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DBLM: Spatiotemporal Resource Management via Deep Black-Litterman Model

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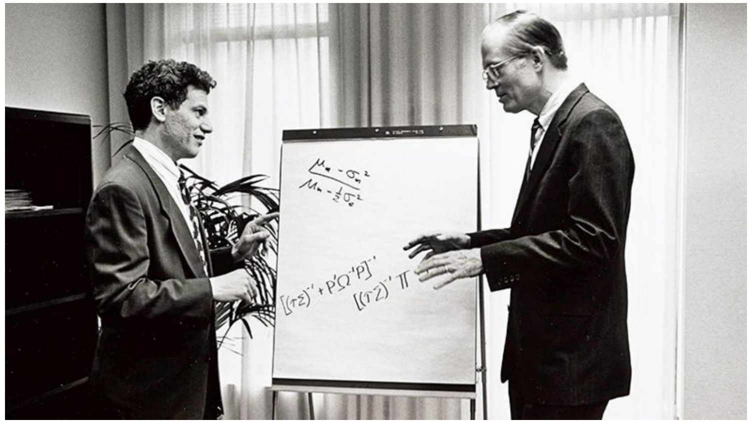
Background

- **Time Series Supplier Allocation**

Time Series Supplier Allocation (TSSA) is to reduce discrepancies and boost efficiency by optimizing supplier capabilities to precisely match order quantities in the future

- **Black-litterman Model**

The Black-Litterman (BL) Model, which originated from the field of financial portfolio management, has a core concept: it incorporates investor subjective perspectives (perspective matrix) to adjust investment decisions, thereby balancing expected returns with investment risks to determine optimal asset allocation ratios.



