



ECML-PKDD23' ML4ITS WORKSHOP – SEPTEMBER 22, 2023

Probabilistic Demand Forecasting with Graph Neural Networks

Nikita Kozodoi¹

Elizaveta Zinovyeva¹

Simon Valentin²

João Pereira³

Rodrigo Agundez³

¹Amazon Web Services ²University of Edinburgh ³adidas AG

Project Team



Amsterdam



Berlin



1. Motivation & Related Work

Demand Forecasting in e-Commerce

Enables optimizing stock planning, logistics, and supply chain operations.

- Ensure product availability online ↔ Under-prediction
- Minimize waste ↔ Over-prediction

Demand Forecasting: Related Work



TRADITIONAL TIME SERIES MODELS

ARIMA, moving average, univariate time series models (e.g., [3]).

LIMITATIONS

Cold starts

Scalability

Demand Forecasting: Related Work

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NEURAL SEQUENCE MODELS

RNNs, DeepAR [4], Seq2Seq, Transformer models.

LIMITATIONS

Cold starts

Scalability

Independent demand predictions

Articles are not “aware” of each other’s existence

Motivation

Article's demand depends on the demand of **related** articles.



Price of similar articles



Stockouts

Demand Forecasting: Related Work

TRADITIONAL TIME SERIES MODELS

ARIMA, moving average, univariate time series models (e.g., [3]).

NEURAL SEQUENCE MODELS

RNNs, DeepAR [4], Seq2Seq, Transformer models.

GRAPH NEURAL NETWORKS

Spatio-temporal GNNs [2].

LIMITATIONS

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Graph NNs in (Demand) Forecasting

- Domains with predefined graph structures
 - Traffic forecasting applications [5]
 - Molecular structures [6]
 - Prominent architectures: DCRNN, Spatio-Temporal GCN, GraphWaveNet
- Demand forecasting in e-Commerce
 - Literature remains **rather limited**
 - Key challenges: high dimensionality, no pre-defined graph structure
 - Previous work combined GNN & LSTM for forecasting in online marketplaces [2]
 - Limitations: multiple-seller setting, point-based forecasts

Our Contributions

- End-to-end forecasting system
 - Based on DeepAR – SOTA LSTM-based forecasting method [4]
 - Integrates Graph-based GNN encoder to account for article relationships
 - Enables probabilistic forecasting
- Generic graph construction approach
 - Does not require expert knowledge and uses data-driven approach
 - Based on article attribute similarity
 - Highly scalable

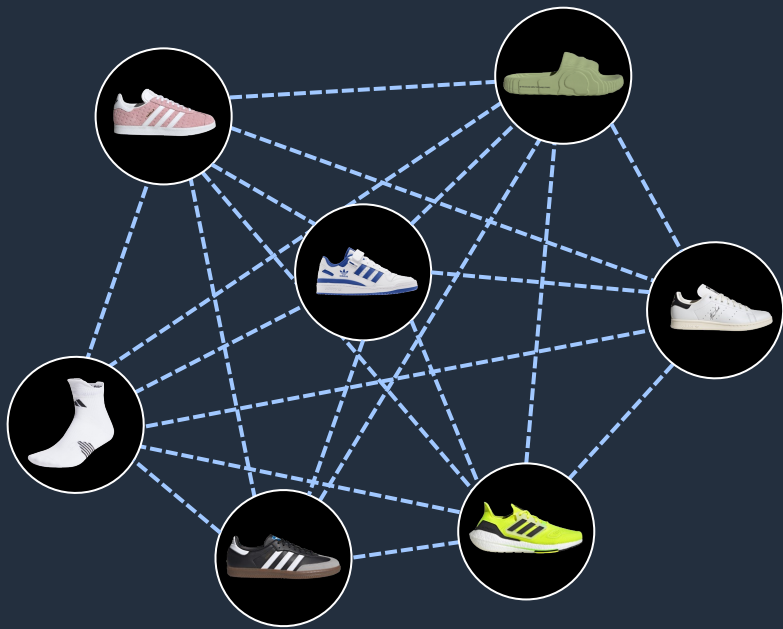
2. Methodology

Graph Construction

Graph Construction [1/3]

- Build a graph based on article similarity
 - Each node represents an article
 - Connections based on cosine similarity
 - Attributes: size, color, category, etc.

