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DBLM: Spatiotemporal Resource Management via Deep Black-Litterman Model

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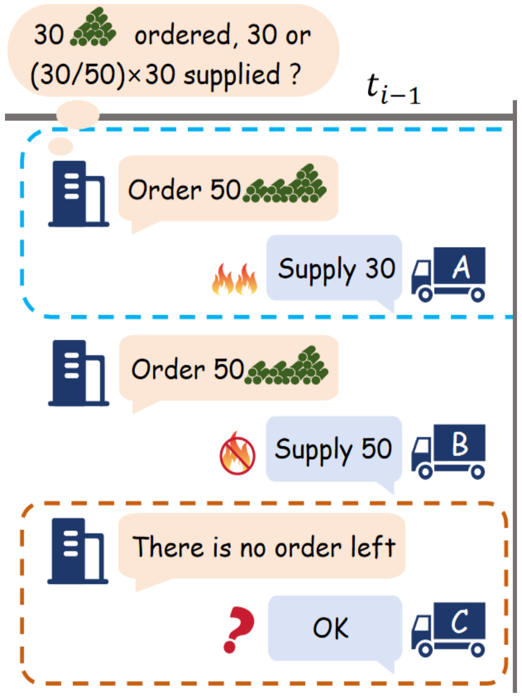
Presenter: Dingyi Zhuang

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.

Suppose you are running an e-bike manufacturing company. You need a constant supply of battery units from three different suppliers (A, B, and C). Your future weekly demand needs to forecast.

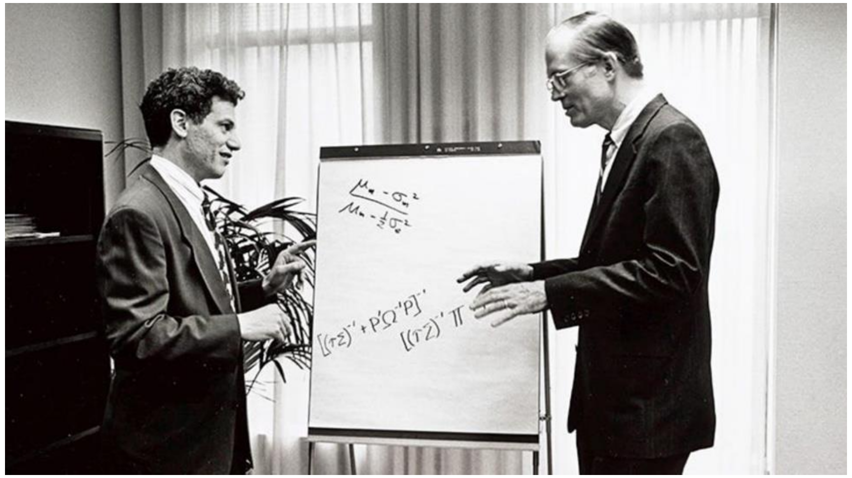


Maximum capacity per week	Cost per unit	Reliability risk
30	10	High (they offer a lower price, but occasionally deliver late or short)
50	12	Medium (they usually deliver on time, but they sometimes face production bottlenecks)
?, approx. 20	15	Low (very reliable but expensive)

Background

- **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.



Financial Term	Supply Chain Equivalent
Asset (Stock/Bond)	Supplier (A, B, C)
Expected Return	Performance Metric (e.g., Cost + Reliability)
Variance, Covariance	Disruption Risk, Correlation in Lead Times
Views on Assets	Forecasted changes in cost/reliability
Market Equilibrium	Historical performance data

Background

- **Black-Litterman Model**

Establish Prior (Equilibrium) Returns

- Historical data on supplier performance
- Covariance matrix for disruptions

Incorporate Subjective Views

- E.g., "Supplier B reliability might drop due to a strike."
- Represent as *views* with a certain confidence level

