Factorization Machine

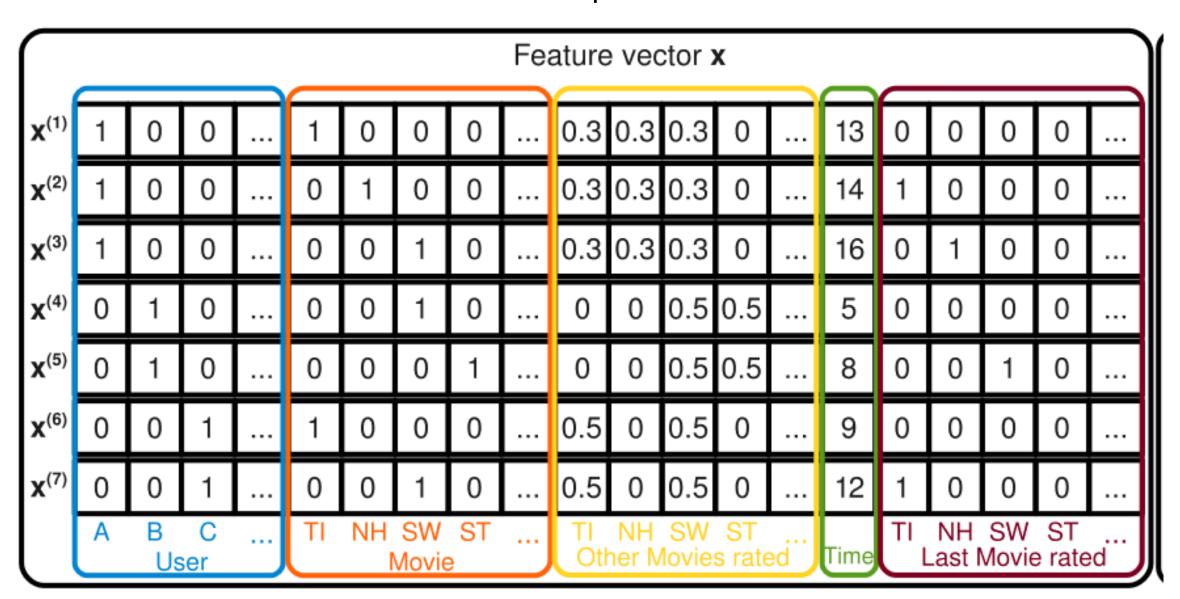
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Enormous sparse data



Purpose

SVM and collaborative filter models:

- Work not well in sparse data
- Work only on very restricted data
- Non-linear complexity

Factorization Machine:

- Allow parameters estimation under very sparse data

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- Linear complexity
- General predictor

Backgrounds

Prediction function:

(W needs to be learned)

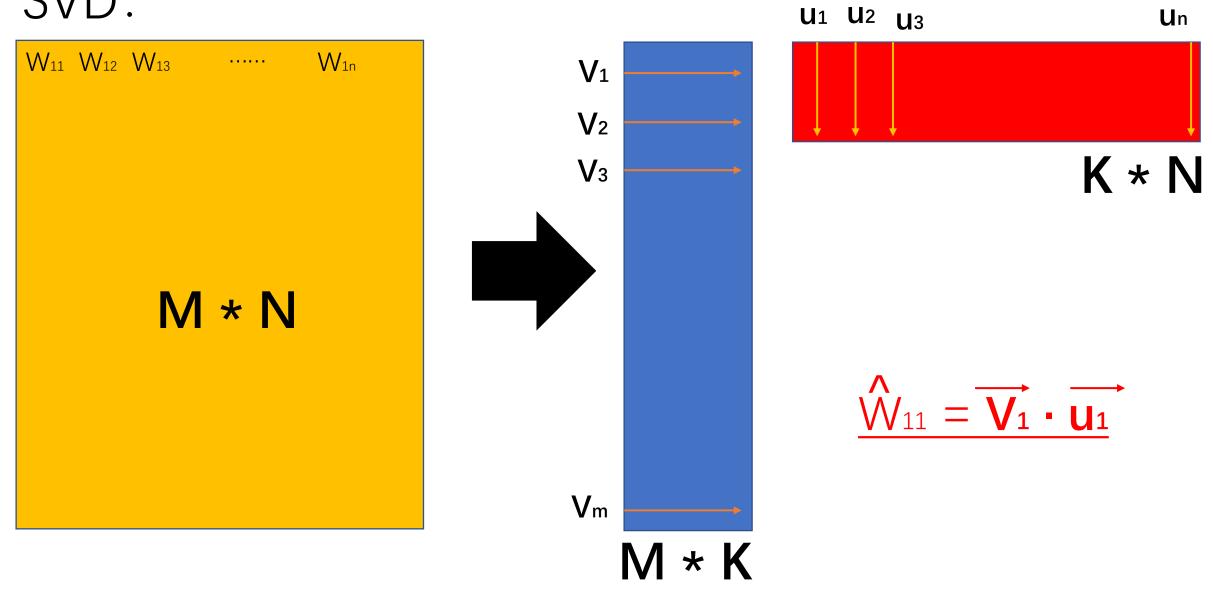
polynomial p=1:
$$\hat{y}(\mathbf{x}) = w_0 + \sum_{i=1}^n w_i x_i, \quad w_0 \in \mathbb{R}, \quad \mathbf{w} \in \mathbb{R}^n$$

