DBLM: Spatiotemporal Resource Management via Deep Black-Litterman Model

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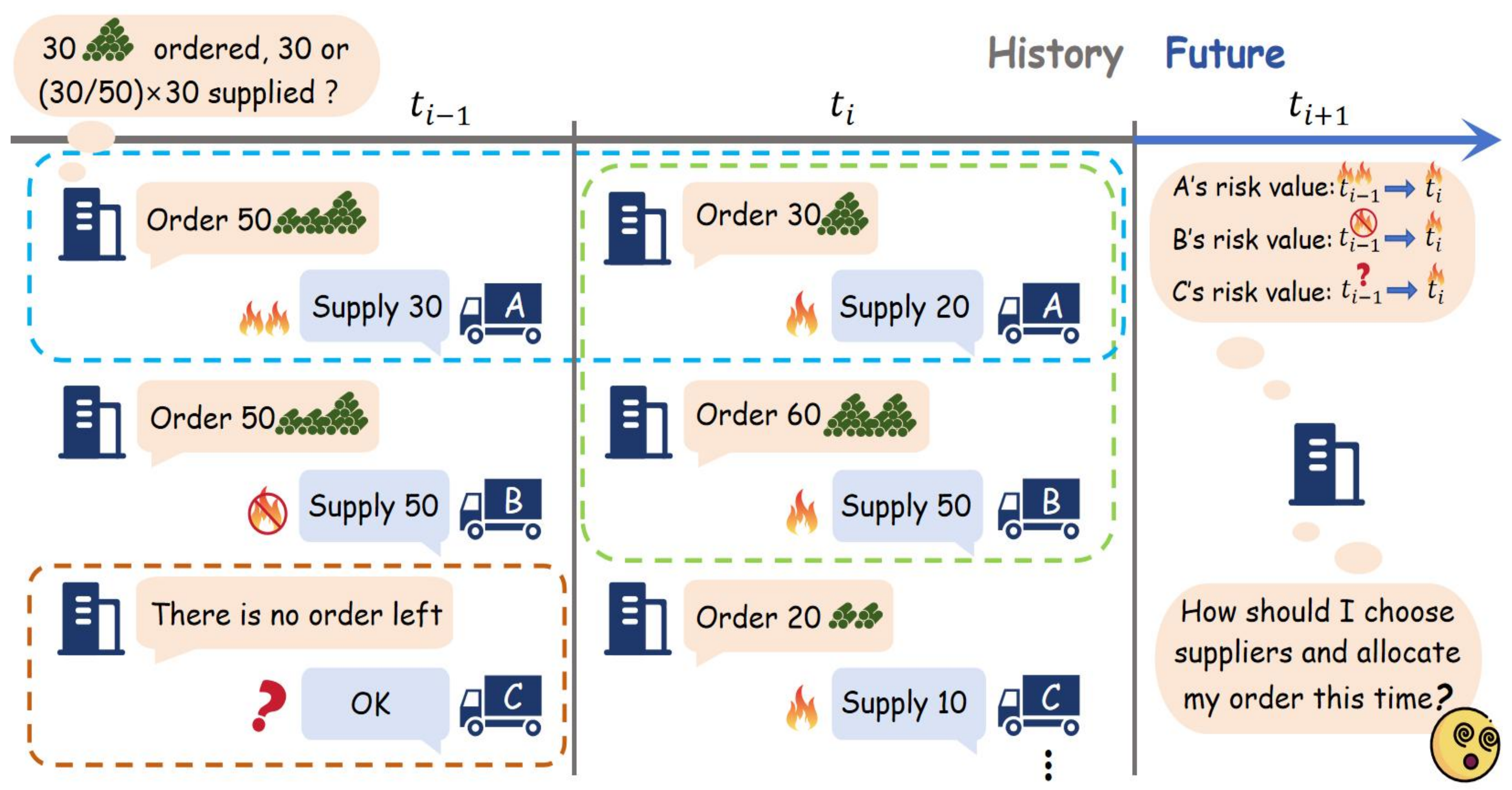
Motivation

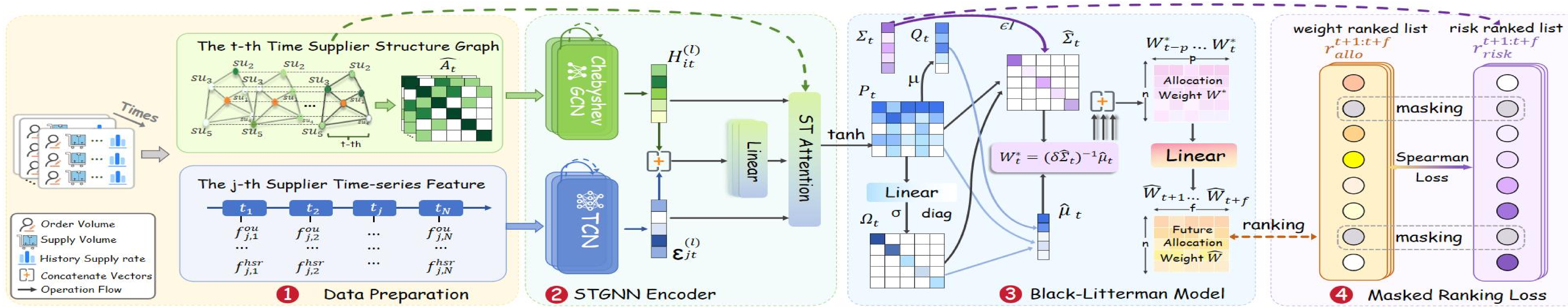
- **Time Series Supplier Allocation**, which optimizes temporal supplier-order matching to maximize resource efficiency, remains a critical challenge due to its NP-hard complexity.
- **The Black-Litterman model**'s perspective matrices, while enhancing portfolio optimization through expert predictions, face uncertainty in manually capturing complex supplier-enterprise dynamics.
- **Deep learning(DL)** frameworks can be utilized to capture non-linear correlations between suppliers and enterprises.