Compute Posterior (Black-Litterman) Returns

- Formula: $\mu = \pi + \Sigma P^T (P\Sigma P^T + \Omega)^{-1} (Q - P\pi)$

where P is the perspective matrix, Ω the error covariance, Q the subjective views, π equilibrium (prior) returns vector, Σ covariance matrix of the underlying assets, and μ (posterior) expected performance for each supplier

Optimize allocation

Mean-Variance Formulation

Maximize $w^T \mu - \lambda w^T \Sigma w$

Subject to:

- $w_A + w_B + w_c = Demand$ (for each week)
- $0 \leq w_i \leq C_i, \forall i \in \{A, B, C\}$

Background

- **Transition to Deep Black-Litterman Model**

Problem: In standard BL, perspective matrices P are manually crafted. That's hard for TSSA, because:

- We need **real-time** updates of supplier relationships.
- We want to capture **nonlinear** spatio-temporal trends (suppliers interacting over time).
- **Solution**: Let a **deep model** learn the perspective matrix automatically from data.

Merge BL with deep neural networks that capture:

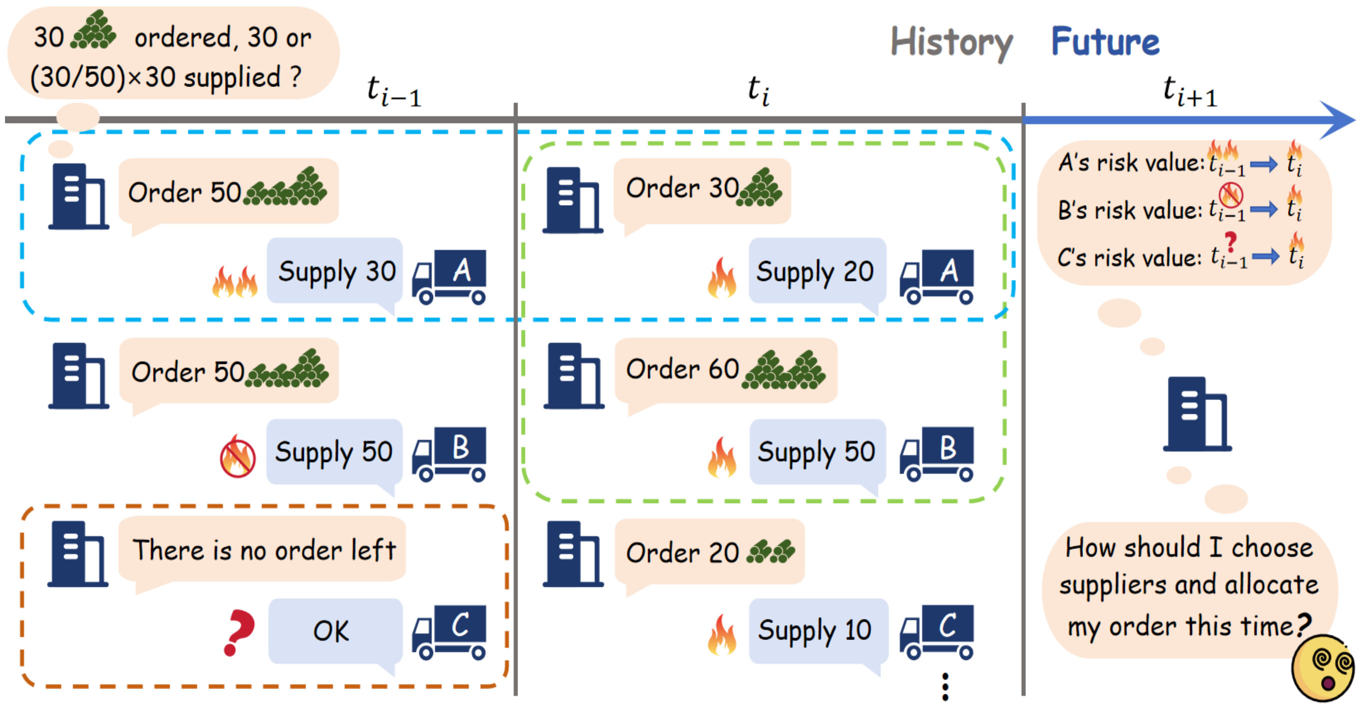
- **Spatio–Temporal Graph Neural Networks (STGNN)** to model time-series supplier data plus inter-supplier relationships.