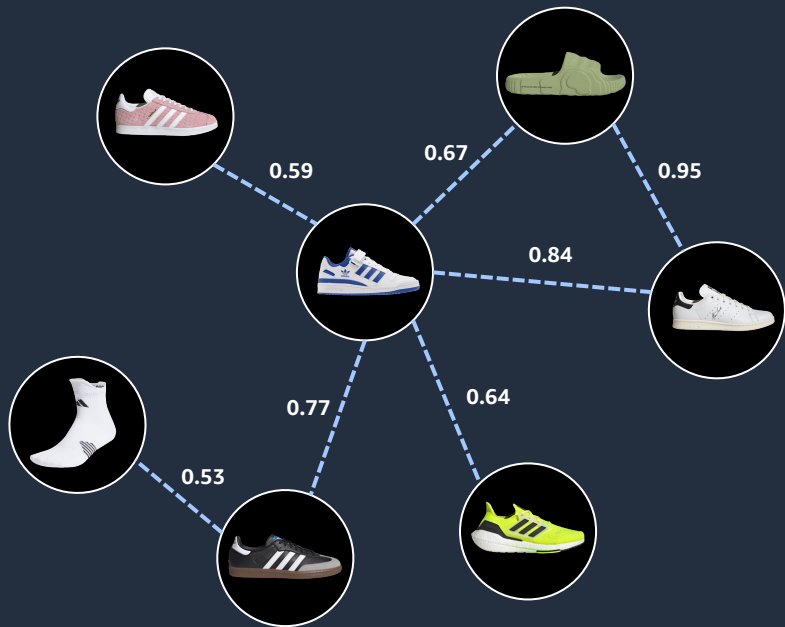
$$\text{similarity}(\mathbf{A}_i, \mathbf{A}_j) := \cos(\mathbf{X}_i, \mathbf{X}_j) = \frac{\mathbf{X}_i \cdot \mathbf{X}_j}{\|\mathbf{X}_i\| \|\mathbf{X}_j\|}$$



Graph Construction [2/3]

- Build a graph based on article similarity
 - Each node represents an article
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 - Keep edges with similarity > cutoff

$$\text{similarity}(\mathbf{A}_i, \mathbf{A}_j) := \cos(\mathbf{X}_i, \mathbf{X}_j) = \frac{\mathbf{X}_i \cdot \mathbf{X}_j}{\|\mathbf{X}_i\| \|\mathbf{X}_j\|}$$



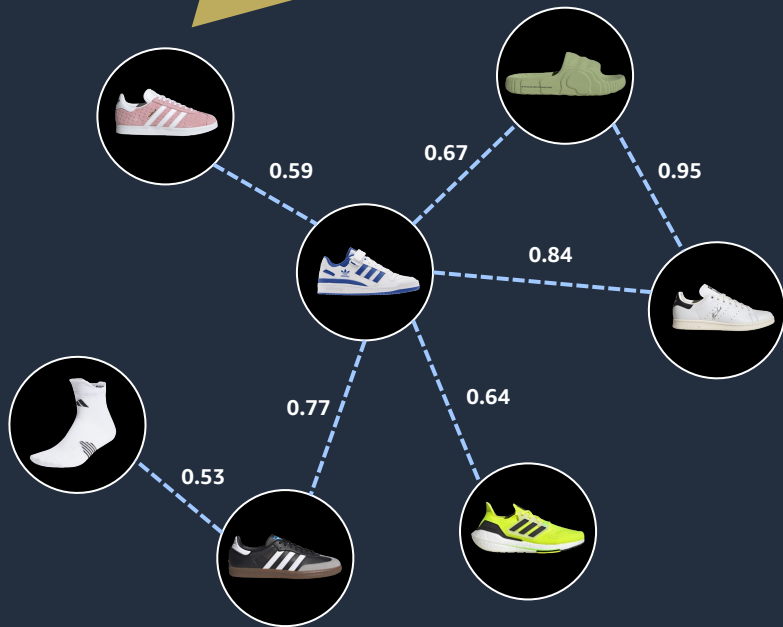
Note: similarity numbers are artificial

Graph Construction [3/3]

- Build a graph based on article similarity
 - Each node represents an article
 - Connections based on cosine similarity
 - Attributes: size, color, category, etc.
 - Keep edges with similarity > cutoff
- Nodes include article features
 - Static article attributes
 - Dynamic demand lags

ARTICLE ATTRIBUTES AND DEMAND LAGS

Color	Age	Demand lag 1	...	Demand lag P	Target demand
PINK	ADULT	y_T^i	...	y_{T-P}^i	y_{T+1}^i