polynomial p=2: $y(x) = w_0 + \sum_{i=1}^n w_i x_i + \sum_{i=1}^n \sum_{j=i+1}^n w_{i,j} x_i x_j$

W_{ij} is difficult to calculate if the matrix is sparse

Backgrounds

SVD:



FM

Core:

$$\hat{y}(\mathbf{x}) := w_0 + \sum_{i=1}^n w_i \, x_i + \sum_{i=1}^n \sum_{j=i+1}^n \langle \mathbf{v}_i, \mathbf{v}_j \rangle \, x_i \, x_j$$

- X: a single input, including n variable, $X = (x_1, x_2, x_3 \cdot \cdot \cdot \cdot x_n)$
- **W**0 Global bias
- Weight of single variable
- $\mathbf{\hat{w}_{i,j}} = \langle \mathbf{v}_i, \mathbf{v}_j \rangle$ Predicted weight of two variable

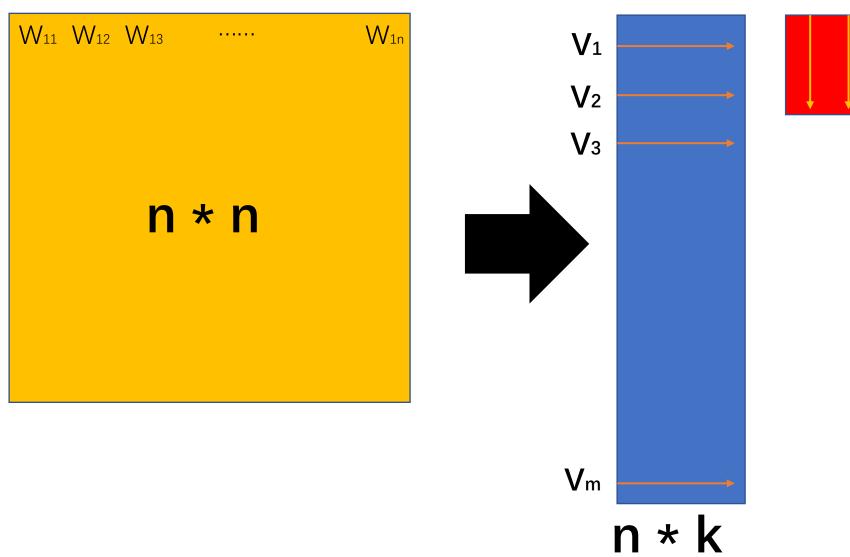
Core

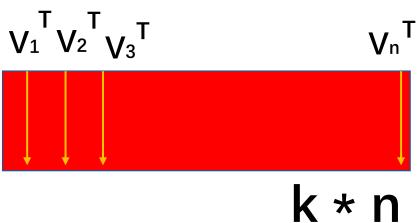
Matrix of Wij(s)

	X 1	X 2	X 3	
X_1	W ₁₁	W ₁₂	W 13	
χ_2	W ₂₁	W ₂₂	W ₂₃	
X ₃	W ₃₁	W ₃₂	W ₃₃	

Core

Decompose weight matrix Wij(symmetry):





$$\bigvee_{12}^{\wedge} = \bigvee_{1}^{\vee} \cdot \bigvee_{2}^{\vee}$$

Core



$$\sum_{i=1}^{n} \sum_{j=i+1}^{n} \langle \mathbf{v}_i, \mathbf{v}_j \rangle \, x_i \, x_j$$