- **Learned Perspective Matrix** P from the STGNN encoder (instead of manual).

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.

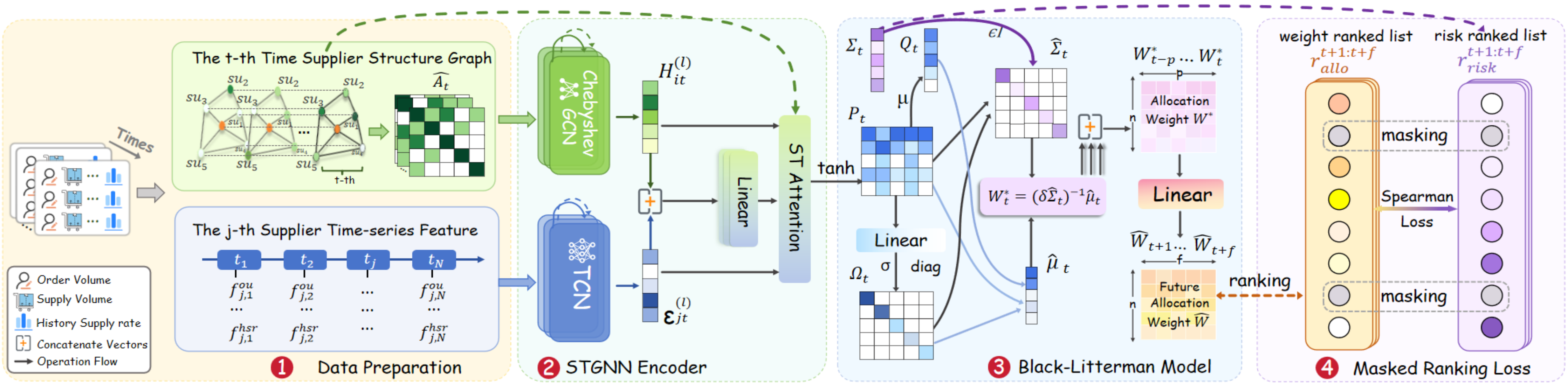
C3. Data Unreliability.

