{y}(x) := w_0 + \sum_{i=1}^{n} w_i \, x_i + \sum_{l=2}^{d} \sum_{i_1=1}^{n} \cdots \sum_{i_l=i_{l-1}+1}^{n} \left(\prod_{j=1}^{l} x_{i_j} \right) \left(\sum_{f=1}^{k_l} \prod_{j=1}^{l} v_{i_j,f}^{(l)} \right)$$

FM?

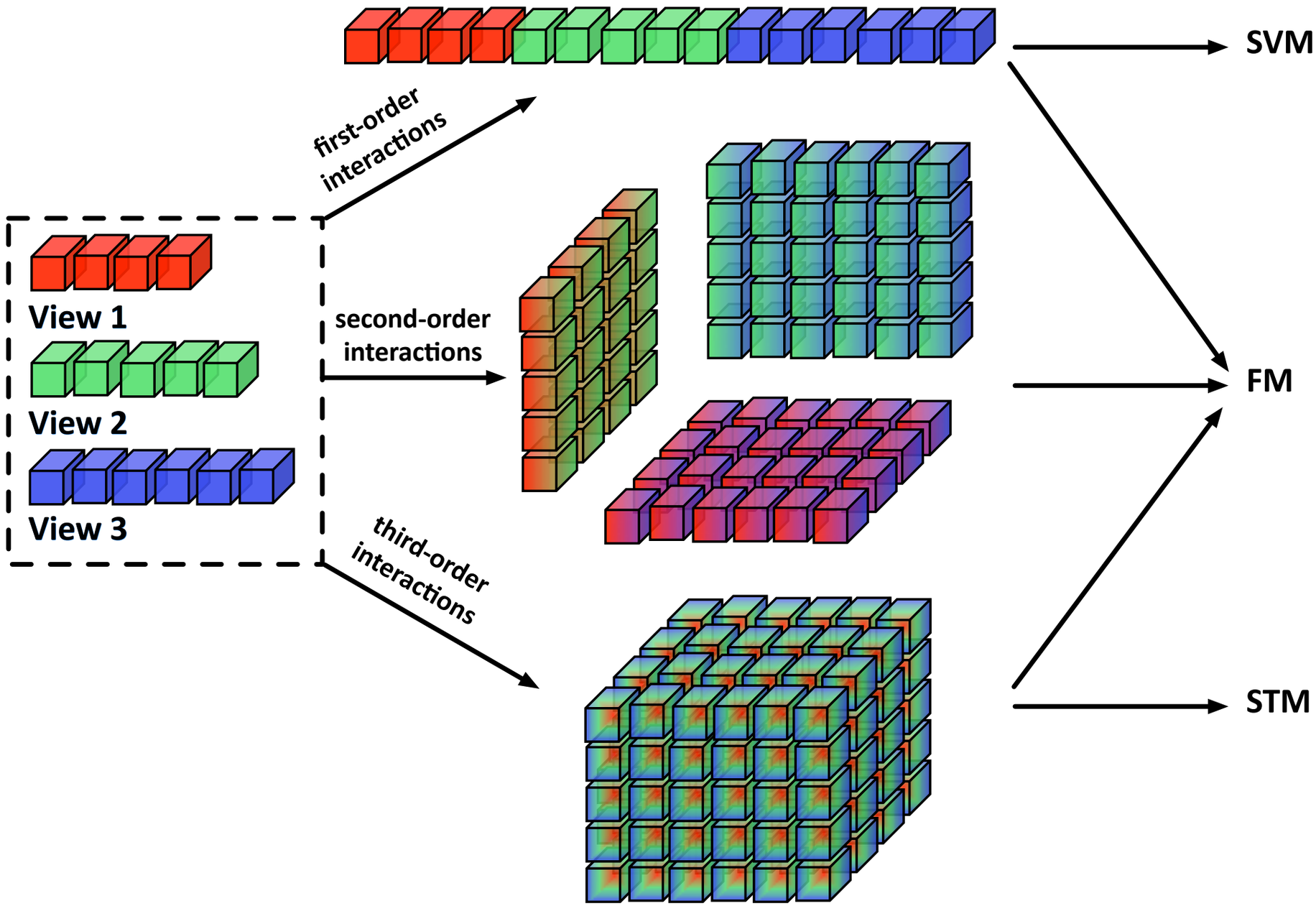
Problem Setting

- (P2) How can we predict the click through rate given a tuple (user, ad, query)?

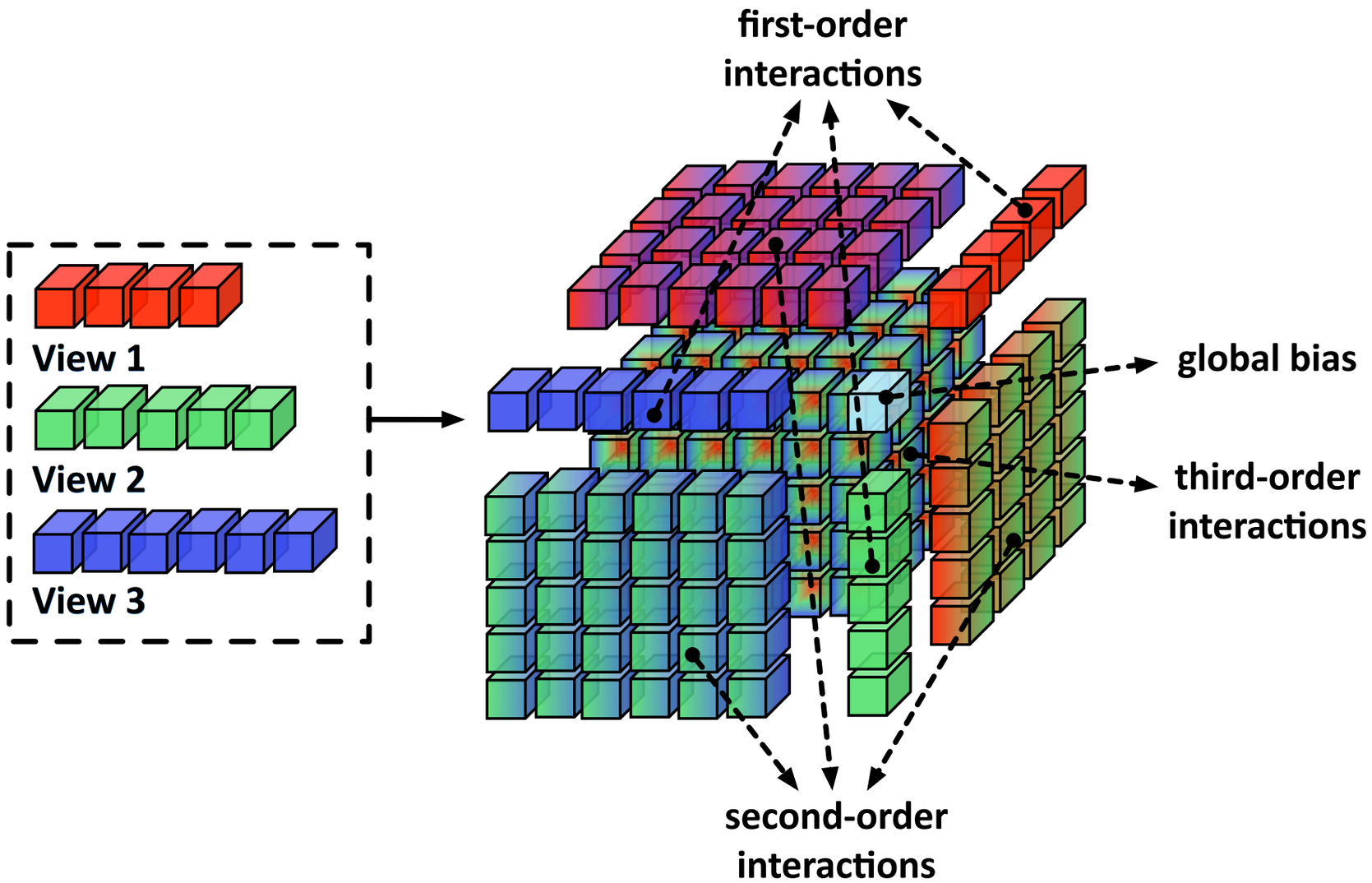
Table 1: An example showing the discrepancy between feature interactions with different orders. $\#1 = user + ad + query$, $\#2 = user \times ad + user \times query + ad \times query$, $\#3 = user \times ad \times query$.

User	Ad	Query	#1	#2	#3
1.20 (+)	1.80 (+)	0.50 (+)	3.50 (+)	3.66 (+)	1.08 (+)
1.20 (+)	1.80 (+)	-0.50 (-)	2.50 (+)	0.66 (+)	-1.08 (-)
1.20 (+)	-1.80 (-)	-0.50 (-)	-1.10 (-)	-1.86 (-)	1.08 (+)

Related Works



Multi-View Machines (MVM)



- Include the full-order interactions across multi-view features.
- Jointly factorize the interaction parameters in different orders.

$$\hat{y} = \underbrace{\beta_0}_{\text{global bias}} + \underbrace{\sum_{p=1}^{m} \sum_{i_p=1}^{I_p} \beta_{i_p}^{(p)} x_{i_p}^{(p)}}_{\text{first-order interactions}}$$

$$+ \underbrace{\sum_{i_1=1}^{I_1} \sum_{i_2=1}^{I_2} \beta_{i_1,i_2}^{(1,2)} x_{i_i}^{(1)} x_{i_2}^{(2)} + \cdots + \sum_{i_{m-1}=1}^{I_{m-1}} \sum_{i_m=1}^{I_m} \beta_{i_{m-1},i_m}^{(m-1,m)} x_{i_{m-1}}^{(m-1)} x_{i_m}^{(m)}}_{\text{second-order interactions}}$$

$$+ \cdots + \underbrace{\sum_{i_1=1}^{I_1} \cdots \sum_{i_m=1}^{I_m} \beta_{i_1,\ldots,i_m} \left(\prod_{p=1}^{m} x_{i_p}^{(p)} \right)}_{m\text{th-order interactions}}$$

$$\hat{y} = \underbrace{\beta_0}_{\text{global bias}} + \underbrace{\sum_{p=1}^{m}\sum_{i_p=1}^{I_p}\beta_{i_p}^{(p)}x_{i_p}^{(p)}}_{\text{first-order interactions}}$$

$$+\underbrace{\sum_{i_1=1}^{I_1}\sum_{i_2=1}^{I_2}\beta_{i_1,i_2}^{(1,2)}x_{i_i}^{(1)}x_{i_2}^{(2)}+\cdots+\sum_{i_{m-1}=1}^{I_{m-1}}\sum_{i_m=1}^{I_m}\beta_{i_{m-1},i_m}^{(m-1,m)}x_{i_{m-1}}^{(m-1)}x_{i_m}^{(m)}}_{\text{second-order interactions}}$$

$$+\cdots+\underbrace{\sum_{i_1=1}^{I_1}\cdots\sum_{i_m=1}^{I_m}\beta_{i_1,\ldots,i_m}\left(\prod_{p=1}^{m}x_{i_p}^{(p)}\right)}_{m\text{th-order interactions}}$$

$$\mathbf{z}^{(p)^T} = (\mathbf{x}^{(p)^T}, 1) \in \mathbb{R}^{I_p+1}, \forall p = 1, ..., m$$

$$\hat{y} = \sum_{i_1=1}^{I_1+1}\cdots\sum_{i_m=1}^{I_m+1} w_{i_1,\ldots,i_m}\left(\prod_{p=1}^{m}z_{i_p}^{(p)}\right)$$