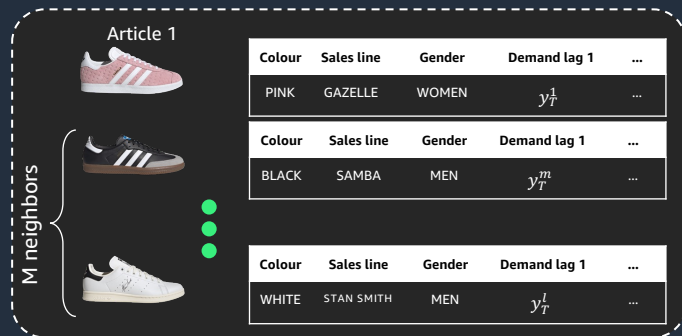
Note: similarity numbers are artificial

2. Methodology

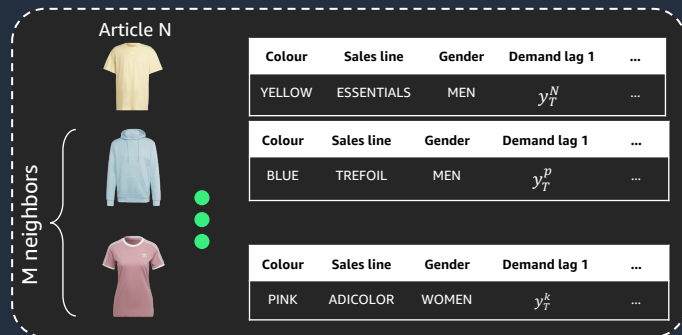
Model Architecture

GNN Encoder

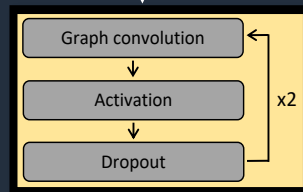
Observation #1



Observation #N



GNN layers