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

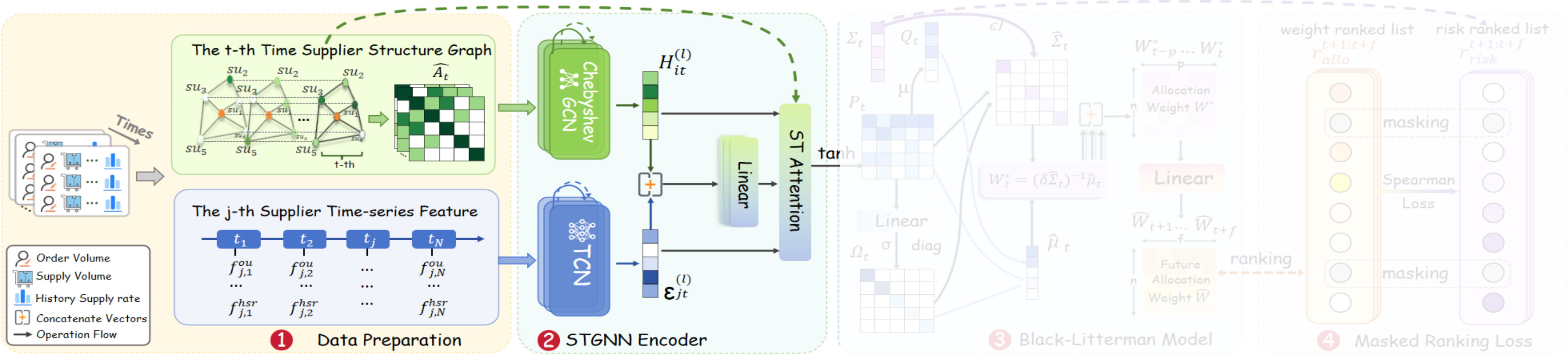
Method

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 ***{Ft−p, ··· , Ft}*** and **dynamic propagation matrices** ***At−p:t*** to obtain representations in both spatial and temporal dimensions.

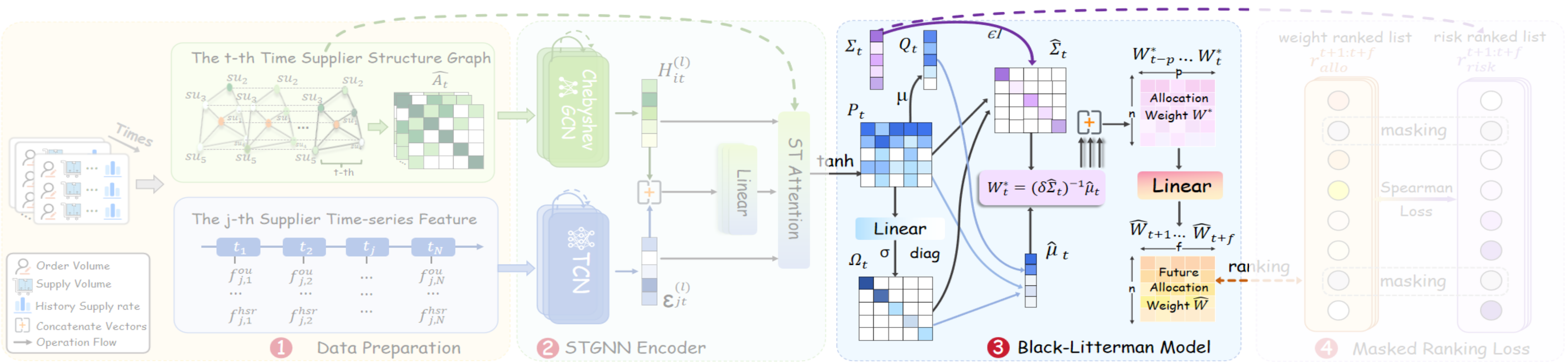
Spatial Convolution Layer.