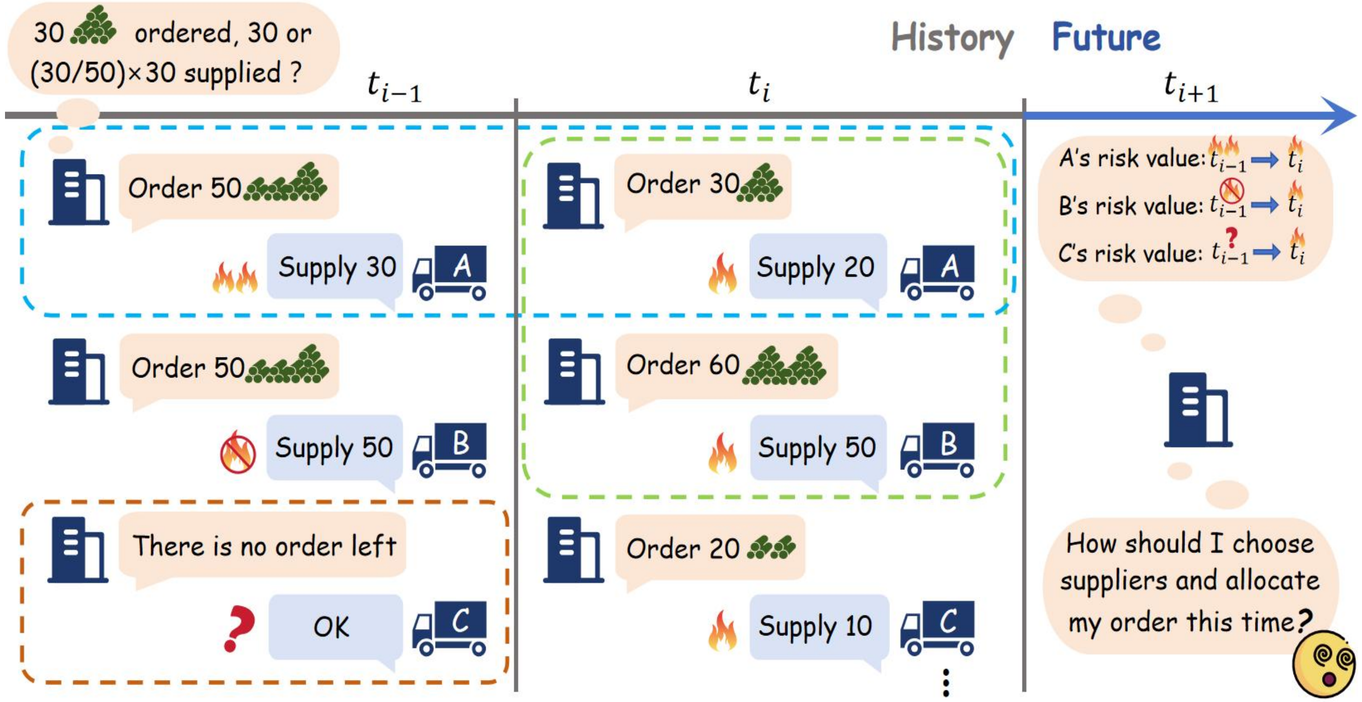
- **DeepLearning**

Deep learning (DL) frameworks have emerged as leading solutions to capture non-linear correlations for analysis

Challenges

C1. Spatio-Temporal Dynamics.

As shown in the **GREEN** rectangle, an increase for A whereas a decrease for B compared to their previous levels at time t_{i-1} respectively.



C2. Lack of Supervisory Signals.

Training deep learning models with perspective matrices is challenging due to insufficient supervisory signals, so our focus is developing appropriate training signals.

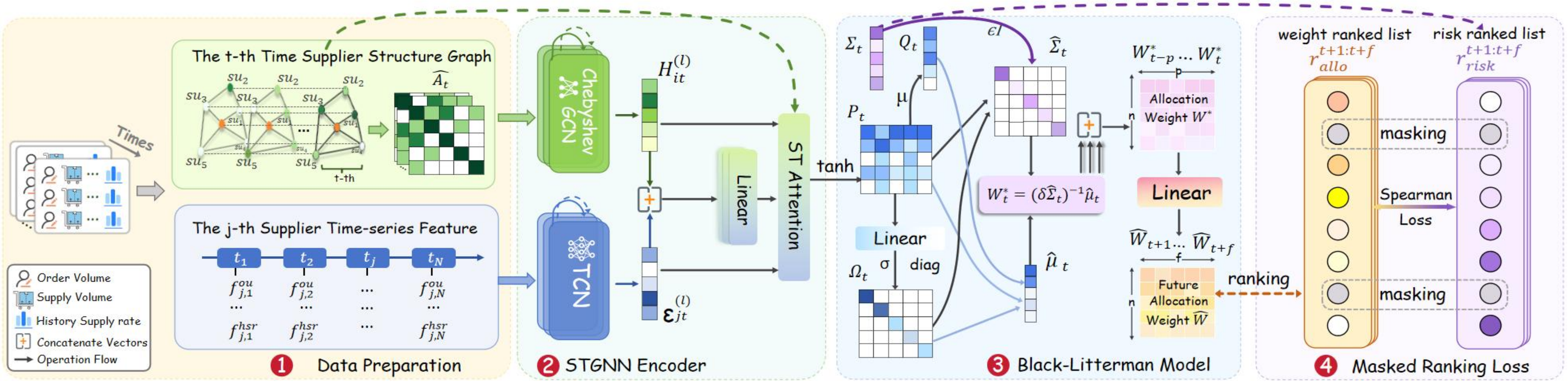
C3. Data Unreliability.

As shown in the **RED** rectanglethe, the absence of historical orders for **supplier C** obscures their supply potential and associated risks.