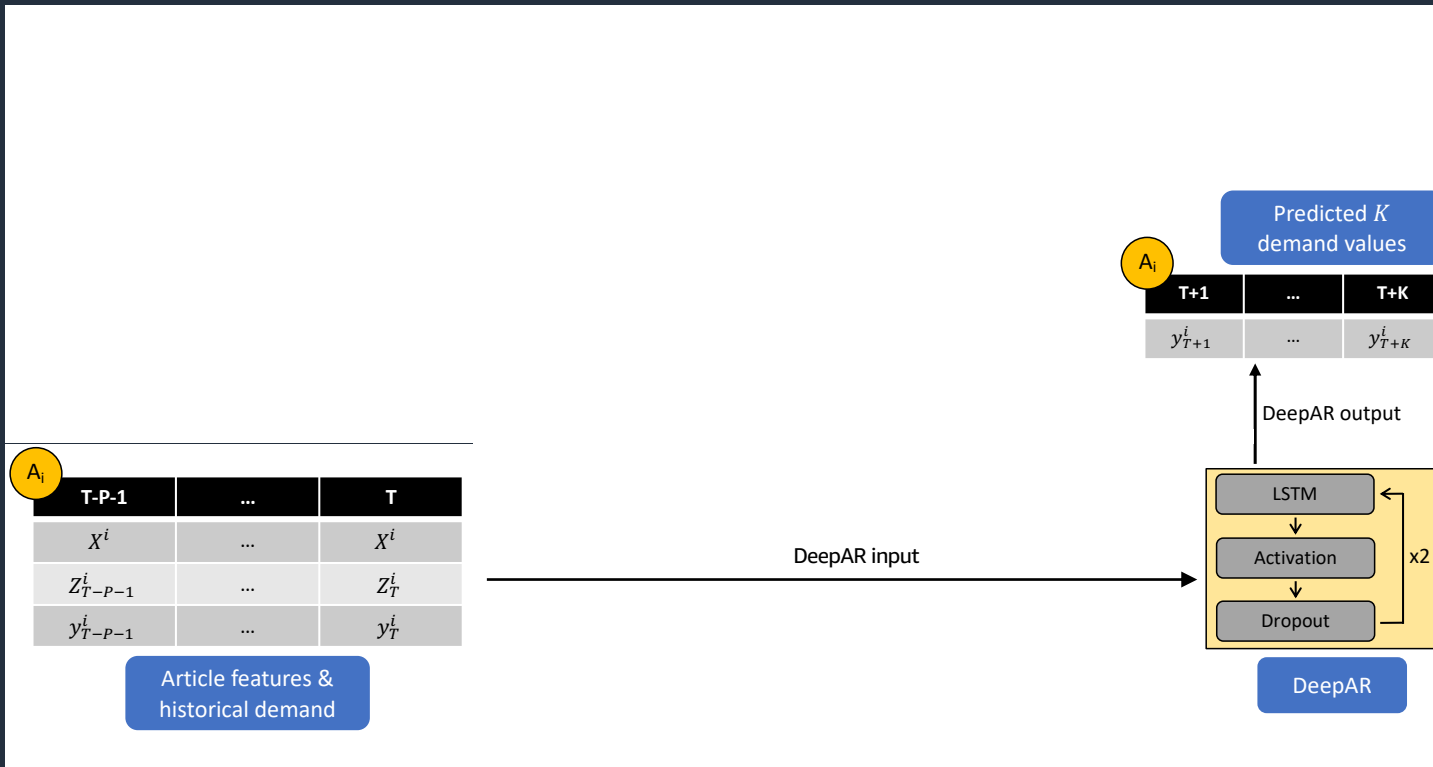
Node embedding



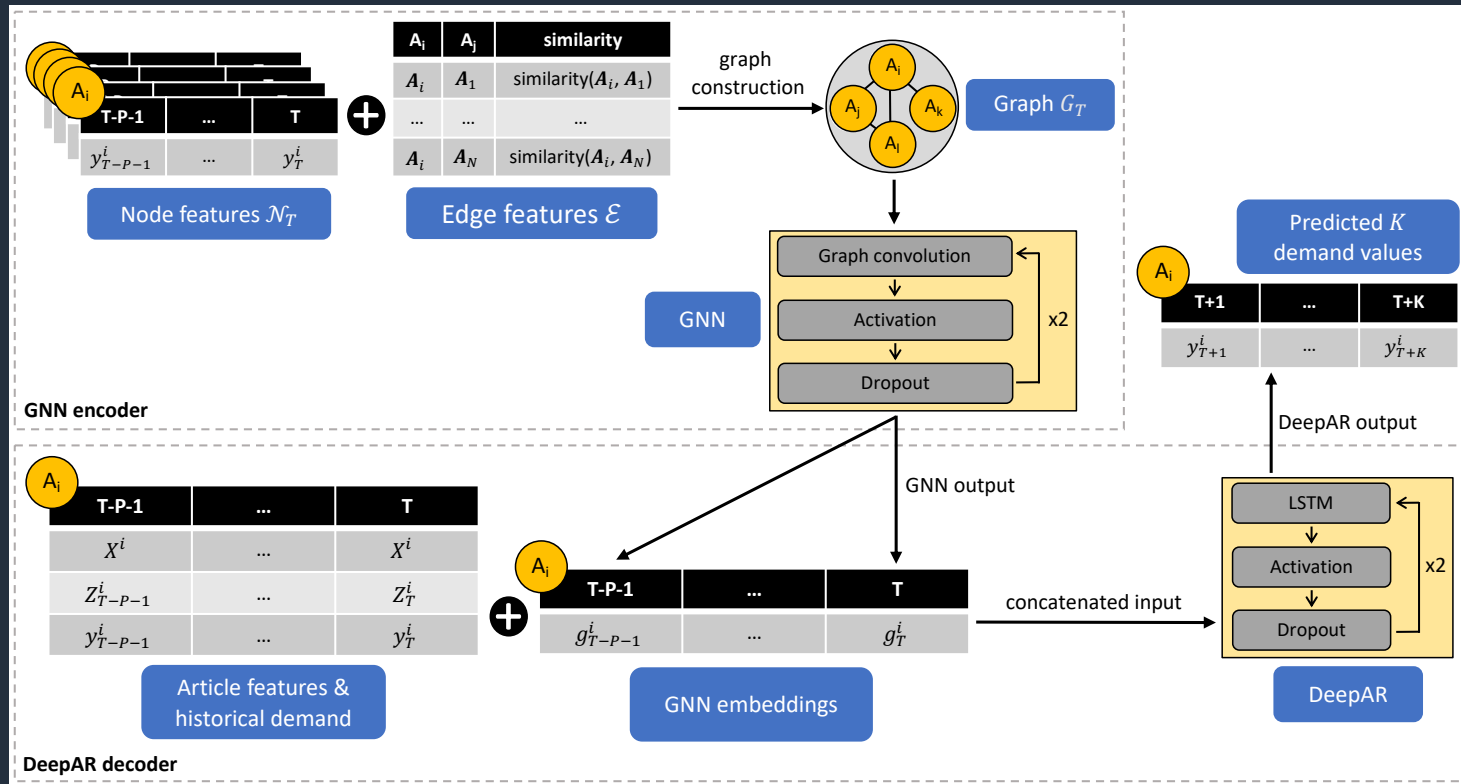
Aggregation over i-th article neighborhood

$$h_{k(i)}^t = \sigma \left(\frac{1}{|\mathcal{N}_j^t|} \sum_{j \in \mathcal{I}} W_k h_{(k-1)(j)}^t \right)$$