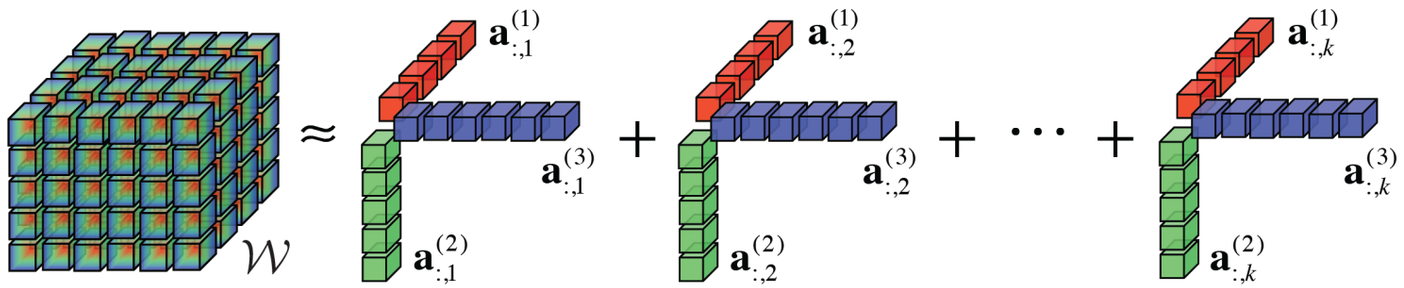
$$\hat{y} = \underbrace{\beta_0}_{\text{global bias}} + \underbrace{\sum_{p=1}^{m}\sum_{i_p=1}^{I_p}\beta_{i_p}^{(p)}x_{i_p}^{(p)}}_{\text{first-order interactions}}$$

$$+\underbrace{\sum_{i_1=1}^{I_1}\sum_{i_2=1}^{I_2}\beta_{i_1,i_2}^{(1,2)}x_{i_i}^{(1)}x_{i_2}^{(2)} + \cdots + \sum_{i_{m-1}=1}^{I_{m-1}}\sum_{i_m=1}^{I_m}\beta_{i_{m-1},i_m}^{(m-1,m)}x_{i_{m-1}}^{(m-1)}x_{i_m}^{(m)}}_{\text{second-order interactions}}$$

$$+\cdots+\underbrace{\sum_{i_1=1}^{I_1}\cdots\sum_{i_m=1}^{I_m}\beta_{i_1,\ldots,i_m}\left(\prod_{p=1}^{m}x_{i_p}^{(p)}\right)}_{m\text{th-order interactions}}$$

$$\mathbf{z}^{(p)^T} = (\mathbf{x}^{(p)^T}, 1) \in \mathbb{R}^{I_p+1}, \forall p = 1, ..., m$$

$$\hat{y} = \sum_{i_1=1}^{I_1+1}\cdots\sum_{i_m=1}^{I_m+1}w_{i_1,\ldots,i_m}\left(\prod_{p=1}^{m}z_{i_p}^{(p)}\right)$$



$$\mathcal{W} = \mathbf{C} \times_1 \mathbf{A}^{(1)} \times_2 \cdots \times_m \mathbf{A}^{(m)}$$

$$\hat{y} = \sum_{i_1=1}^{I_1+1}\cdots\sum_{i_m=1}^{I_m+1}\left(\prod_{p=1}^{m}z_{i_p}^{(p)}\right)\left(\sum_{f=1}^{k}\prod_{p=1}^{m}a_{i_p,f}^{(p)}\right)$$

Experimental Setup

- **Datasets**.
  - MovieLens: users (138,493), movies (27,278) and implicit feedback (27,278).
  - BingAds: queries (958,426), ads (1,935,510) and impressions (18).
- **Baselines**.
  - Linear regression/logistic regression (LR), tensor factorization (TF) and multi-view FMs (mvFM, mvFM-3d, mvFM-reg).
- **Implementation**.
  - AdaGrad, GraphX in Spark with iterative forward and backward steps.
  - Code available at https://goo.gl/Mi4aPx.

Experimental Result

Table 5: Prediction accuracy. ↓ indicates the smaller the value the better the performance; ↑ indicates the larger the value the better the performance.

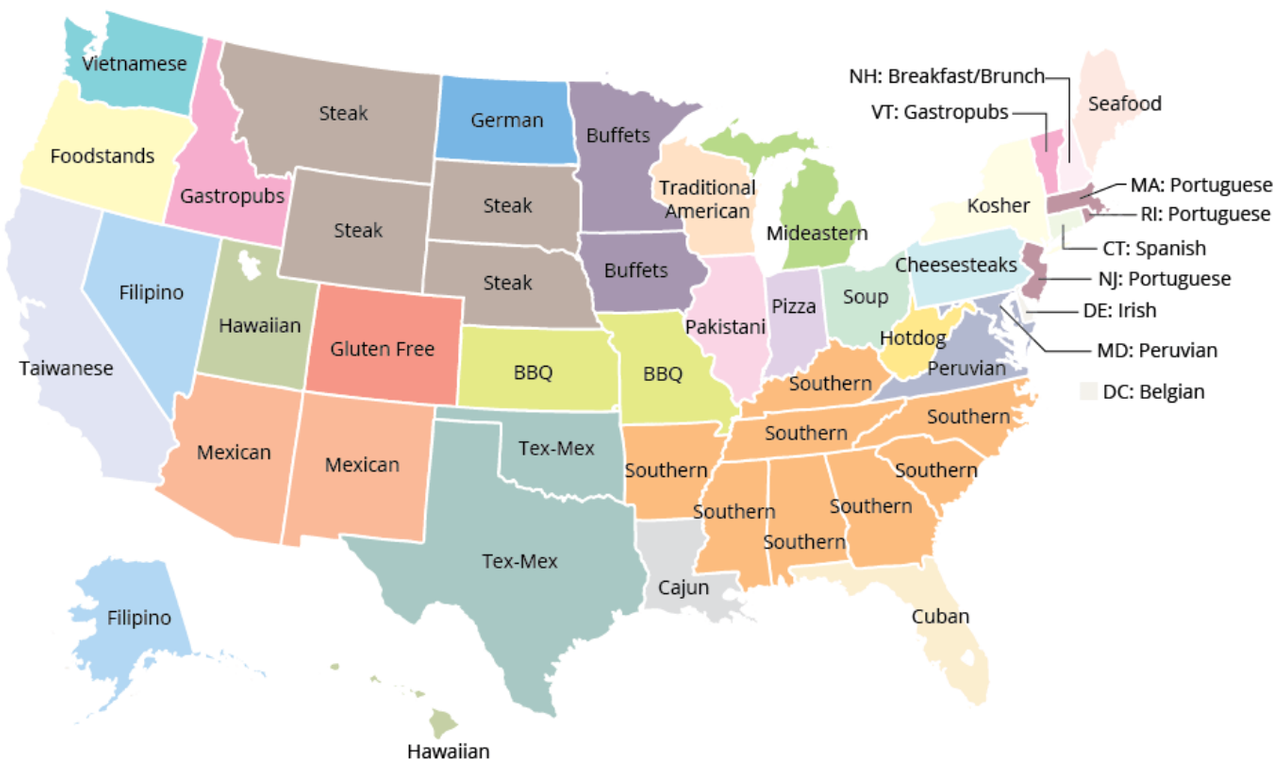
Dataset	MovieLens (RMSE) ↓	BingAds (AUC) ↑
MVM	0.8376	0.7917
FM	0.8681	0.7872
mvFM	0.8447	0.7729
mvFM-3d	0.9060	0.7201
mvFM-reg	0.9807	0.6947
TF	0.8572	0.6645
LR	1.0017	0.7450

The Next

- To explore shared feature interactions for multi-task learning.

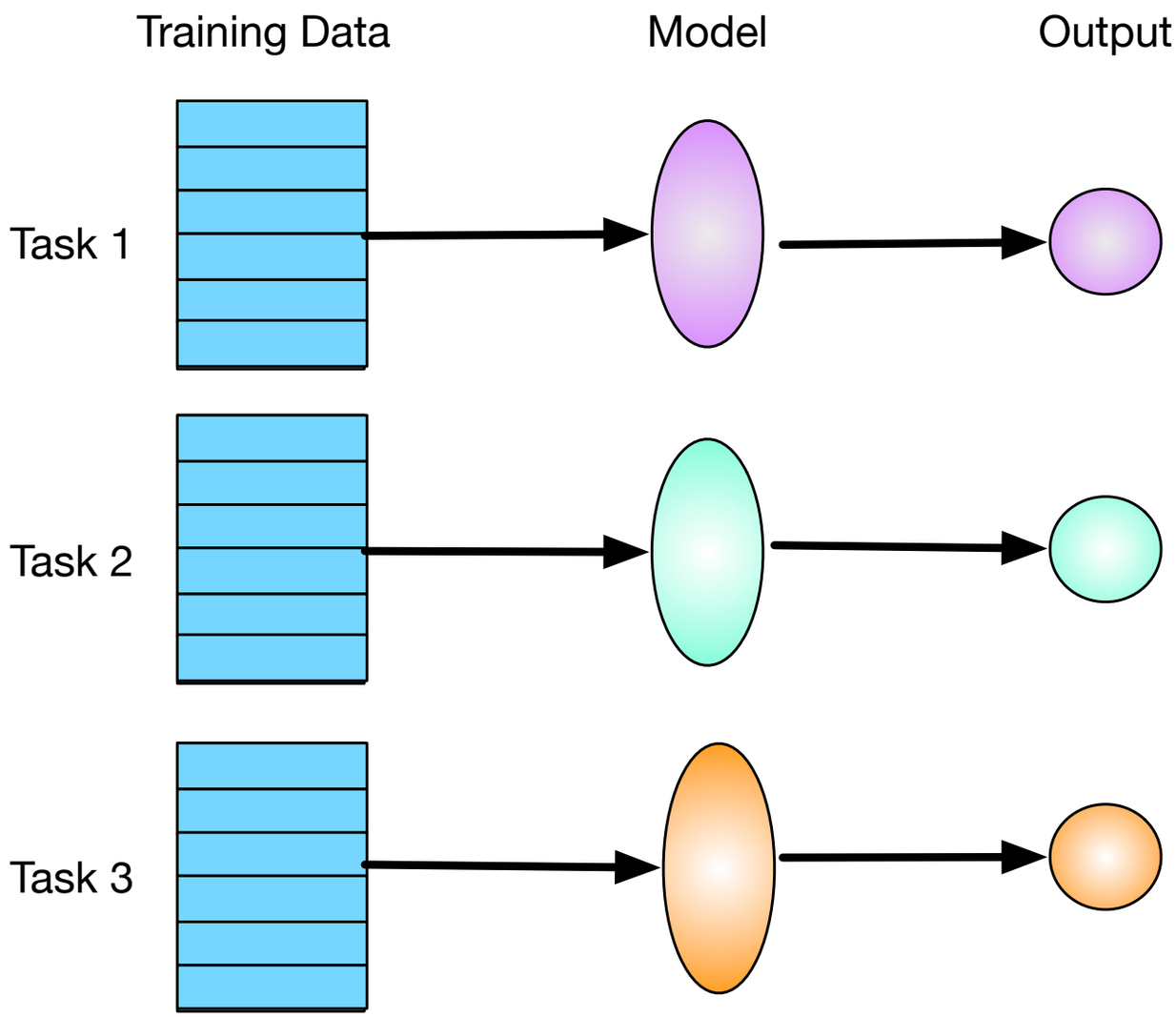
Problem Setting

- (P3) How can we predict ratings for multiple genres of movies on IMDb, or for multiple categories of items on Amazon, etc.?