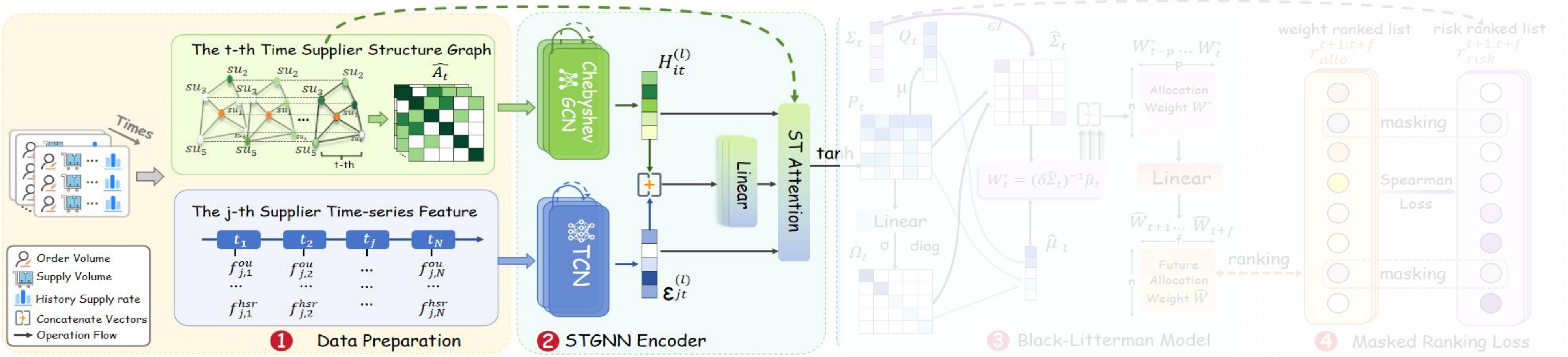
Method

The method of DBLM contain four parts:

Data Preparation, STGNN Encoder, Black-Litterman Model and Masked Ranking Loss



Method



Data preparation and STGNN Encoder

Encode the prepared supplier sequence features *{F_{t-p}, ··· , F_t}* and **dynamic propagation matrices** $A_{t-p:t}$ to obtain representations in both spatial and temporal dimensions.

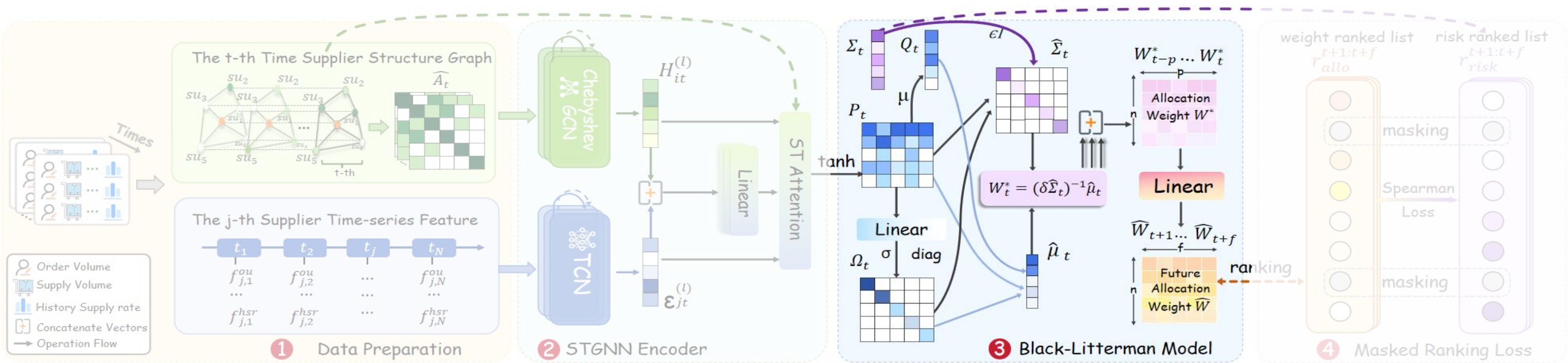
Spatial Convolution Layer.

$$\mathcal{H}_t^{(l)} = \sigma\left(\sum_{c=1}^{C} \mathbf{T}_c(\hat{A}_t)\mathcal{H}_t^{(l-1)}\mathbf{W}_{\text{sp}}^{(l)}\right)$$

Temporal Convolution Layer

$$\mathcal{E}_t^{(l)} = f\left(\mathbf{W}_{\text{te}}^{(l)} * \mathcal{E}_{t-1}^{(l-1)} + \mathbf{b}_{\text{te}}^{(l)}\right)$$