Model Architecture: Vanilla DeepAR

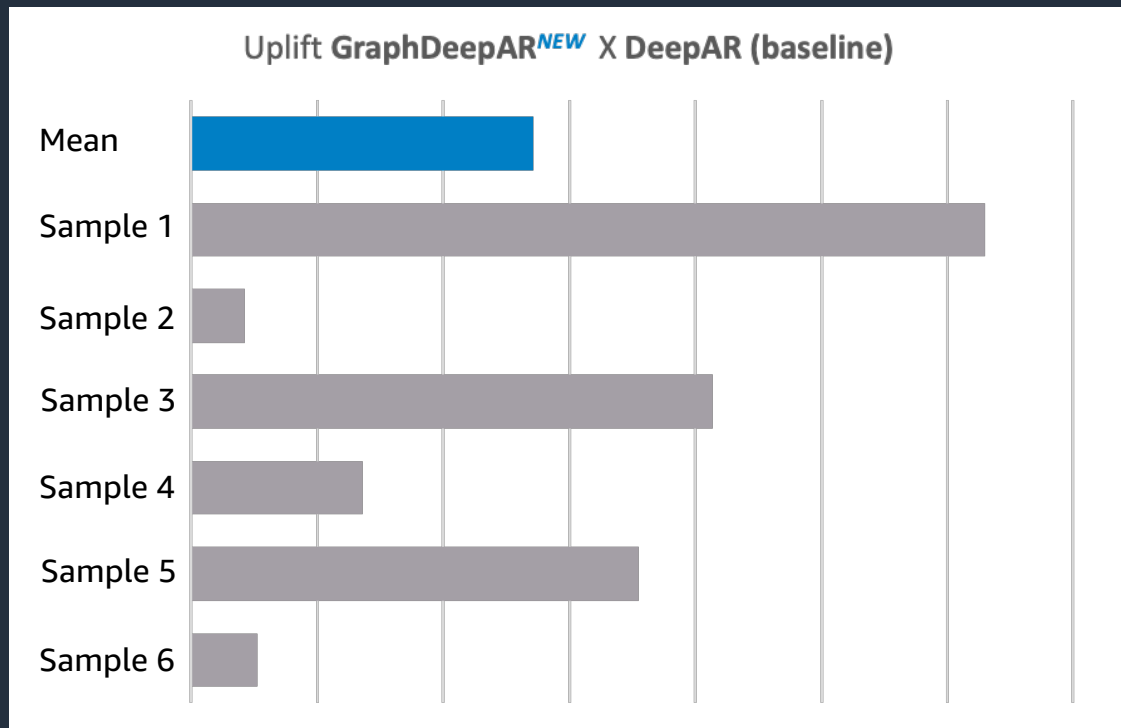


Model Architecture: GraphDeepAR



3. Experimental Results

Performance on adidas Data



Comparing two models:

- **DeepAR (benchmark)**
- **GraphDeepAR (ours)**

GraphDeepAR wins:

- **6/6 times**

Mean financial uplift:

- **2.05%**

Performance on Public Datasets

Dataset	Subset	Model	RMSE	MAE	WMAPE
Retail	All articles	DeepAR	204.68	51.53	0.43
		GraphDeepAR	196.13	50.35	0.42
	Cold starts	DeepAR	44.79	19.83	0.66
		GraphDeepAR	41.78	18.84	0.63
	Connected articles	DeepAR	207.12	52.34	0.42
		GraphDeepAR	198.46	51.12	0.41
	Top-100 articles	DeepAR	419.40	171.28	0.36
		GraphDeepAR	401.27	164.10	0.35
E-commerce	All articles	DeepAR	30.36	3.39	0.67
		GraphDeepAR	20.65	3.08	0.61
	Cold starts	DeepAR	8.66	2.62	0.79
		GraphDeepAR	8.72	2.62	0.79
	Connected articles	DeepAR	31.40	3.59	0.69
		GraphDeepAR	21.40	3.18	0.61
	Top-100 articles	DeepAR	164.68	42.78	0.98
		GraphDeepAR	110.50	29.60	0.68

Note: we define cold starts as articles with less than five demand lags at the time of the forecast. Connected articles are articles that have edges with other articles.

Mean RMSE uplift:

- **4% for retail**
- **32% for e-commerce**

Benefiting groups:

- **connected articles**
- **top-100 articles**

Running Time Difference

Dataset	Model	Training time	Inference time	Total difference
Retail	DeepAR	10.80 min	0.14 min	160.96%
	GraphDeepAR	28.33 min	0.22 min	
E-commerce	DeepAR	90.28 min	3.26 min	154.64%
	GraphDeepAR	234.73 min	3.46 min	
adidas	DeepAR	55.92 min	20.69 min	120.28%
	GraphDeepAR	139.80 min	28.96 min	

- Article similarity is calculated and stored **before training**
- **Training is slower** due to the need to backpropagate through graphs
- Inference speed of GraphDeepAR is **comparable**