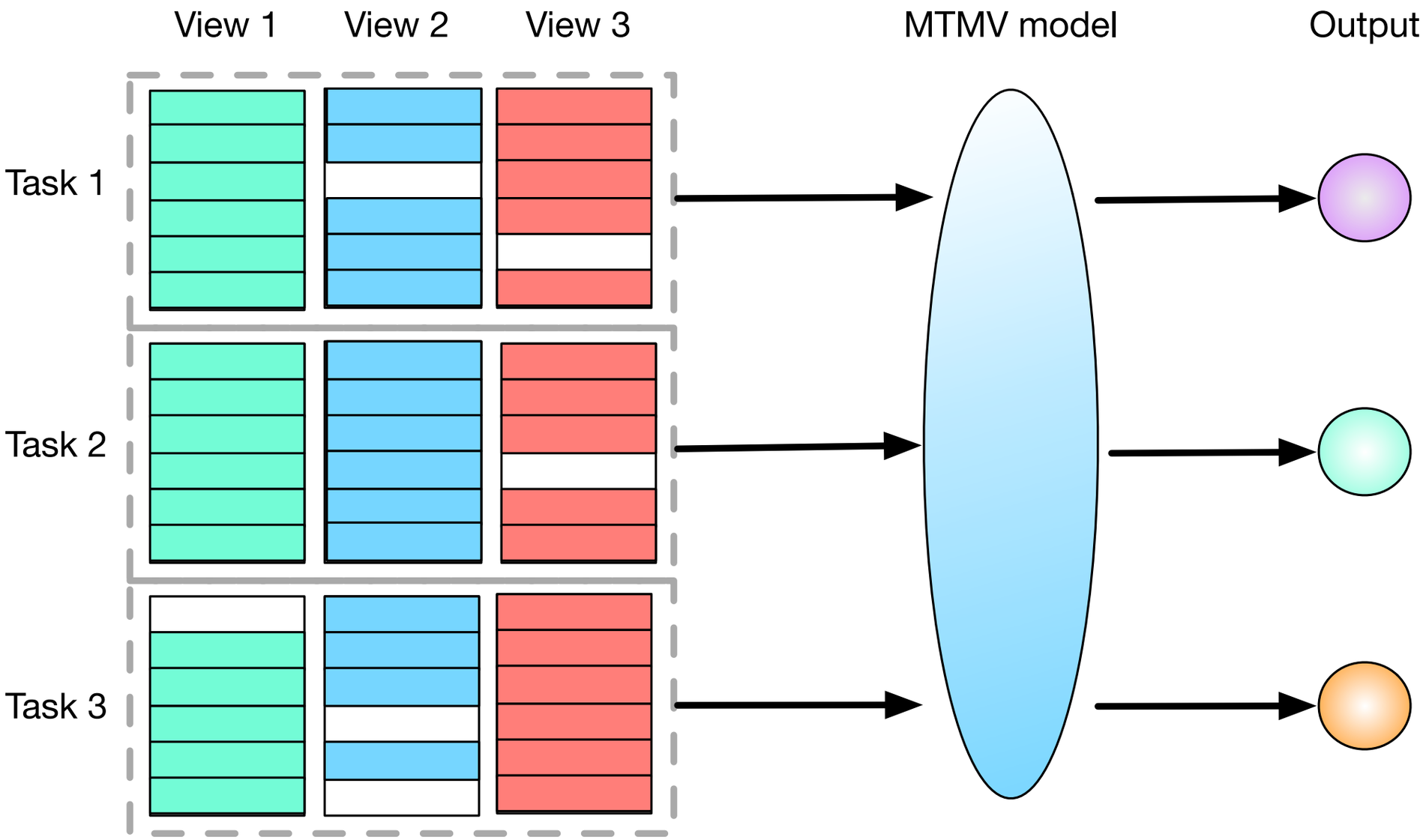
Imagine source: The Huffington Post

Single-Task Learning



- Limited data available for each task.
- Unable to learn from related tasks.

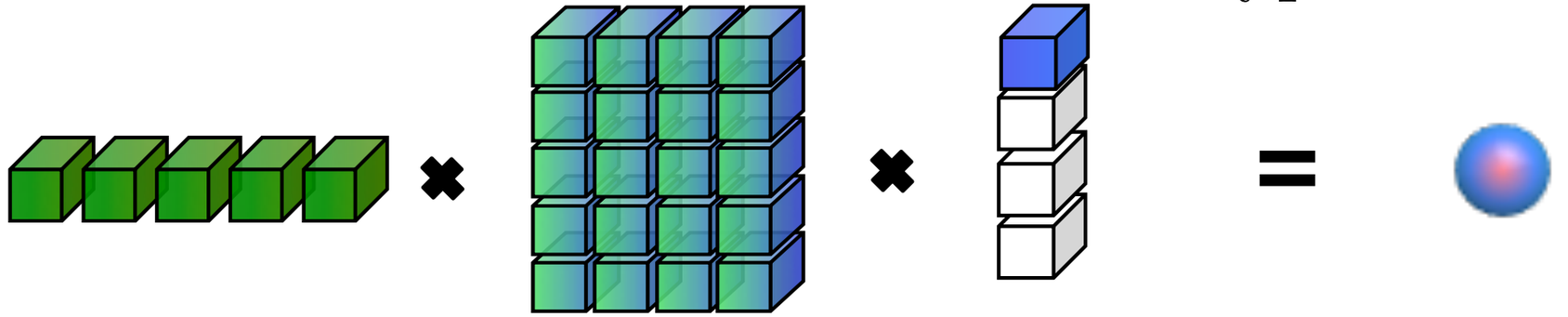
Multi-Task Multi-View Learning



Bilinear Predictive Models

- MTL w/ single view is to learn a bilinear map.

$$\mathbf{e}_t = [\underbrace{0, \cdots, 0}_{\text{t-1}}, 1, 0, \cdots, 0]^{\mathrm{T}}$$



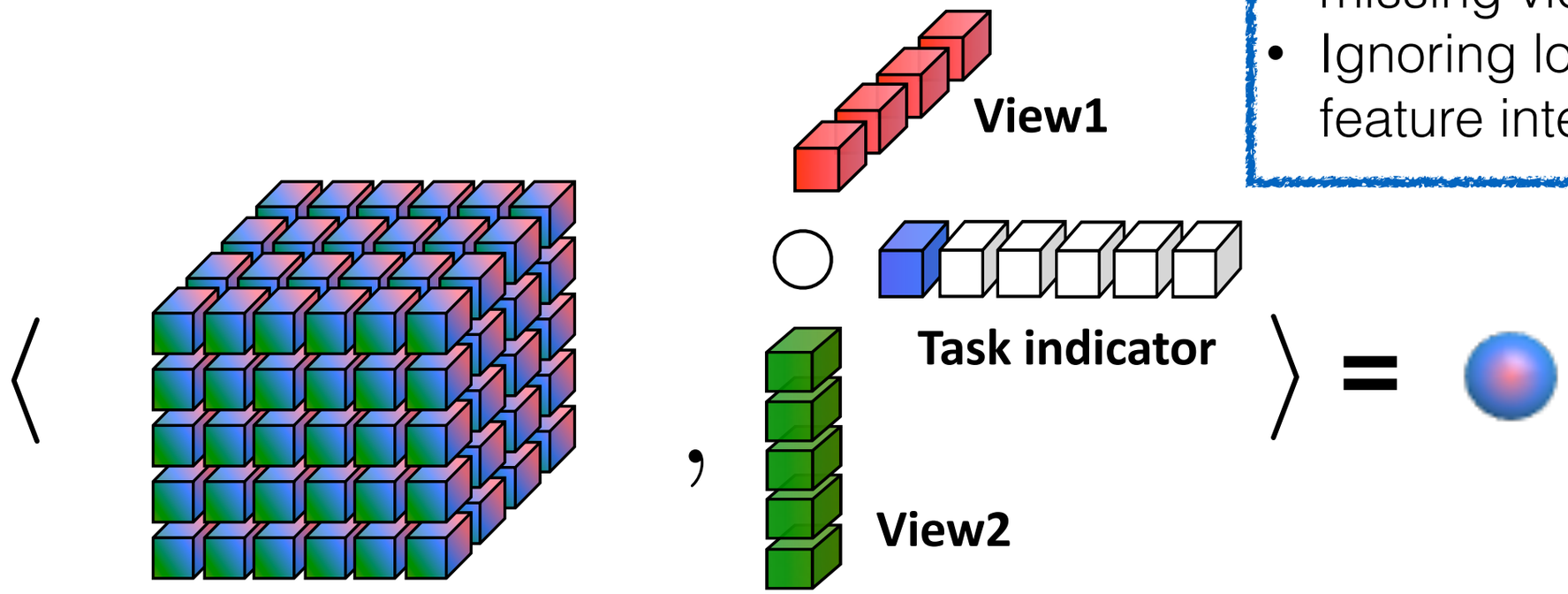
Feature vector **Weight matrix** **Task indicator** **Predicted value**

$$f_t(\mathbf{x}) = \mathbf{x}^{\mathrm{T}}\mathbf{w}_t = \mathbf{x}^{\mathrm{T}}\mathbf{W}\mathbf{e}_t = \langle \mathbf{W}, \mathbf{x} \circ \mathbf{e}_t \rangle = f(\{\mathbf{x}, \mathbf{e}_t\})$$

Multilinear Predictive Models

- MTMVL is to learn a multilinear map.

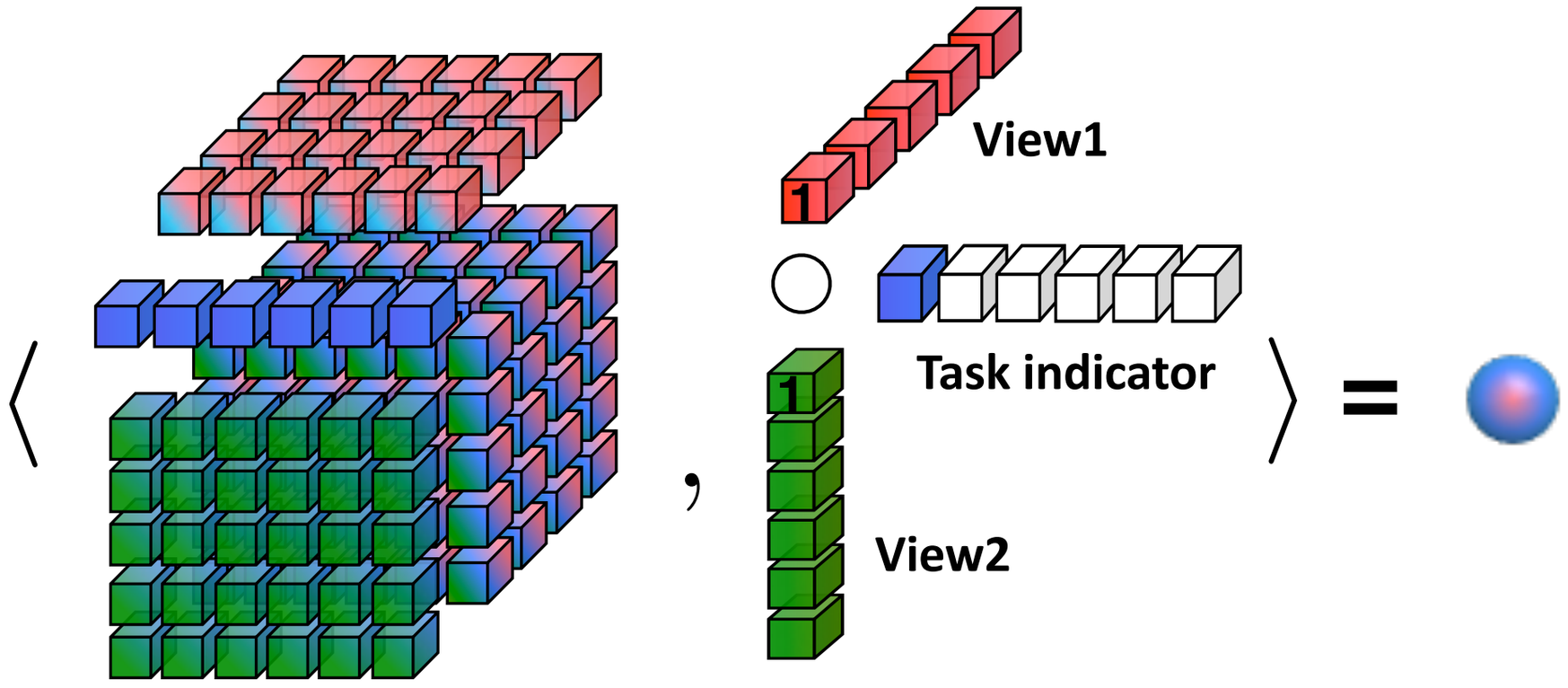
- Unable to handle missing views.
- Ignoring lower-order feature interactions.



$$f_t(\{\mathbf{x}^{(1)}, \mathbf{x}^{(2)}\}) = \mathbf{x}^{(1)^{\mathrm{T}}} \mathbf{W}_t \mathbf{x}^{(2)} = \left\langle \mathcal{W}, \mathbf{x}^{(1)} \circ \mathbf{x}^{(2)} \circ \mathbf{e}_t \right\rangle$$

Multilinear Predictive Models

- Nest full-order feature interactions.