Method



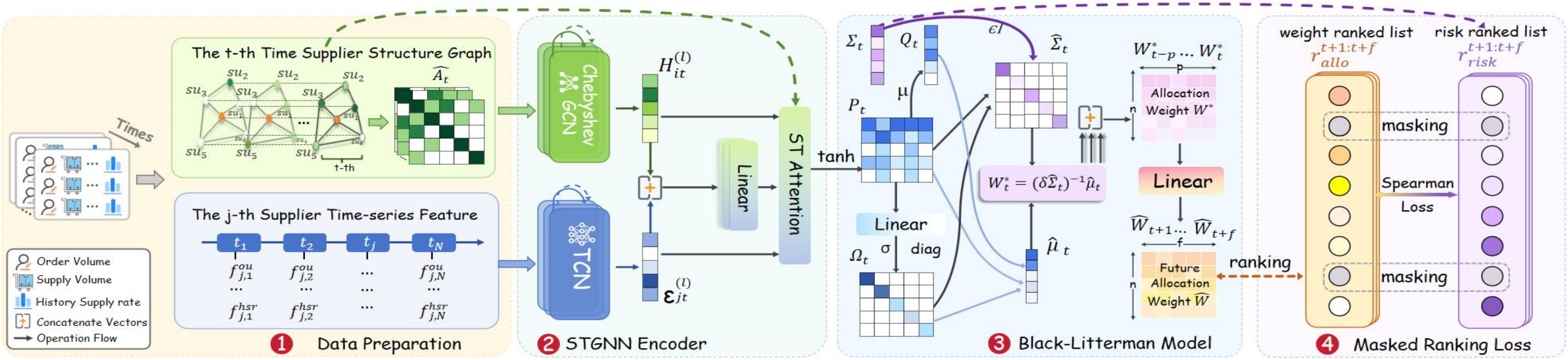
Black-Litterman Model

- Automatically generate perspective matrices that reflect market dynamics

$$\mathcal{P}_t = \tanh\Big(\sum_{\hat{\mathcal{A}}_t(i,j)>0} \alpha_{ij,t}\hat{\mathcal{A}}_t(i,j)[\mathcal{H}_{it}^{(l)} \times \mathcal{E}_{jt}^{(l)}]\Big) \qquad \Omega_t = \mathrm{diag}\big(\sigma(\mathbf{W}_{\mathrm{om}}\mathcal{P}_t\Sigma_t\mathcal{P}_t^T + \mathbf{b}_{\mathrm{om}})\big)$$

- Adjust return and risk parameters based on perspective matrices

Method



Masked Ranking Loss

- Construct ranking loss based on Spearman correlation coefficient
- Introduce masking mechanism to reduce the impact of unreliable data
- Guide model learning through monotonicity optimization

$$\min_{\Theta} \mathcal{L} = \sum_{t=0}^{T_{train}} \sum_{j=t}^{t+f} \frac{6\sum_{i=1}^{N-|\mathcal{S}_j|}(r^j_{i,\text{risk}} - r^j_{i,\text{allo}})^2}{(N-|\mathcal{S}_j|)\big((N-|\mathcal{S}_j|)^2-1\big)} + \eta||\Theta||^2$$

Experiment

Dataset

- The MCM dataset comprises supply and order data from 401 suppliers over 240 weeks,
- The SZ dataset includes data from 218 suppliers across 2 years (731 days).