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

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



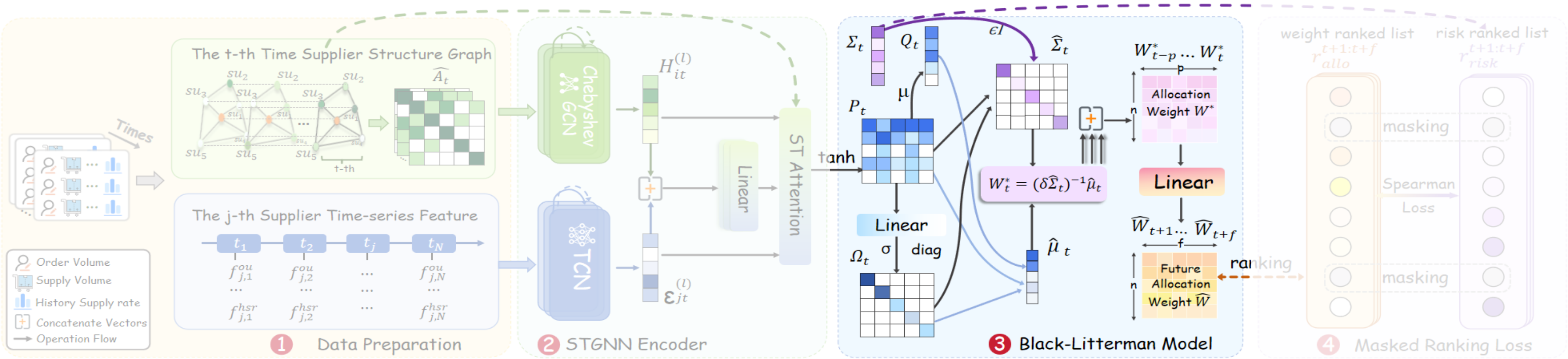
Black-Litterman Model

- 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

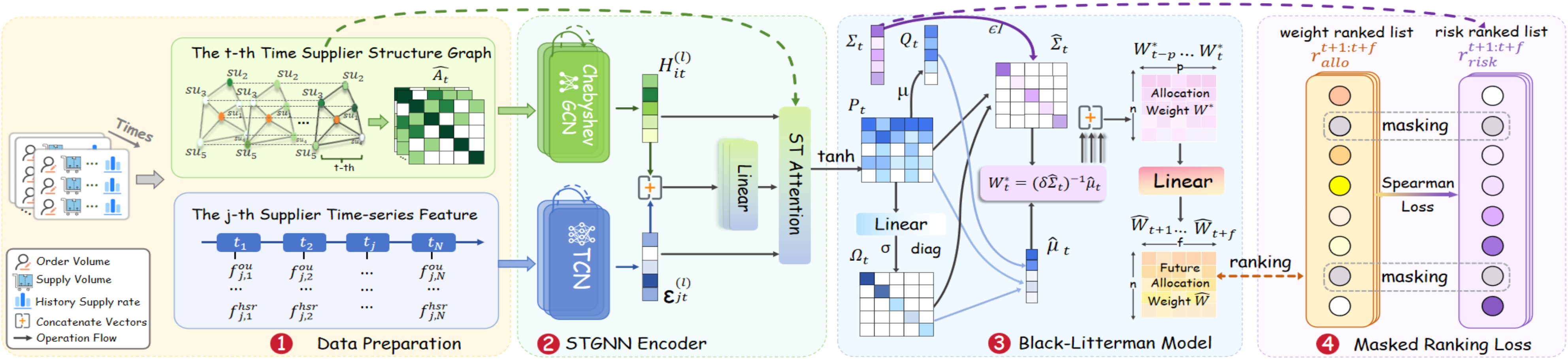


Black-Litterman Model

4.3.2 *Black-Litterman Solver.* The BL Model is enhanced by incorporating the perspective matrix $\mathcal{P}$ and error covariance matrix Ω from enterprise to adjust the return vector μ to $\hat{\mu}$ and risk vector Σ to $\widehat{\Sigma}$, as detailed in Appendix B. Given the equilibrium supplier profits Π normalized from μ via Eq. (16), and perspective return vector $Q = \mathcal{P} \times \mu + N(0, \Omega)$, we adjust the profit and risk components as:

$$\begin{aligned} \widehat{\mu}_t &= \Pi_t + \tau\Sigma_t\mathcal{P}_t^T(\mathcal{P}_t\tau\Sigma_t\mathcal{P}_t^T + \Omega_t)^{-1}(Q_t - \mathcal{P}_t\Pi_t), \\ \widehat{\Sigma}_t &= (1+\tau)(\Sigma_t + \epsilon I) - \tau(\Sigma_t + \epsilon I)\mathcal{P}_t^T \\ &\quad \times (\mathcal{P}_t\tau\Sigma_t\mathcal{P}_t^T + \Omega_t)^{-1}\mathcal{P}_t\tau\Sigma_t, \end{aligned} \tag{9}$$

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

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

Pesudocode

Algorithm 1 Training Procedure of DBLM.