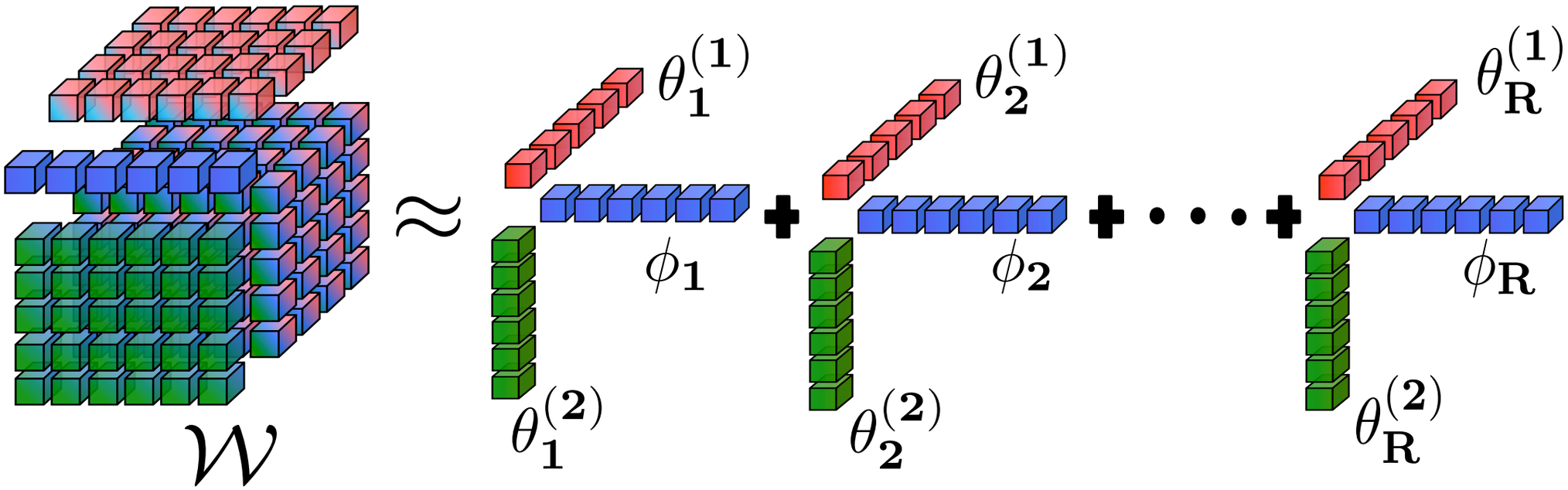


$$f_t(\{\mathbf{x}^{(1)}, \mathbf{x}^{(2)}\}) = w_t + \sum_{v=1}^{2} \mathbf{x}^{(v)^{\mathrm{T}}} \mathbf{w}_t^{(v)} + \mathbf{x}^{(1)^{\mathrm{T}}} \mathbf{W}_t \mathbf{x}^{(2)} = \left\langle \mathcal{W}, [1; \mathbf{x}^{(1)}] \circ [1; \mathbf{x}^{(2)}] \circ \mathbf{e}_t \right\rangle$$

$$= \left\langle \mathcal{W}, \mathbf{z}^{(1)} \circ \mathbf{z}^{(2)} \circ \mathbf{e}_t \right\rangle = \langle \mathcal{W}, \mathcal{Z}_t \rangle$$

Multilinear Factorization Machines (MFM)

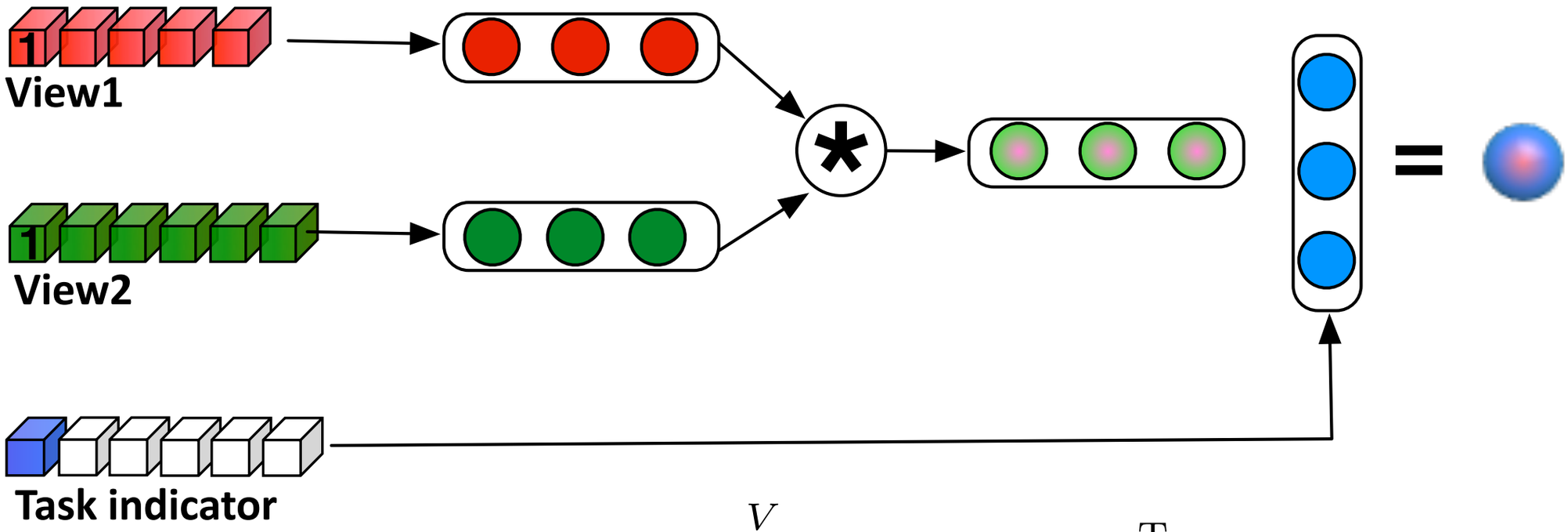
- CP factorization on the weight tensor.



$$\mathcal{W} = \sum_{r=1}^{R} \phi_{\mathbf{r}} \circ \theta_{\mathbf{r}}^{(\mathbf{1})} \circ \theta_{\mathbf{r}}^{(\mathbf{2})}$$

Multilinear Factorization Machines (MFM)

- Computational graph perspective.

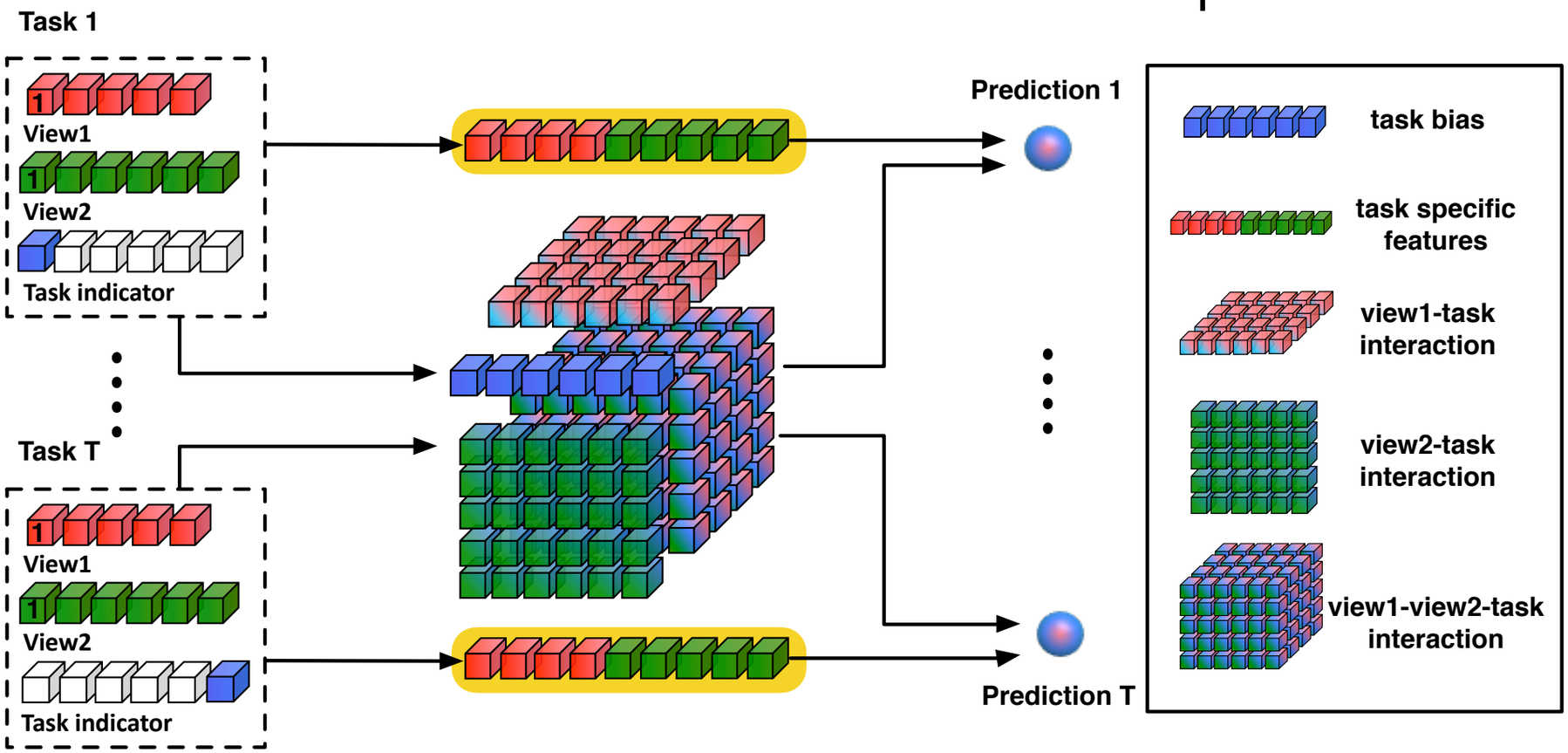


$$\langle \mathcal{W}, \mathcal{Z}_t \rangle = \boldsymbol{\phi}^t \prod_{v=1}^{V} * \left(\mathbf{z}^{(v)^{\mathrm{T}}} \boldsymbol{\Theta}^{(v)} \right)^{\mathrm{T}}$$

- Too restrictive to assume all tasks share the same subspace.

Multilinear Factorization Machines (MFM)

- Learn from both the task-specific linear space and task-view shared multilinear feature space.



$$f_t(\{\mathbf{x}^{(v)}\}) = \mathbf{x}^{\mathrm{T}}\mathbf{u}_t + \phi^t \prod_{v=1}^{V} * \left(\mathbf{z}^{(v)^{\mathrm{T}}}\mathbf{\Theta}^{(v)}\right)^{\mathrm{T}}$$

Data Collection

- FOX: multi-class w/ image and text features.
- DBLP: multi-label w/ textual and linkage features.
- MovieLens: regression w/ users, items and tags.
- Amazon: large-scale regression w/ users, items and text.

Classification	#Feature	T	N_p	N_n
FOX	image(996), text(2,711)	4	178∼635	888∼1,345
DBLP	linkage(4,638), text(687)	6	635∼1,950	2,688∼3,985
Regression	**#Feature**	T	N	**Density**
MovieLens	users(943), movies(1,599), tags(1,065)	10	758∼39,895	6.3%
Amazon	users(1,805,364), items(192,978), text(83,143)	5	349,038∼1,015,189	0.001%

- Report the average results of 10 times of random sampling: n% labeled instances as training set (n=10,20,30), 10% as validation set and 40% as testing set.