DBLM **shows outstanding performance and achieves state-of-the-art scores on almost all metrics.**

Method	Dataset	MCM-TSSA				SZ-TSSA			
	Metric	HR@10	HR@20	HR@50	MRE	HR@10	HR@20	HR@50	MRE
Baselines	HA	0.045±0.087	0.125±0.058	0.268±0.049	0.968±0.092	0.039±0.086	0.104±0.117	0.230±0.099	0.929±0.087
	MC	0.053±0.096	0.148±0.072	0.276±0.087	0.924±0.053	0.059±0.147	0.141±0.152	0.245±0.104	0.859±0.057
	Greedy	0.078±0.050	0.166±0.061	0.307±0.044	0.902±0.108	0.072±0.088	0.154±0.120	0.349±0.109	0.995±0.149
	DP	0.075±0.082	0.155±0.070	0.303±0.053	0.930±0.124	0.069±0.075	0.137±0.096	0.346±0.142	0.942±0.155
	Fuzzy-AHP	0.204±0.197	0.241±0.132	0.311±0.155	0.897±0.162	0.169±0.098	0.217±0.133	0.306±0.129	0.742±0.140
	Fuzzy-TOPSIS	0.104±0.128	0.187±0.140	0.233±0.165	0.887±0.143	0.095±0.087	0.127±0.094	0.149±0.138	0.939±0.143
	Markowitz	0.139±0.170	0.227±0.158	0.309±0.106	0.997±0.191	0.118±0.149	0.154±0.110	0.289±0.128	0.844±0.185
	DT	0.040±0.492	0.098±0.524	0.204±0.460	0.974±0.680	0.038±0.612	0.106±0.598	0.206±0.720	0.977±0.749
	Lasso	0.066±0.544	0.137±0.670	0.296±0.399	0.872±0.721	0.061±0.482	0.161±0.670	0.350±0.648	0.736±0.725
	MLP	0.199±0.344	0.245±0.287	0.331±0.225	0.973±0.339	0.182±0.291	0.246±0.348	0.382±0.306	0.556±0.320
	ECM	0.272±0.282	0.289±0.299	0.348±0.310	0.641±0.407	0.253±0.238	0.290±0.288	0.412±0.271	0.493±0.377
	SGOMSM	0.263±0.397	0.311±0.403	0.327±0.454	0.844±0.429	0.204±0.140	0.282±0.198	0.369±0.245	0.671±0.298
	AGA	0.158±0.237	0.206±0.228	0.310±0.296	0.772±0.357	0.180±0.205	0.242±0.167	0.374±0.152	0.629±0.261
Ours	**DBLM**	**0.403**±0.284	**0.449**±0.293	**0.487**±0.356	**0.518**±0.292	**0.481**±0.158	**0.543**±0.187	**0.662**±0.182	**0.327**±0.323
Ablation	DBLM(w/o BL)	0.154±0.488	0.238±0.462	0.347±0.529	0.820±0.442	0.112±0.658	0.148±0.495	0.325±0.431	0.729±0.480
	DBLM (w/o STGNN)	0.306±0.280	0.348±0.305	0.377±0.340	0.852±0.319	0.274±0.144	0.309±0.195	0.420±0.170	0.438±0.266
	DBLM (w/o TCN)	0.314±0.277	0.370±0.284	0.393±0.342	0.648±0.320	0.293±0.109	0.341±0.132	0.448±0.240	0.361±0.258
	DBLM (w/o DGCN)	0.323±0.211	0.419±0.277	0.431±0.330	0.719±0.376	0.340±0.172	0.442±0.249	0.473±0.150	0.377±0.342
	DBLM (w/o Fusion)	0.379±0.299	0.420±0.311	0.453±0.328	0.588±0.347	0.364±0.455	0.425±0.298	0.588±0.211	0.367±0.243
	DBLM (w/o Mask)	0.376±0.280	0.390±0.246	0.426±0.359	0.626±0.341	0.349±0.240	0.426±0.328	0.539±0.331	0.427±0.397
	DBLM (w/o Rank Loss)	0.290±0.279	0.317±0.194	0.335±0.243	0.692±0.287	0.307±0.198	0.373±0.276	0.501±0.453	0.486±0.493

Summary

- DBLM is the first initiative to integrate financial investment management strategies with supply chain demand challenges.

- We introduce a novel masked ranking loss to guide the training of DBLM, which is implemented by the Spearman rank correlation coefficient.

- Our comprehensive experimental evaluation on two supplier allocation datasets demonstrates the superior performance of DBLM over existing baselines.

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Thank You !!!

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