Require: Suppliers set $\mathcal{SU}$, supply chain data $\mathcal{O}$, $\mathcal{S}$, total target volume M, hyper-parameters $\delta, \kappa, \tau, l, \epsilon, \eta$.

Prepare feature $\mathcal{F}_t$ and construct dynamic propagation matrix $\hat{\mathcal{A}}_t$.

Initialize parameters $\Theta = \{\mathbf{W}_{\mathrm{sp}}^{(l)}, \mathbf{W}_{\mathrm{te}}^{(l)}, \mathbf{b}_{\mathrm{te}}^{(l)}, \mathbf{W}_{\mathrm{attn}}, \mathbf{b}_{\mathrm{attn}}, \vec{a}, \mathbf{W}_{\mathrm{om}}, \mathbf{b}_{\mathrm{om}}, \mathbf{W}_{\mathrm{out}}, \mathbf{b}_{\mathrm{out}}\}$ via Xavier Initializer.

while $\mathcal{L}$ does not converge **do** ▷ **Train**

  Encode spatial $\mathcal{H}_t^{(l)}$ and temporal $\mathcal{E}_t^{(l)}$ representation via ChebGCN and TCN;

  Fuse $\mathcal{H}_t^{(l)}$ and $\mathcal{E}_t^{(l)}$ to construct Perspective Matrix $\mathcal{P}_t$; ▷ Fusion

  Drive Error Covarianze Matrix Ω_t by $\mathcal{P}_t$ via Eq.(8);

  Calculate history optimist $\mathcal{W}^*$ via Eq.(18) and Eq.(10) by $\mathcal{P}_t, \Omega_t$; ▷ BL Solve

  Predict $\hat{\mathcal{W}}^*_{t+1:t+f}$ via Eq.(11); ▷ **Predict**

  Minimizing $\mathcal{L}$ via Eq. (12) using Adam Optimizer;

end while

End optimizing parameters Θ;

return predicted low-risk allocation weight matrix $\hat{\mathcal{W}}^*$.

Research questions

We want to answer the following research questions:

- **RQ1:** How does DBLM compare with state-of-the-art approaches in optimizing allocation SoS risk for time-series suppliers?
- **RQ2:** What contributions do the key components of DBLM make to improving supplier allocation outcomes?
- **RQ3:** Can the perspective matrix learned through STGNNs significantly enhance the optimization of allocation risk?
- **RQ4:** How does the model's performance vary with adjustments to the risk coefficient δ and the reweight coefficient η?

Experiment (RQ1)

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.

19.2% to 48.2% on the MCM dataset and 33.7% to 90.1% on the SZ dataset.

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

Ablation study (RQ2)

We conduct the ablation study:

1. without BL models, utilizing Markowitz weights and spatiotemporal embedding for prediction
2. without the STGNN encoder, replaced by MLP
3. without the TCN encoder
4. without the DGCN encoder
5. without Fusion Attention, opting to combine spatial and temporal embeddings directly rather than using the attention mechanism
6. without Mask Rank Loss, ignoring the data unreliability and removing mask mechanism
7. without Rank Loss, using only MAE loss to verify the lack of supervisory signals

Observations:

- BL models are vital
- Spatiotemporal embeddings are necessary
- Lack of supervisory signal significantly impacts the model’s effectiveness

Visualization (RQ3)