Compared Methods

- **rMTFL**: robust multi-task feature learning algorithm.
- **IteM^2**: transductive MTMV classification algorithm.
- **CSL-MTMV**: state-of-the-art inductive MTMV learning algorithm.
- **Factorization Machine (FM)**: state-of-the-art factorization model.
- **Tensor Factorization (TF)**: factorizing the highest-order weight tensor.
- **Multilinear Tensor Factorization (MFM)**:
  - **MFM-T**: removing the task-specific linear space.
  - **MFM-F**: using F-norm regularizers for all parameters.
  - **MFM-F-S**: using L2,1-norm on U for joint feature selection, F-norm on the rest of parameters.

Classification on FOX Dataset

Training Ratio	Measure	rMTFL	FM	TF	ItеM^2
10%	ACC	0.8816±0.011	0.7883±0.011	0.8460±0.035	0.4052±0.076
	F1	0.6911±0.035	0.2930±0.046	0.6362±0.044	0.3598±0.030
	AUC	0.9109±0.013	0.7764±0.018	0.8681±0.038	0.5326±0.036
20%	ACC	0.9039±0.013	0.8087±0.011	0.8546±0.025	0.5091±0.078
	F1	0.7654±0.026	0.3764±0.050	0.6632±0.051	0.3306±0.068
	AUC	0.9353±0.016	0.8260±0.012	0.8751±0.029	0.4954±0.043
30%	ACC	0.9314±0.005	0.8255±0.007	0.8767±0.082	0.4289±0.134
	F1	0.8051±0.015	0.4448±0.026	0.7302±0.132	0.3314±0.056
	AUC	0.9709±0.005	0.8393±0.012	0.9010±0.091	0.5365±0.039

Training Ratio	Measure	CSL-MTMV	MFM-T	MFM-F	MFM-F-S
10%	ACC	0.8986±0.011	0.9259±0.019	**0.9343±0.012**	**0.9364±0.011**
	F1	0.7335±0.029	0.7799±0.053	**0.8076±0.038**	**0.8119±0.027**
	AUC	0.9342±0.011	0.9678±0.015	**0.9763±0.008**	**0.9777±0.009**
20%	ACC	0.9264±0.005	0.9551±0.005	**0.9569±0.010**	**0.9612±0.005**
	F1	0.8004±0.012	0.8721±0.012	**0.8769±0.027**	**0.8882±0.014**
	AUC	0.9705±0.003	0.9883±0.003	**0.9885±0.006**	**0.9922±0.002**
30%	ACC	0.9390±0.004	0.9641±0.007	**0.9709±0.003**	**0.9697±0.004**
	F1	0.8341±0.012	0.9000±0.018	**0.9185±0.010**	**0.9149±0.010**
	AUC	0.9812±0.003	0.9916±0.003	**0.9949±0.001**	**0.9949±0.001**

Classification on DBLP Dataset

Training Ratio	Measure	rMTFL	FM	TF	IteM^2
10%	ACC	0.8057±0.004	0.7264±0.004	0.7471±0.011	0.6223±0.004
	F1	0.5395±0.015	0.0732±0.019	0.5606±0.011	0.3176±0.007
	AUC	0.7888±0.007	0.6264±0.023	0.7723±0.009	0.5310±0.007
20%	ACC	0.8319±0.004	0.7628±0.007	0.7878±0.007	0.6309±0.003
	F1	0.6447±0.008	0.2680±0.038	0.6247±0.014	0.3494±0.006
	AUC	0.8374±0.005	0.7548±0.022	0.8200±0.010	0.5550±0.006
30%	ACC	0.8412±0.004	0.7978±0.005	0.8191±0.008	0.6256±0.003
	F1	0.6796±0.010	0.4312±0.021	0.6670±0.021	0.3569±0.009
	AUC	0.8590±0.005	0.8351±0.010	0.8498±0.009	0.5563±0.006

Training Ratio	Measure	CSL-MTMV	MFM-T	MFM-F	MFM-F-S
10%	ACC	0.7290±0.005	0.8008±0.004	**0.8058±0.004**	**0.8062±0.005**
	F1	0.4402±0.004	0.5278±0.018	**0.5469±0.014**	**0.5471±0.015**
	AUC	0.6890±0.006	0.8039±0.010	**0.8113±0.010**	**0.8120±0.009**
20%	ACC	0.7760±0.002	0.8346±0.004	**0.8374±0.004**	**0.8371±0.004**
	F1	0.5295±0.007	0.6274±0.013	**0.6499±0.012**	**0.6508±0.012**
	AUC	0.7655±0.005	0.8531±0.006	**0.8658±0.005**	**0.8632±0.005**
30%	ACC	0.8037±0.003	0.8501±0.004	**0.8527±0.004**	**0.8535±0.004**
	F1	0.5869±0.007	0.6800±0.013	**0.6891±0.012**	**0.6892±0.009**
	AUC	0.8083±0.006	0.8757±0.005	**0.8866±0.006**	**0.8866±0.006**

Regression on MovieLens Dataset

Training Ratio	Measure	rMTFL	FM	TF	CSL-MTMV
10%	RMSE	1.1861±0.008	1.0251±0.003	1.5679±0.099	1.05013±0.005
	MAE	0.8516±0.004	0.8422±0.004	1.2497±0.088	0.8516±0.004
20%	RMSE	1.0631±0.005	0.9898±0.003	1.2519±0.069	1.0214±0.004
	MAE	0.8539±0.005	0.7997±0.004	0.9801±0.053	0.8294±0.004
30%	RMSE	0.9917±0.003	**0.9765±0.003**	1.2066±0.061	1.0082±0.003
	MAE	0.8159±0.003	**0.7815±0.003**	0.9380±0.045	0.8189±0.003

Training Ratio	Measure	MFM-T	MFM-F	MFM-F-S
10%	RMSE	1.0078±0.005	**1.0069±0.005**	**0.9976±0.004**
	MAE	0.8142±0.005	**0.8082±0.005**	**0.8022±0.004**
20%	RMSE	**0.9877±0.003**	0.9977±0.003	**0.9857±0.003**
	MAE	0.**7987±0.003**	0.8023±0.003	**0.7927±0.004**
30%	RMSE	0.9795±0.003	0.9887±0.004	**0.9785±0.003**
	MAE	0.7885±0.002	0.7823±0.004	**0.7789±0.004**

Regression on Amazon Dataset

Training Ratio	Measure	FM	TF	MFM-T	MFM-F	MFM-F-S
10%	RMSE	0.9834±0.001	3.6044±0.003	**0.9775±0.001**	0.9857±0.001	**0.9825±0.002**
	MAE	0.7420±0.001	3.4574±0.005	0.7249±0.001	**0.7158±0.002**	**0.7129±0.001**
20%	RMSE	0.9814±0.001	3.5611±0.018	**0.9764±0.001**	0.9845±0.001	**0.9775±0.001**
	MAE	0.7343±0.002	3.3965±0.030	0.7255±0.001	**0.7112±0.001**	**0.7086±0.001**
30%	RMSE	0.9782±0.002	3.4962±0.018	**0.9705±0.002**	0.9841±0.001	**0.9733±0.001**
	MAE	0.7257±0.002	3.2945±0.034	**0.7001±0.001**	0.7115±0.001	**0.7078±0.001**

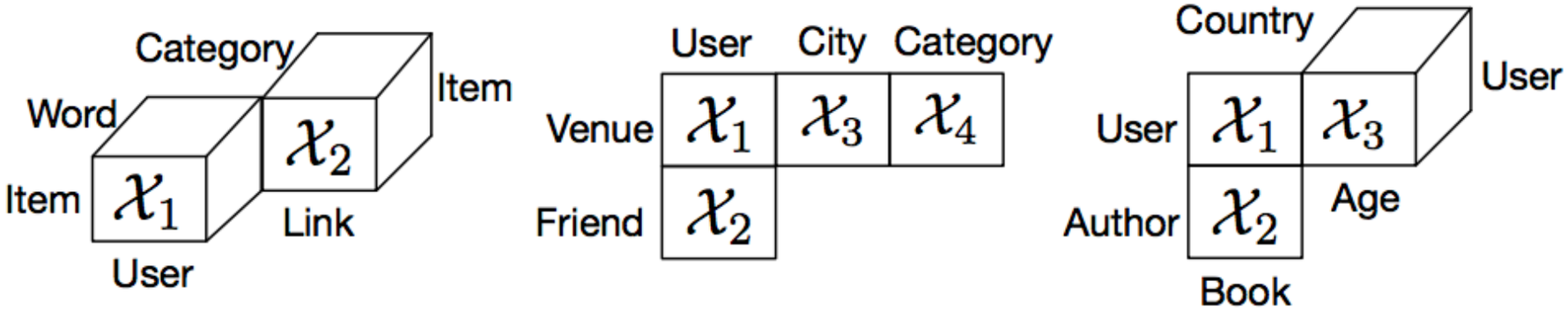
- Due to memory overhead, rMTFL and CSL-MTMV are not compared.

The Next

- To extend to overlapping groups of views.