Summary

- Incorporating article relationships in demand forecasting is challenging
- Our graph-based solution can address this challenge
 - Data-driven graph construction based on article attribute similarity
 - Integrates GNN encoder into the DeepAR forecasting model
 - Supports probabilistic forecasts
- Experimental results show that GraphDeepAR performs well
 - 2% financial uplift on adidas datasets
 - Up to 32% RMSE uplift on public datasets

Appendix

References

1. Huber, J., & Stuckenschmidt, H. (2020). Daily retail demand forecasting using machine learning with emphasis on calendric special days. *International Journal of Forecasting*, 36(4), 1420-1438.
2. Gandhi, A., Aakanksha, Kaveri, S., & Chaoji, V. (2021, September). Spatio-temporal multi-graph networks for demand forecasting in online marketplaces. In *Joint European Conference on Machine Learning and Knowledge Discovery in Databases* (pp. 187-203). Cham: Springer International Publishing.
3. Box, G. E., & Cox, D. R. (1964). An analysis of transformations. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, 26(2), 211-243
4. Salinas, D., Flunkert, V., Gasthaus, J., & Januschowski, T. (2020). DeepAR: Probabilistic forecasting with autoregressive recurrent networks. *International Journal of Forecasting*, 36(3), 1181-1191.
5. Yu, B., Yin, H., & Zhu, Z. (2017). Spatio-temporal graph convolutional networks: A deep learning framework for traffic forecasting. *arXiv preprint arXiv:1709.04875*.
6. Veličković, P. (2023). Everything is connected: Graph neural networks. *Current Opinion in Structural Biology*, 79, 102538.

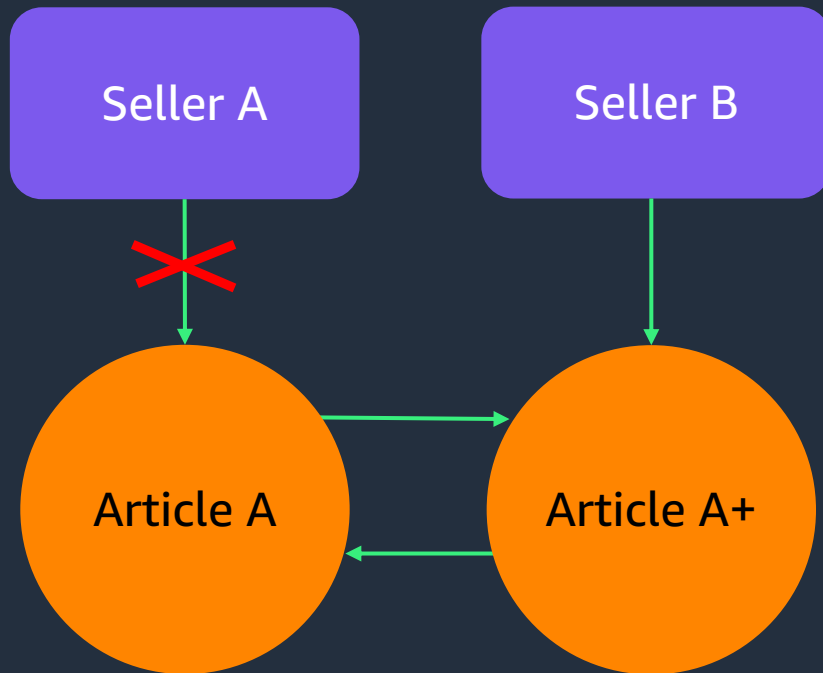
Data Summary

- Two public datasets & one proprietary adidas dataset
- Contain time series with:
 - Article demand
 - Static features (e.g., color, size)
 - Time-varying features (e.g., week number, month number)