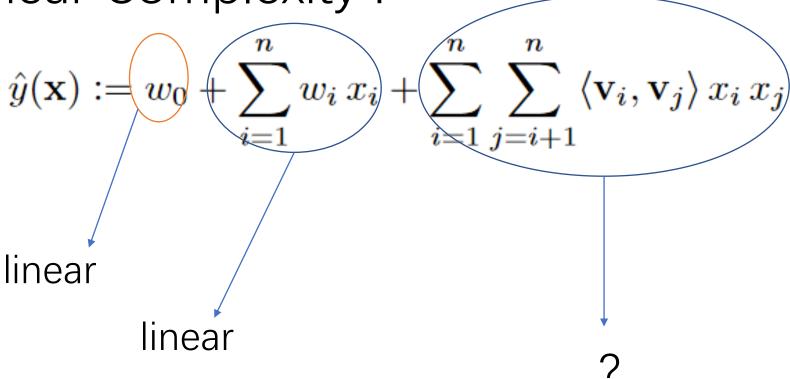
$$\langle \mathbf{v}_i, \mathbf{v}_j \rangle := \sum_{f=1}^k v_{i,f} \cdot v_{j,f}$$
 (K: a chosen number)

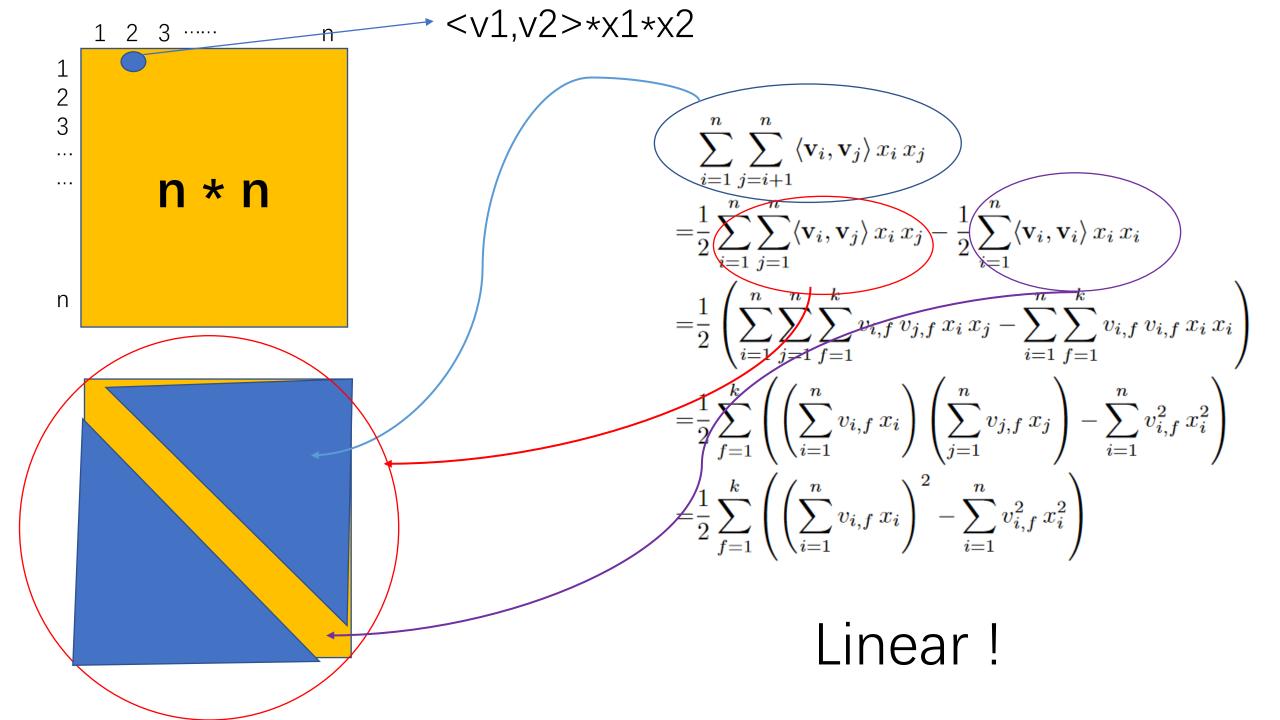
$$\langle \mathbf{v}_1, \mathbf{v}_4 \rangle = 3*5 + 1*2 + 2*4 + 2*2 + 3*1$$

= 25

Explanation

• Linear Complexity:





Explanation

Parameters: gradient descent

$$\hat{y}(\mathbf{x}) := w_0 + \sum_{i=1}^n w_i \, x_i + \sum_{i=1}^n \sum_{j=i+1}^n \langle \mathbf{v}_i, \mathbf{v}_j \rangle \, x_i \, x_j$$

$$\frac{\partial}{\partial \theta} \hat{y}(\mathbf{x}) = \begin{cases} 1, & \text{if } \theta \text{ is } w_0 \\ x_i, & \text{if } \theta \text{ is } w_i \\ x_i \sum_{j=1}^n v_{j,f} x_j - v_{i,f} x_i^2, & \text{if } \theta \text{ is } v_{i,f} \end{cases}$$