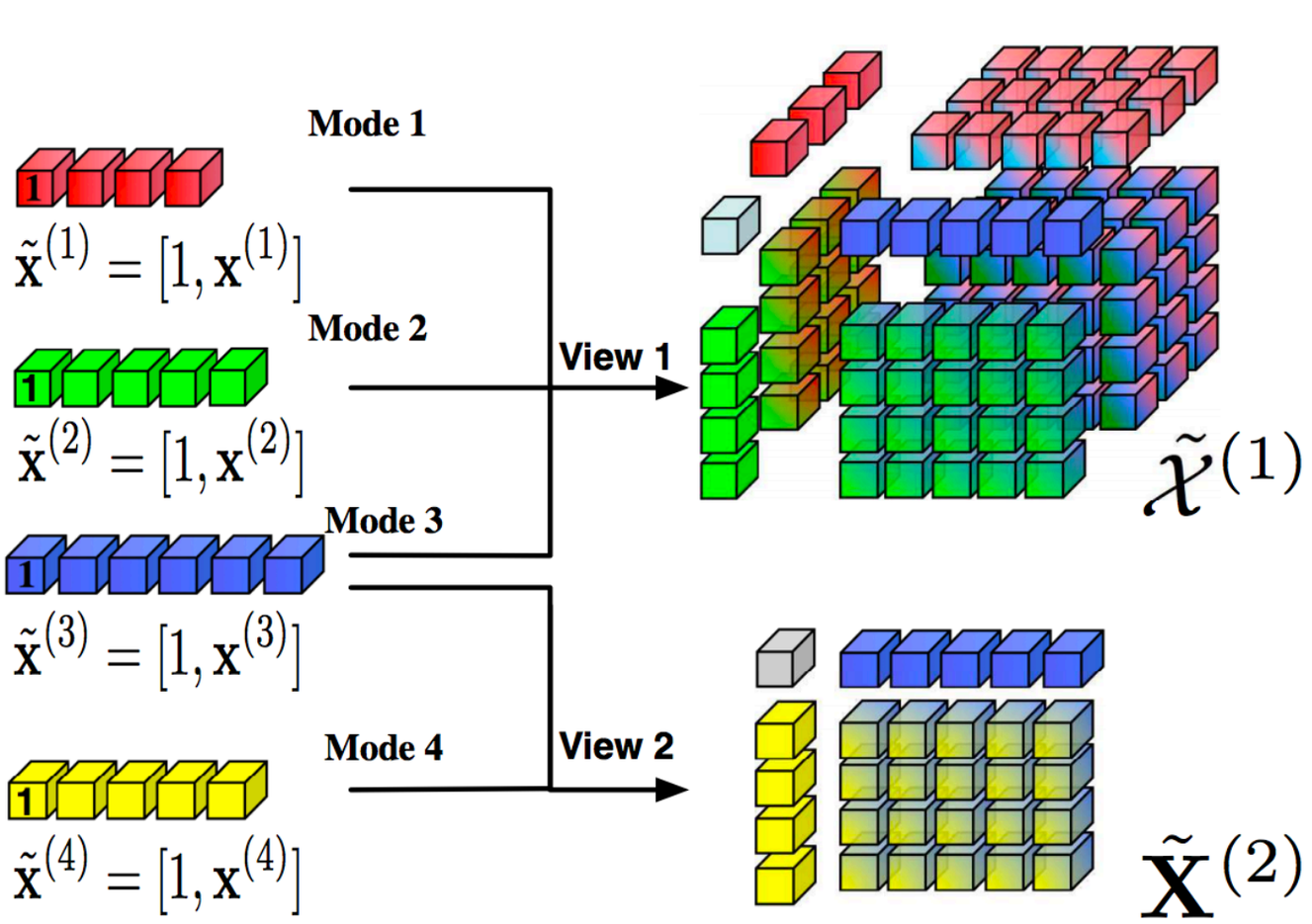
Problem Setting

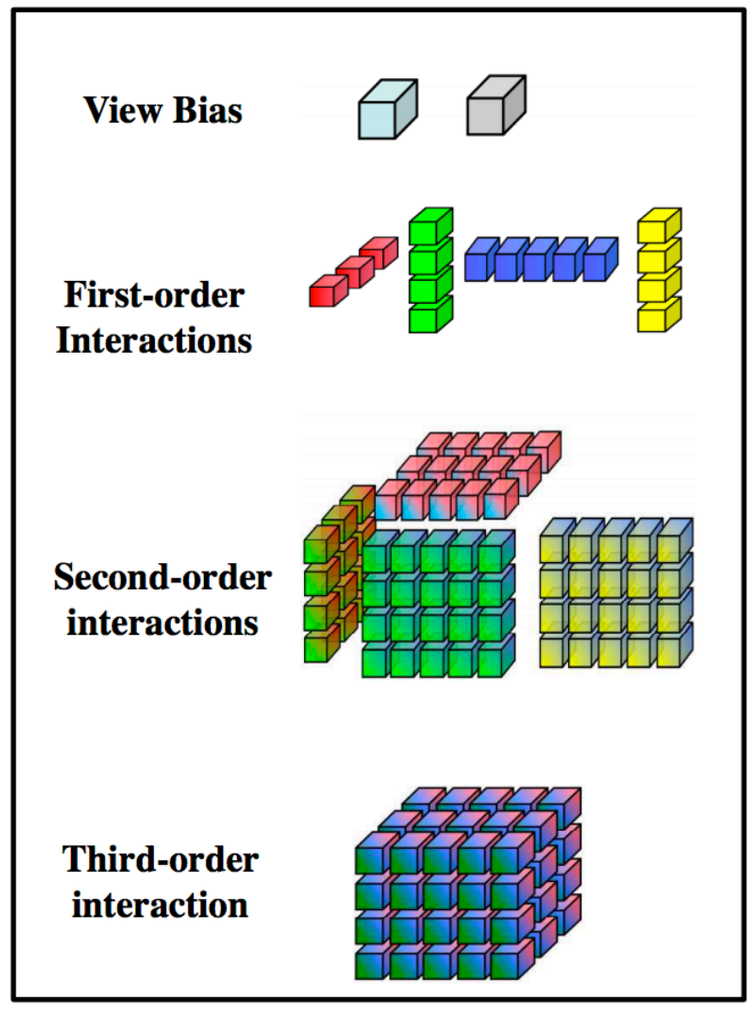
- (P4) How can we predict ratings between entities with rich meta information?



(a) Amazon (b) Yelp (c) BookCrossing

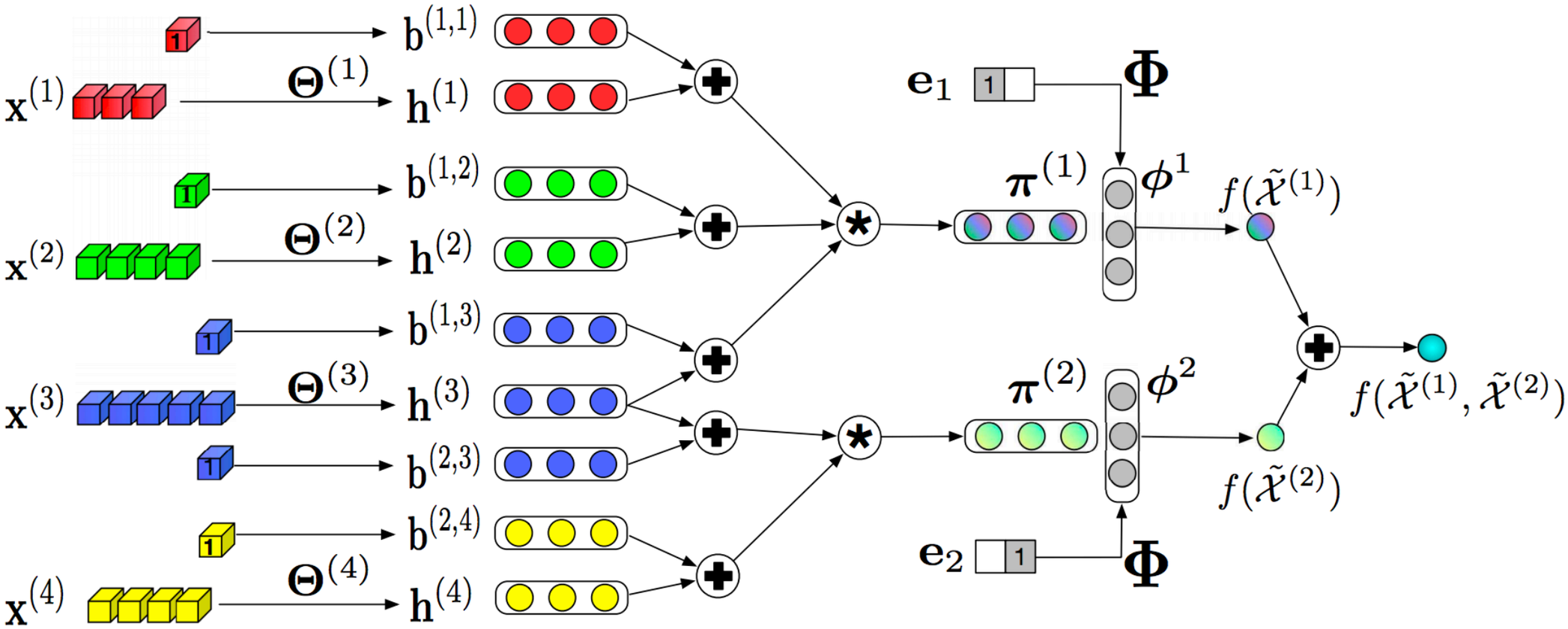
Structural Factorization Machines (SFM)





Structural Factorization Machines (SFM)

- Computational graph perspective.



Experiments

Dataset	#Samples	Mode					Density	$N_z(X)$	$N_z(\mathcal{B})$
Amazon		#Users	#Items	#Words	#Categories	#Links			
Game	231,780	24,303	10,672	7,500	193	17,974	0.089%	32.9M	15.2M
Cloth	278,677	39,387	23,033	3,493	1,175	107,139	0.031%	25.6M	7.3M
Sport	296,337	35,598	18,357	5,202	1,432	73,040	0.045%	34.2M	10.2M
Health	346,355	38,609	18,534	5,889	849	80,379	0.048%	33.6M	12.1M
Home	551,682	66,569	28,237	6,455	970	99,090	0.029%	46.8M	19.4M
Elec	1,689,188	192,403	63,001	12,805	967	89,259	0.014%	161.5M	69M
		#Users	#Venues	#Friends	#Categories	#Cities			
Yelp	1,319,870	88,009	40,520	88,009	892	412	0.037%	70.5M	1.4M
		#Users	#Books	#Countries	#Ages	#Authors			
BX	244,848	24,325	45,074	57	8	17,178	0.022%	1.2M	163K

Dataset	(a) **MF**	(b) **MVM**	(c) **FM-2**	(d) **FM-3**	(e) **PolyNet-2**	(f) **PolyNet-3**	(g) **SFM**	Improvement of SFM verus b	min(c,d)	min(e,f)
Game	1.569 ± 0.005	0.753 ± 0.007	0.764 ± 0.006	0.749 ± 0.007	0.749 ± 0.004	0.748 ± 0.006	**0.723 ± 0.006**	4.06%	3.52%	3.35%
Cloth	1.624 ± 0.009	0.725 ± 0.046	0.678 ± 0.004	0.679 ± 0.004	0.678 ± 0.007	0.680 ± 0.005	**0.659 ± 0.013**	9.03%	2.82%	2.84%
Sport	1.290 ± 0.004	0.646 ± 0.019	0.638 ± 0.003	0.632 ± 0.007	0.631 ± 0.005	0.632 ± 0.005	**0.614 ± 0.011**	5.00%	2.91%	2.79%
Health	1.568 ± 0.007	0.807 ± 0.012	0.779 ± 0.004	0.778 ± 0.004	0.779 ± 0.005	0.776 ± 0.005	**0.763 ± 0.019**	5.47%	2.02%	1.77%
Home	1.591 ± 0.004	0.729 ± 0.067	0.714 ± 0.002	0.714 ± 0.004	0.690 ± 0.003	0.692 ± 0.005	**0.678 ± 0.008**	6.93%	5.00%	1.72%
Elec	1.756 ± 0.002	0.792 ± 0.042	0.776 ± 0.006	0.749 ± 0.007	0.760 ± 0.004	0.757 ± 0.001	**0.747 ± 0.006**	5.69%	0.27%	1.33%
Yelp	1.713 ± 0.003	1.2575 ± 0.013	1.277 ± 0.002	1.277 ± 0.002	1.272 ± 0.002	1.272 ± 0.002	**1.256 ± 0.010**	0.09%	1.58%	1.19%
BX	4.094 ± 0.025	2.844 ± 0.024	2.766 ± 0.012	2.767 ± 0.014	2.654 ± 0.013	2.658 ± 0.013	**2.541 ± 0.025**	10.66%	8.16%	4.27%
Average on all datasets								5.87%	3.29%	2.41%

The Next

- To handle structured input.
- To explicitly model feature interactions in a deep framework.

Problem Setting

- (P5) How can we monitor the mental health using time series data collected from multiple sensors?

Accelerometer

Keyboard

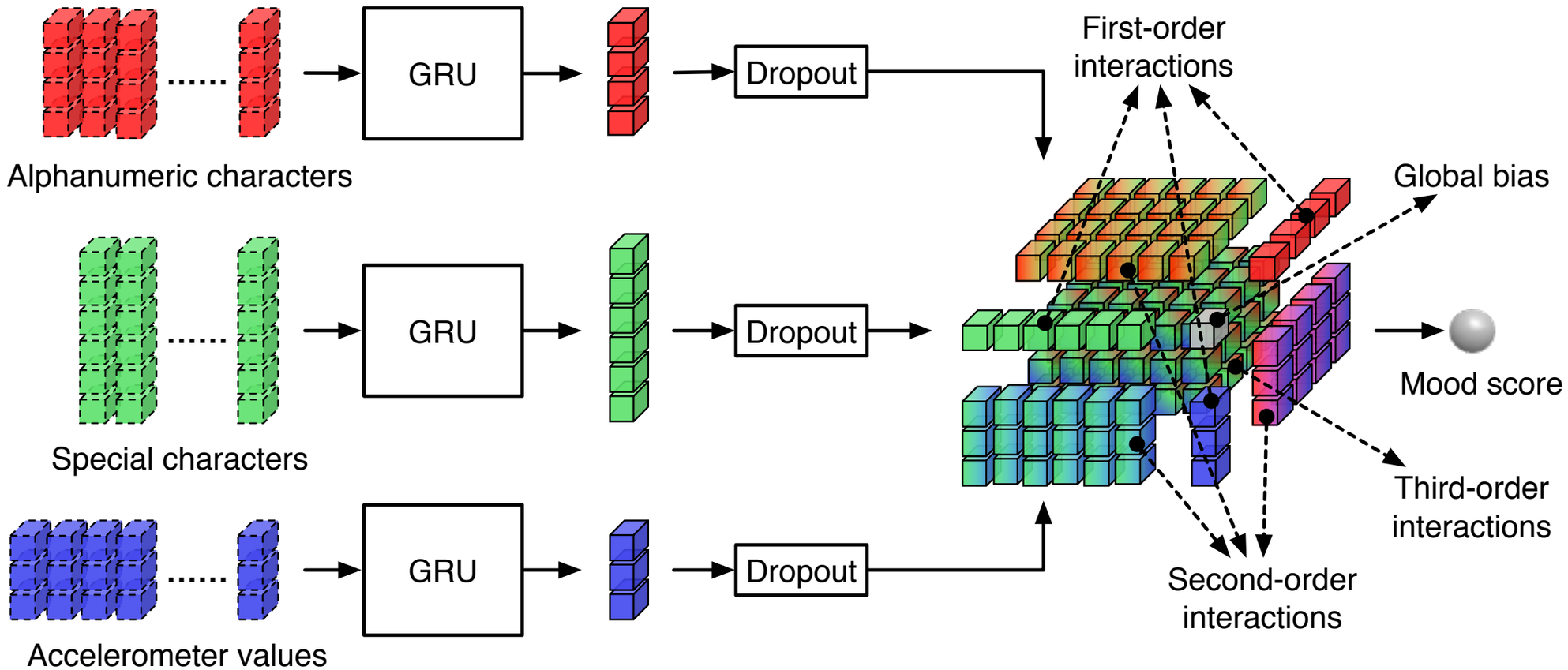
😀 Mood detection 😭

Gyroscope

GPS

Microphone

DeepMood


Alphanumeric characters
GRU
Dropout
Special characters
GRU
Dropout
Accelerometer values
GRU
Dropout
First-order interactions
Global bias
Mood score
Third-order interactions
Second-order interactions