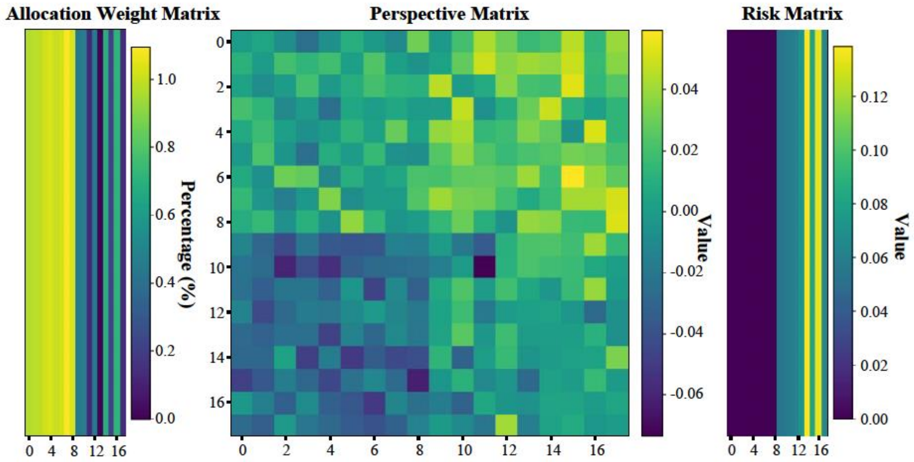


Figure 3: The Risk Matrix (Left.) composed of the top 9 and bottom 9 suppliers sorted by ascending risk, along with their corresponding Allocation Weight Matrix (Right.) and Perspective Matrix (Middle.).

Visually comparing suppliers' risks vs. their final allocation weights.

Ranking Suppliers: Sort them by ascending risk (lowest risk = top 9, highest risk = bottom 9).

Matrices Compared:

- **Risk Matrix:** Lists suppliers from lowest to highest risk.
- **Allocation Matrix:** Shows how many orders each supplier receives.
- **Perspective Matrix:** Visualizes the model's learned "competitiveness" between suppliers.

Observations:

- **Lower-Risk → Higher Allocation:** The top 9 low-risk suppliers get visibly higher order percentages than the bottom 9 high-risk suppliers.
- **Perspective Matrix Alignment:** Lighter shading corresponds to stronger competitiveness among low-risk suppliers, matching their higher allocations.

Hyperparameter Study (RQ4)

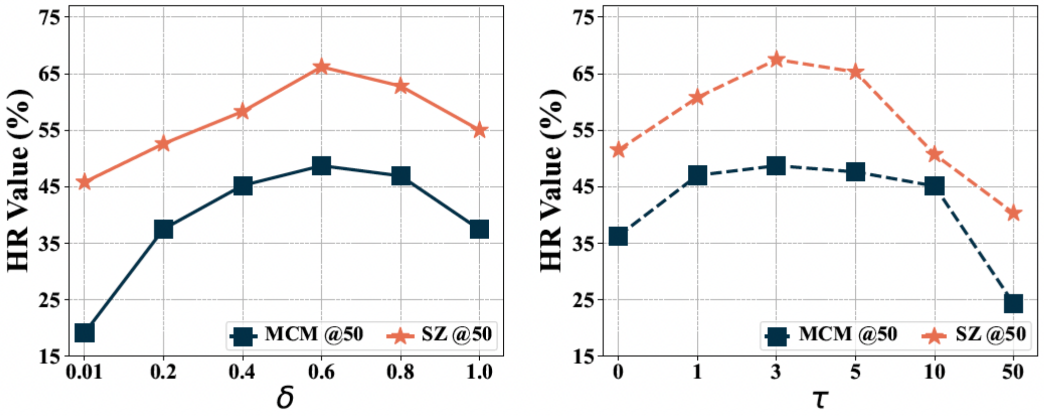


Figure 4: (Left.) Hyper-parameter study with δ on *MCM* and *SZ* datasets from 0.01 to 1.0. (Right.) Hyper-parameter study with τ on *MCM* and *SZ* datasets from 0 to 50.

Evaluate how two key hyper-parameters—δ(profit-risk weighting) and τ (modulation of the perspective matrix)—affect DBLM's performance.

- Both δ and τ significantly impact DBLM's ability to allocate orders effectively.
- Fine-Tuning these hyper-parameters ensures the model neither under-nor overestimates risk, maximizing hit ratios and minimizing supply shortfalls.

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.
- Ensures low-risk suppliers receive higher allocation while handling unreliable data.
- 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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