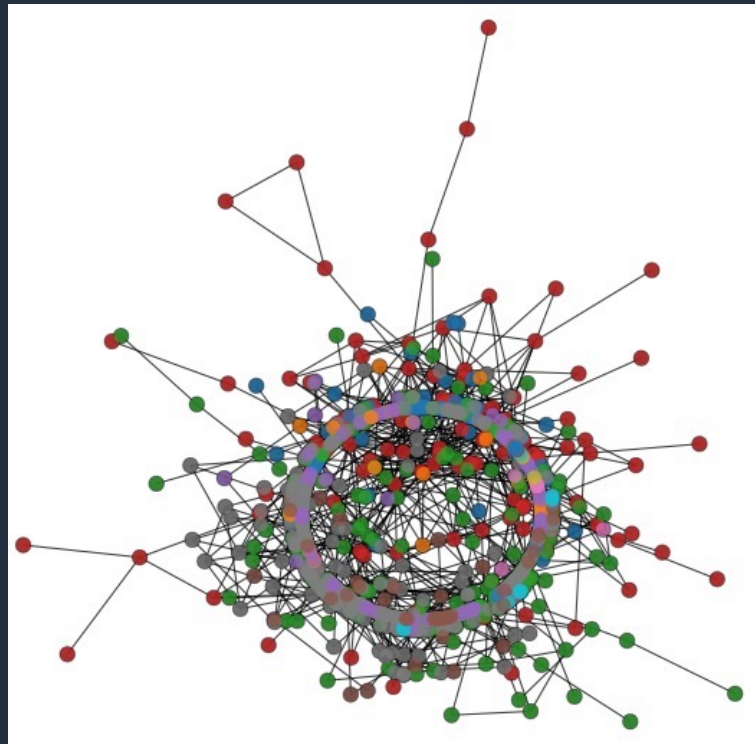
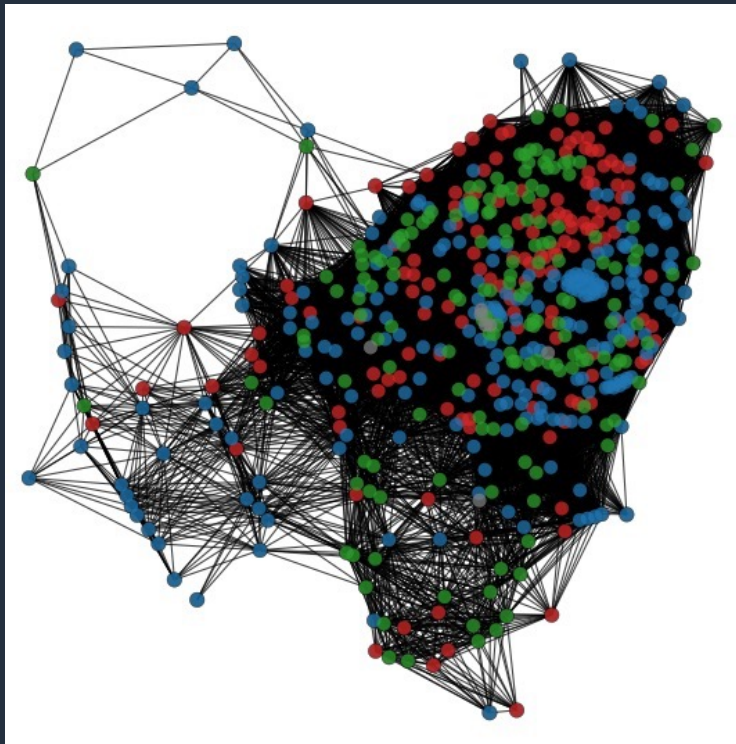
Dataset	No. articles	No. weeks	No. features
Retail	629	148	12
E-commerce	8,810	128	5
adidas	80,838	140	20

Importance of Article Relationships

- **Out of stock** status for the same article from other sellers
- Launch of **competing** articles
- **Price change** on a similar article by other sellers
- Sudden **change** in competitor's **performance**



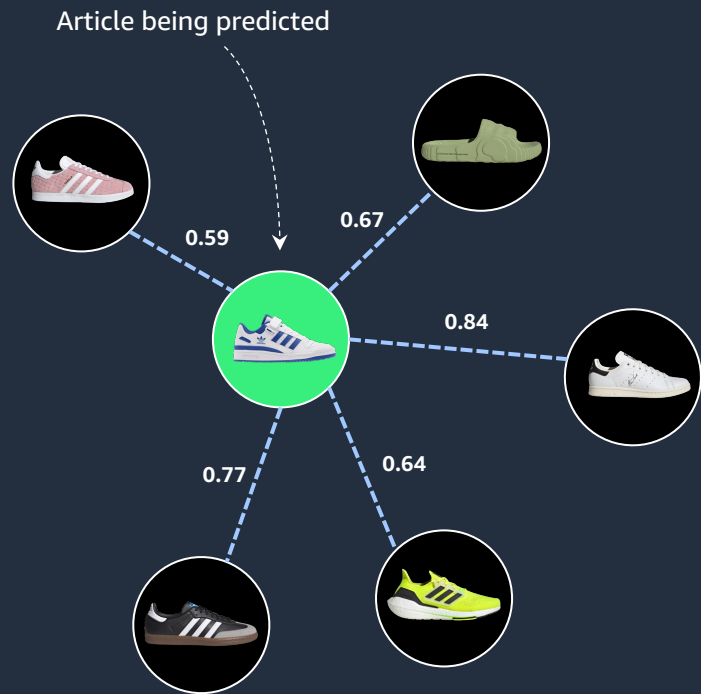
Graph Illustration



Article graphs for *Retail* dataset (left) and *E-commerce* dataset (right).