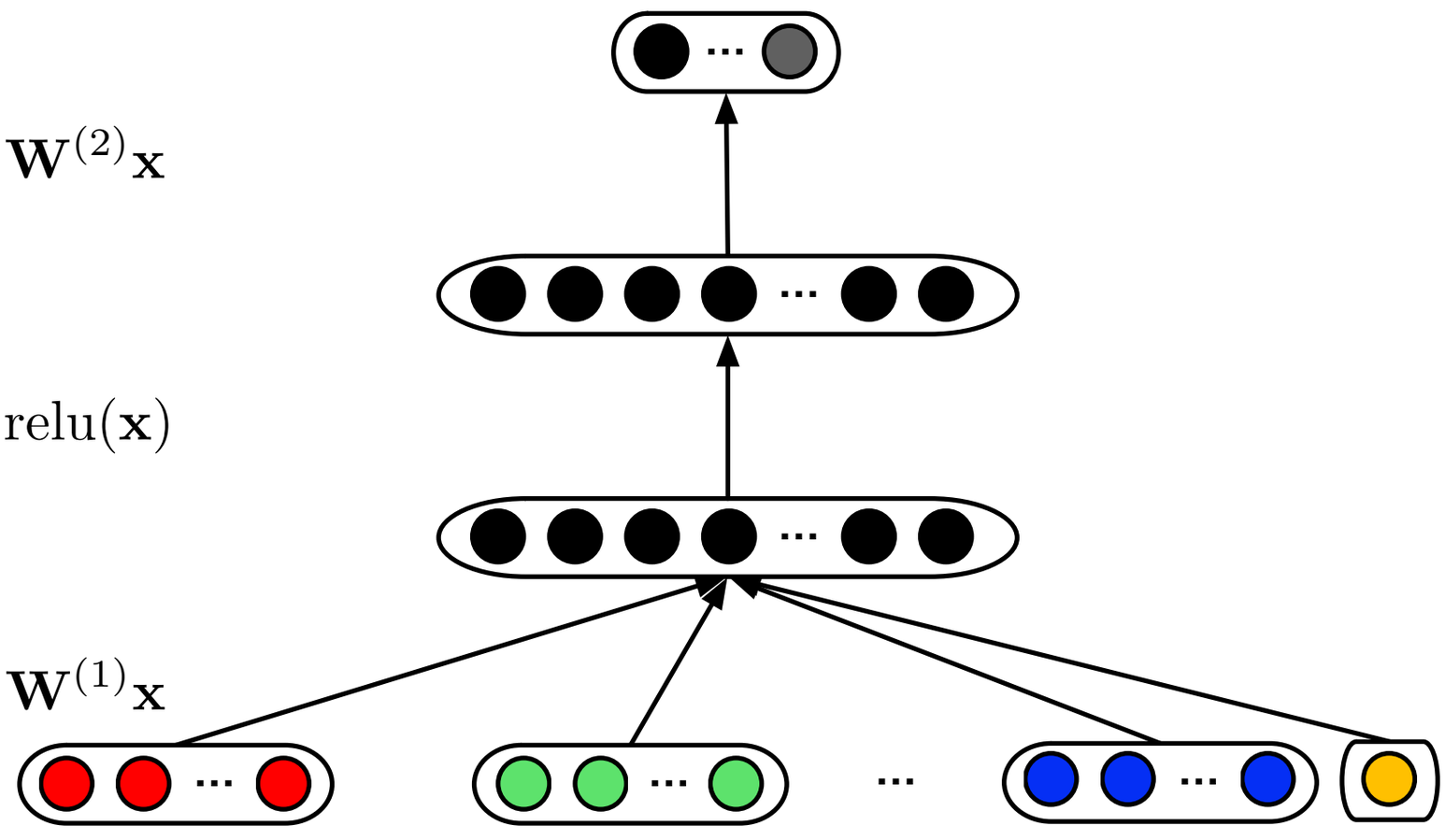
Fully Connected Layer

- **DNN**: DeepMood framework with a fully connected layer for data fusion.

$f(\mathbf{x}) = \mathbf{W}^{(2)}\mathbf{x}$

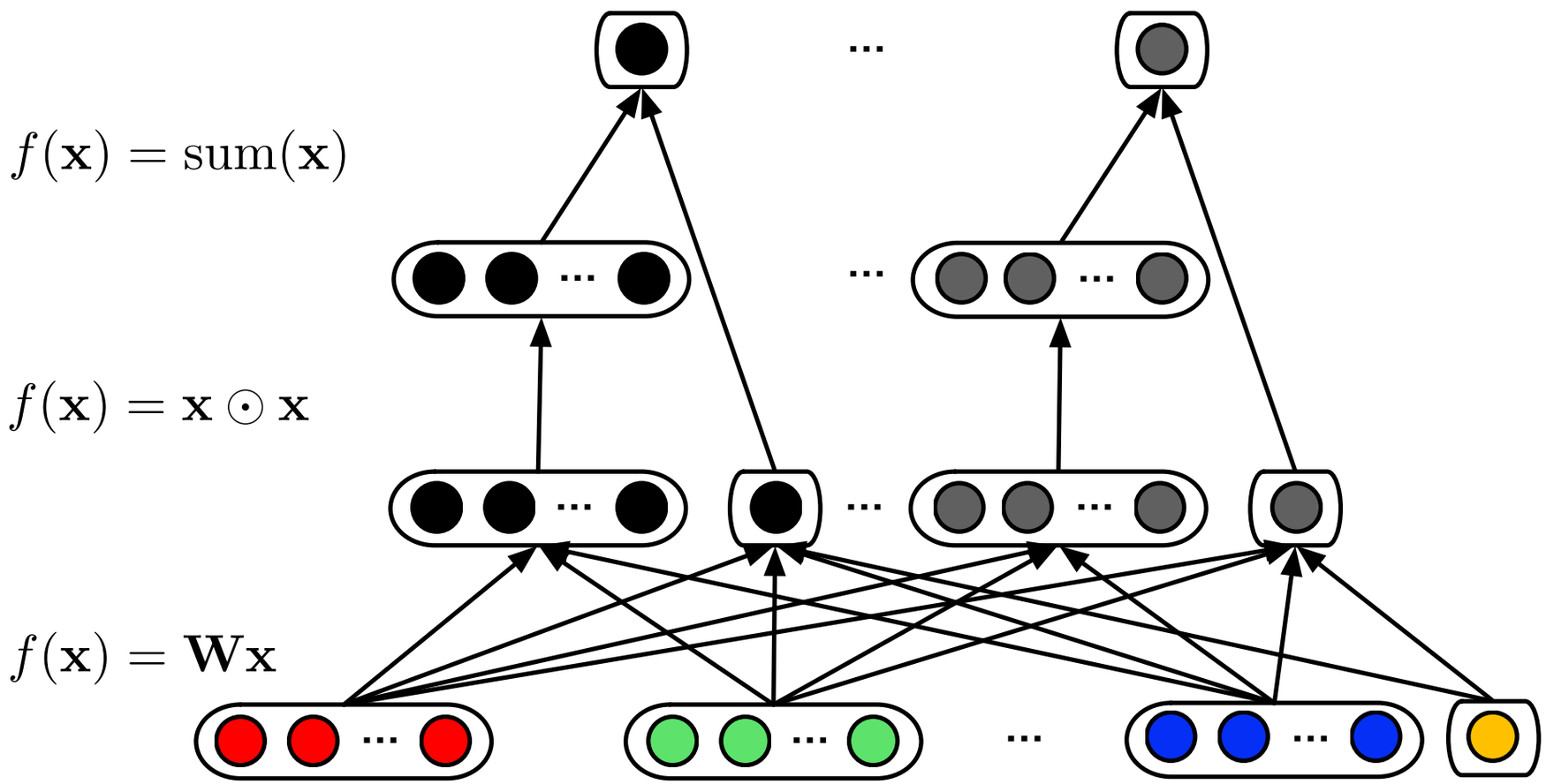
$f(\mathbf{x}) = \text{relu}(\mathbf{x})$

$f(\mathbf{x}) = \mathbf{W}^{(1)}\mathbf{x}$



Factorization Machine Layer

- **DFM**: DeepMood framework with a Factorization Machine layer for data fusion.



Factorization Machine Layer

$$\mathbf{q}_a = \mathbf{U}_a \mathbf{h}$$

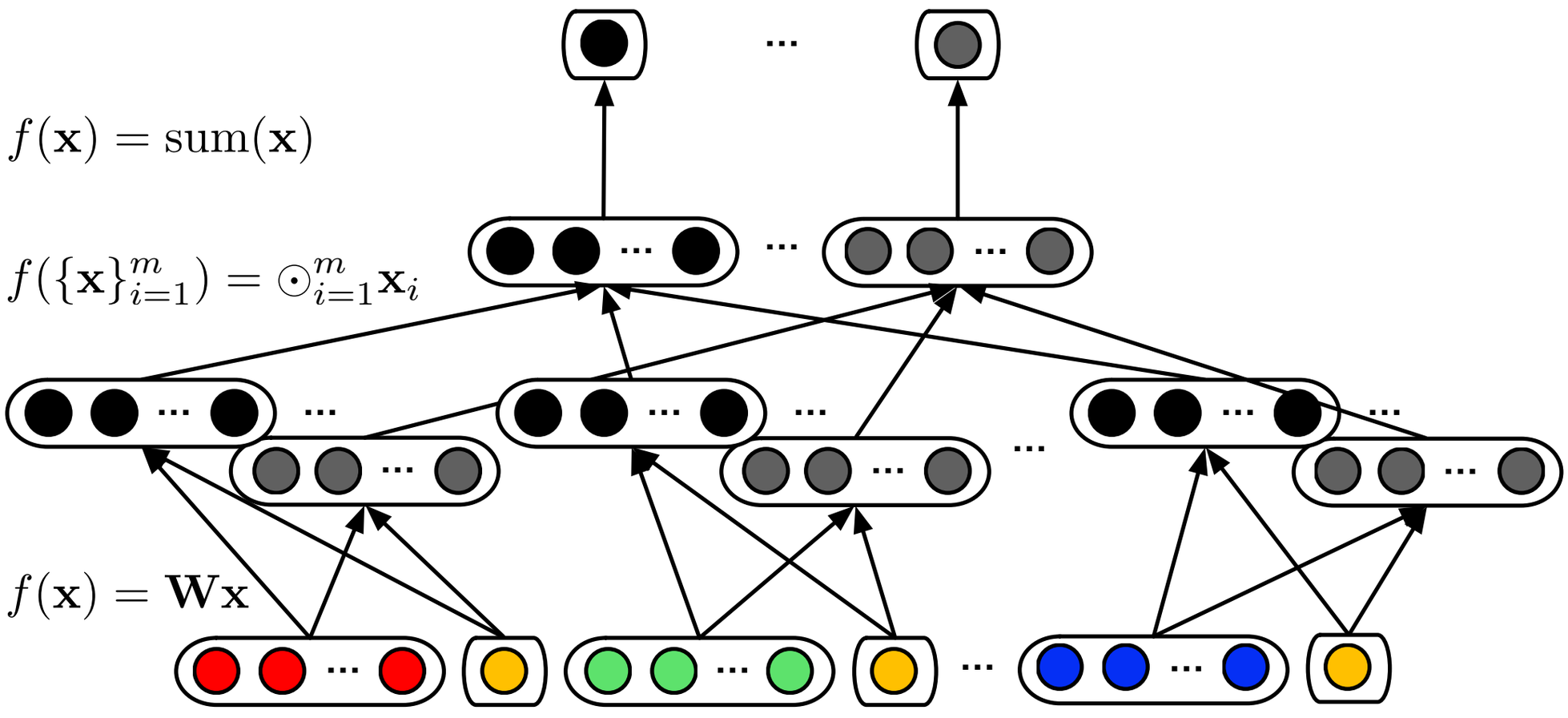
$$b_a = \mathbf{w}_a^T [\mathbf{h}; 1]$$