Challenges

However, applying deep learning frameworks to BL models still faces the following challenges:

- **C1. Spatio-Temporal Dynamics**. Supplier capacity exhibits inherent spatio-temporal dynamics crucial for future allocation.
- **C2. Lack of Supervisory Signals**. Training DL models require robust supervisory signals to navigate gradient towards the optimal direction to objection while in this filed there is no proper supervisory signal before.
- **C3. Data Unreliability**. Data unreliability is a common issue in supply chain datasets, leading to biases in DL models, especially towards untradedor new suppliers with unassessed capabilities



Method

Data Preparation

Construct quantitative supply indicators from order and supply volumes to serve as the initial features of the suppliers' capacity and stability

STGNN Encoder

We encode the prepared supplier sequence features $\{\mathcal{F}_{t-p},\cdots,\mathcal{F}_t\}$ and dynamic propagation matrices $\mathcal{A}_t(i,j)=\frac{\mathrm{sim}_t(i,j)+1}{2}$ to obtain representations in both spatial and temporal dimensions. $\mathcal{H}_t^{(l)}$ is the representation matrix in l-th layer at time t. $\mathcal{E}_t^{(l)}$ is the representation matrix in l-th layer at time t.

Black-Litterman Predictor

The optimization task at any time t aims to

$$\begin{cases} \max & \underbrace{\mathcal{W}_t\mu}_{\text{Profit Item}} - \frac{\delta}{2}\underbrace{\mathcal{W}_t^T(\mathcal{O}_t-\mathcal{S}_t)^{\kappa}\mathcal{W}_t}_{\text{Risk Item}} \\ \text{subject to} & \sum_{i=1}^{N} w_{it}=1, i=\mathbb{N}^{+}. w_{it}\in[0,1] \end{cases}$$

We derive the Perspective Matrix

$$\mathcal{P}_t=\tanh\Big(\sum_{\hat{\mathcal{A}}_t(i,j)>0}\alpha_{ij,t}\hat{\mathcal{A}}_t(i,j)[\mathcal{H}_{it}^{(l)}\times\mathcal{E}_{jt}^{(l)}]\Big)$$

and Error Covariance Matrix

$$\Omega_t=\mathrm{diag}\big(\sigma(\mathbf{W}_{\mathrm{om}}\mathcal{P}_t\Sigma_t\mathcal{P}_t^T+\mathbf{b}_{\mathrm{om}})\big)$$

through a spatiotemporal fusion layer in the BL model, enabling parameter adjustments that reconcile historical data with future expectations to project optimal allocation solutions.

Loss Function

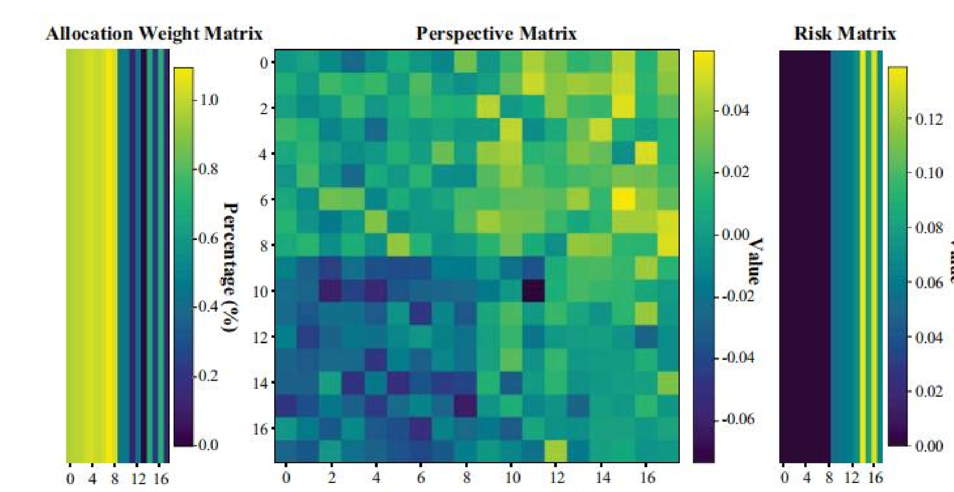
The loss function aims to minimize the negative correlation between risk sequences and allocation weight sequences to ensure high-risk assets receive low weight allocations.

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

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).



Risk Matrix (**Left**) composed of the top and bottom 9 suppliers in ascending sort, with corresponding Allocation Weight (**Right**) and Perspective Matrix (**Middle**)

Hit Ratio@K(HR@K) and **Mask Risk Expect (MRE)**, to more accu_x0002_rately and fairly evaluate the model's performance.

Method	Dataset / Metric	MCM-TSSA HR@10	MCM-TSSA HR@20	MCM-TSSA HR@50	MCM-TSSA MRE	SZ-TSSA HR@10	SZ-TSSA HR@20	SZ-TSSA HR@50	SZ-TSSA 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