Sampling Mechanism [1/2]

- Graph contains thousands of articles
 - Average number of neighbors is high
 - Aggregating neighbors data is costly



Sampling Mechanism [2/2]

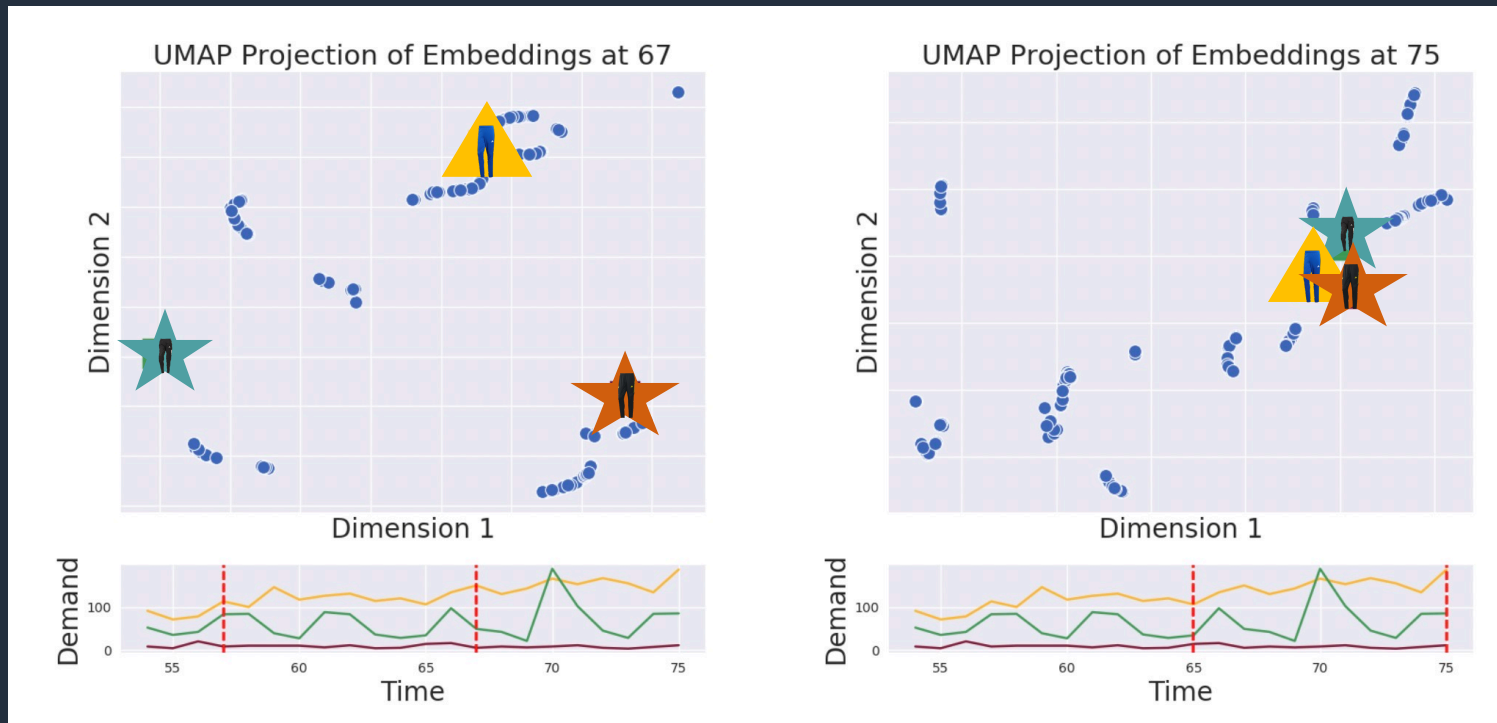
- Graph contains thousands of articles
 - Average number of neighbors is high
 - Aggregating neighbors data is costly
- Solution: randomly sample neighbors
 - Different subset on each epoch
 - Helps scaling the solution



Time-Varying GNN Embeddings

Week 67

Week 75



Meta-Parameters (Retail Dataset)

Dataset	Component	Meta-parameter	DeepAR	GraphDeepAR
retail	Sequential model	No. layers	2	2
		Hidden size	[128, 128]	[128, 128]
		Cell type	LSTM	LSTM
		Dropout	0.2	0.2
		Context length	10	10
	GNN encoder	No. layers	–	2
		Hidden size	–	[16, 8]
		Cell type	–	GCN
		Dropout	–	0.2
		Similarity cutoff	–	0.95
		Max no. neighbors	–	10
		Context length	–	10
	Training procedure	Max no. epochs	50	50
		Early stopping	5	5
		Learning rate	5×10^{-3}	5×10^{-3}
		Optimizer	Ranger	Ranger
		Loss function	t-distribution	t-distribution
		Batch sampler	Random	Synchronized

Example Predictions (Retail Dataset)