$$\hat{y}_a = \text{sum}([\mathbf{q}_a \odot \mathbf{q}_a; b_a])$$

$$\begin{aligned}
\hat{y}_a &= \sum_{f=1}^{k} \left(\sum_{i=1}^{d} \mathbf{U}_a(f, i)\mathbf{h}(i) \right)^2 + \sum_{i=1}^{d+1} \mathbf{w}_a(i)\bar{\mathbf{h}}(i) \\
&= \sum_{f=1}^{k} \left(\sum_{i=1}^{d} \mathbf{U}_a(f, i)\mathbf{h}(i) \right) \left(\sum_{j=1}^{d} \mathbf{U}_a(f, j)\mathbf{h}(j) \right) + \sum_{i=1}^{d+1} \mathbf{w}_a(i)\bar{\mathbf{h}}(i) \\
&= \sum_{f=1}^{k} \sum_{i=1}^{d} \sum_{j=1}^{d} \mathbf{U}_a(f, i)\mathbf{U}_a(f, j)\mathbf{h}(i)\mathbf{h}(j) + \sum_{i=1}^{d+1} \mathbf{w}_a(i)\bar{\mathbf{h}}(i) \\
&= \sum_{i=1}^{d} \sum_{j=1}^{d} \langle \mathbf{U}_a(:, i), \mathbf{U}_a(:, j) \rangle \mathbf{h}(i)\mathbf{h}(j) + \sum_{i=1}^{d} \mathbf{w}_a(i)\mathbf{h}(i) + \mathbf{w}_a(d+1)
\end{aligned}$$

Multi-View Machine Layer

- **DMVM**: DeepMood framework with a Multi-View Machine layer for data fusion.



Multi-View Machine Layer

$$\mathbf{q}_a^{(p)} = \mathbf{U}_a^{(p)}[\mathbf{h}^{(p)}; 1]$$

$$\hat{y}_a = \text{sum}([\mathbf{q}_a^{(1)} \odot \cdots \odot \mathbf{q}_a^{(m)}])$$

$$\hat{y}_a = \sum_{f=1}^{k} \prod_{p=1}^{m} \left(\sum_{i_p=1}^{d_h+1} \mathbf{U}_a^{(p)}(f, i_p) \bar{\mathbf{h}}^{(p)}(i_p) \right)$$

$$= \sum_{f=1}^{k} \sum_{i_1=1}^{d_h+1} \cdots \sum_{i_m=1}^{d_h+1} \left(\prod_{p=1}^{m} \mathbf{U}_a^{(p)}(f, i_p) \bar{\mathbf{h}}^{(p)}(i_p) \right)$$

$$= \sum_{i_1=1}^{d_h+1} \cdots \sum_{i_m=1}^{d_h+1} \left(\sum_{f=1}^{k} \prod_{p=1}^{m} \mathbf{U}_a^{(p)}(f, i_p) \right) \left(\prod_{p=1}^{m} \bar{\mathbf{h}}^{(p)}(i_p) \right)$$

Data Collection

Statistics of the BiAffect dataset.

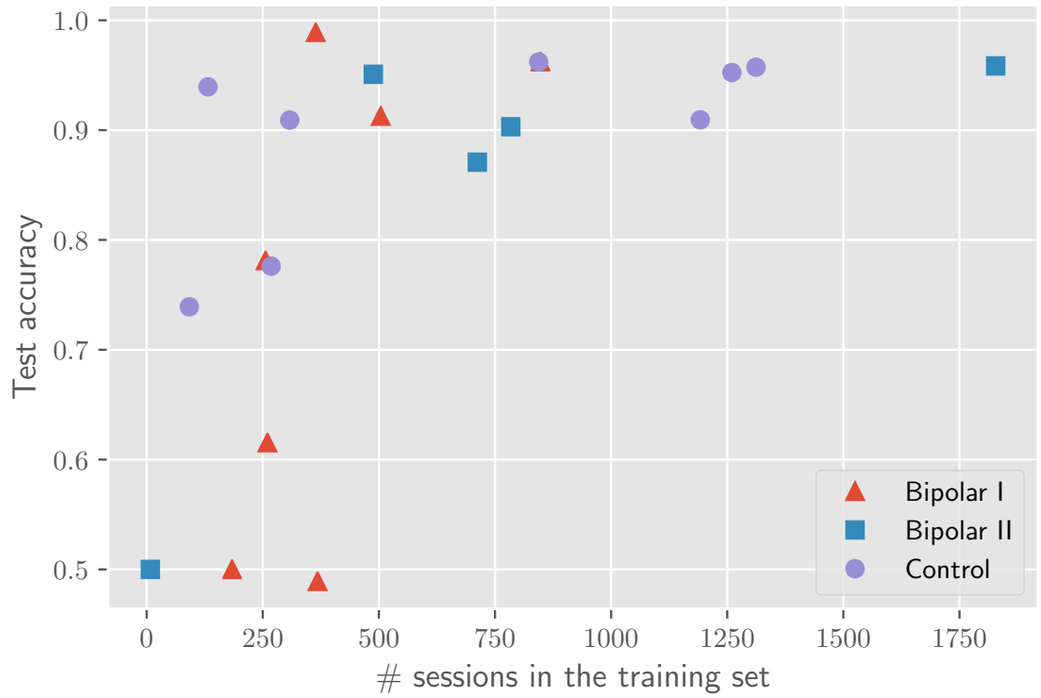
Statistics	ALPH.	SPEC.	ACCEL.
# data points	836,027	538,520	14,237,503
# sessions	34,993	33,385	37,647
Mean length	24	16	378
Median length	14	9	259
Maximum length	538	437	90,193

- Participants: 7 bipolar I, 5 bipolar II, 8 controls.
- Features: keypress metadata and accelerometer movement.
- Labels: Hamilton Depression Rating Scale (HDRS) and Young Mania Rating Scale (YMRS).

Prediction Performance

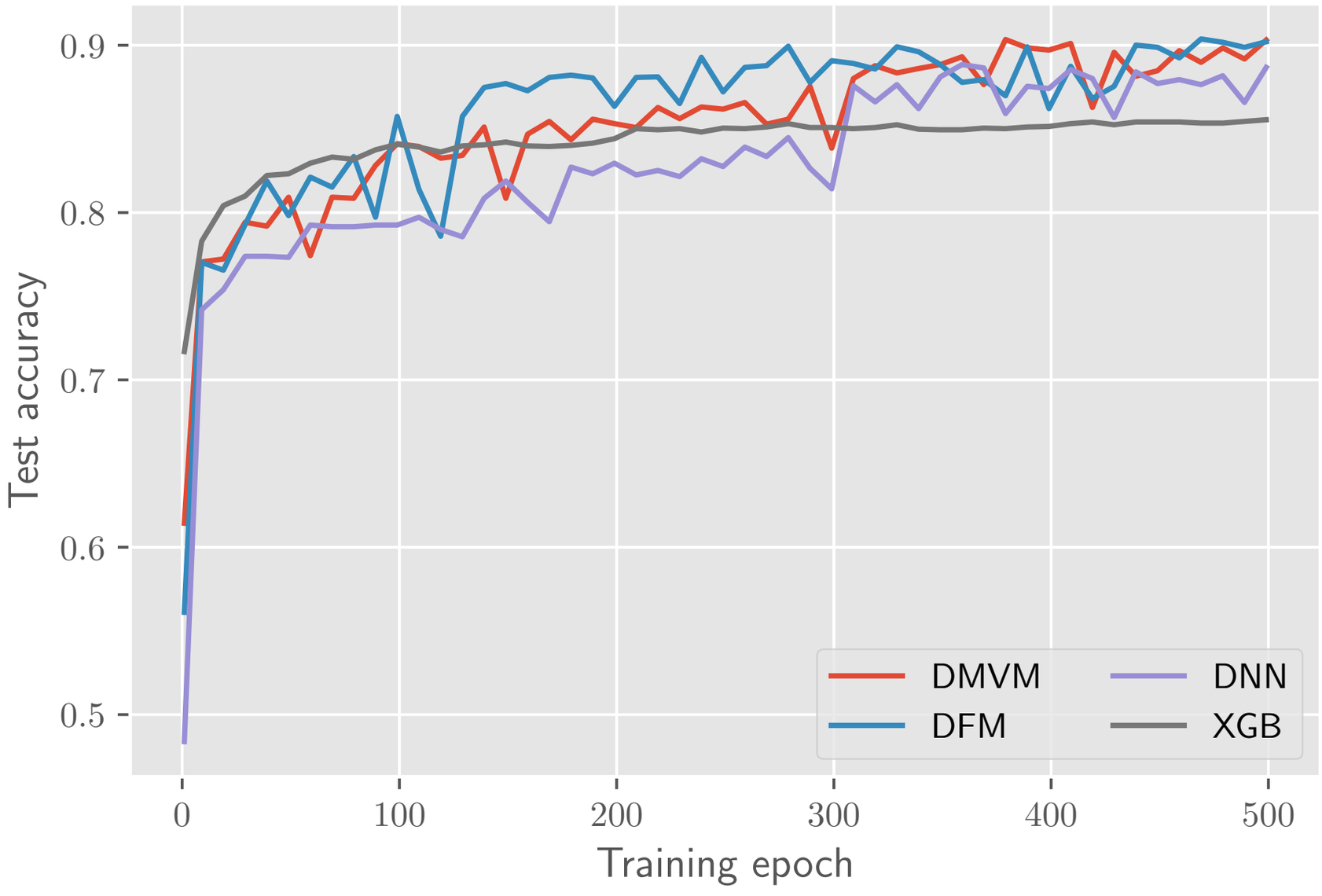
Prediction performance for mood detection.

Methods	Classification		Regression
	Accuracy	F-score	RMSE
DMVM	0.9031	0.9070	3.5664
DFM	0.9021	0.9029	3.6767
DNN	0.8868	0.8929	3.7874
XGB	0.8555	0.8562	3.9634
SVM	0.7323	0.7237	4.1257
LR	0.7293	0.7172	4.1822



- DMVM: DeepMood with a Multi-view Machine layer for data fusion.
- DFM: DeepMood with a Factorization Machine layer for data fusion.
- DNN: DeepMood with a conventional fully connected layer for data fusion.
- XGB: Tree boosting system XGBoost.
- SVM: Linear Support Vector Classification/Regression from scikit-learn.
- LR: Logistic/Ridge Regression from scikit-learn.

Convergence Efficiency



Summary

- Although NN models are capable of approximating many complicated functions in theory, there are practical difficulties in the learning process (e.g., local minima).
- It is critical to design NN modules that are suitable for different applications: convolution layers for computer vision, recurrent nets for sequence data, and some interaction operators for multi-view learning in the many other domains.

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