



图神经网络在实时风控中的应用





讲师简介



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eBay Payments and Risk 机器学习工程师，负责多个领域风险评估，包括实时交易，共谋和合规风险。入职 eBay 前有多多年金融行业从业经验，包括对冲基金和投资银行。专注于时间序列决策问题。





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1. 实时交易反欺诈场景介绍
2. 图神经网络在实时场景的挑战
3. 端到端的解决方案
4. 小结和展望





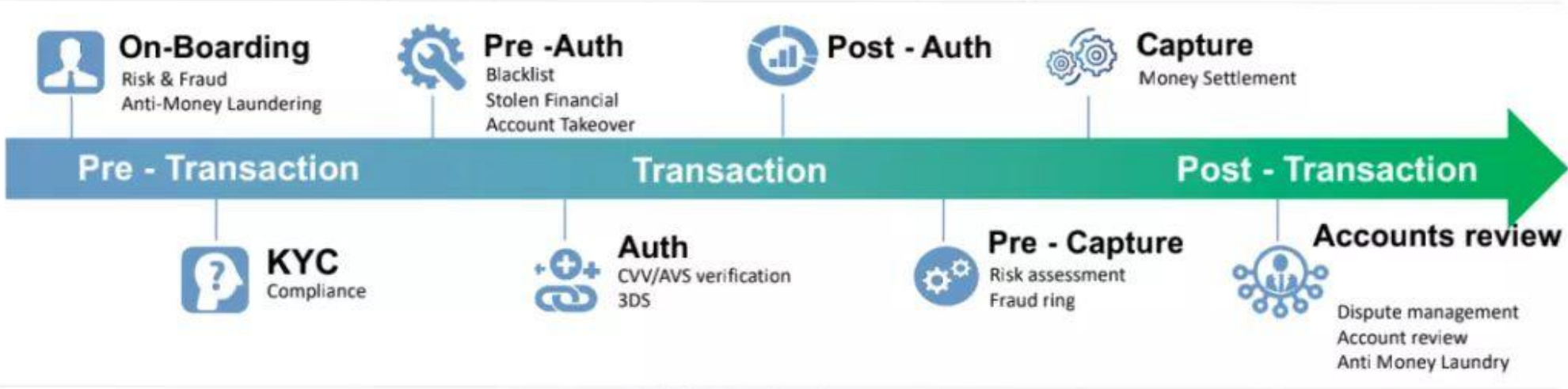
- 实时交易的风险检测对模型推断的延迟要求较高
- 利用有向时序异构图方式构建动态图
 - 解决实验阶段信息穿越问题
 - 提高在线推断速度





实时交易反欺诈场景介绍

Risk Assessment in Transaction Flow

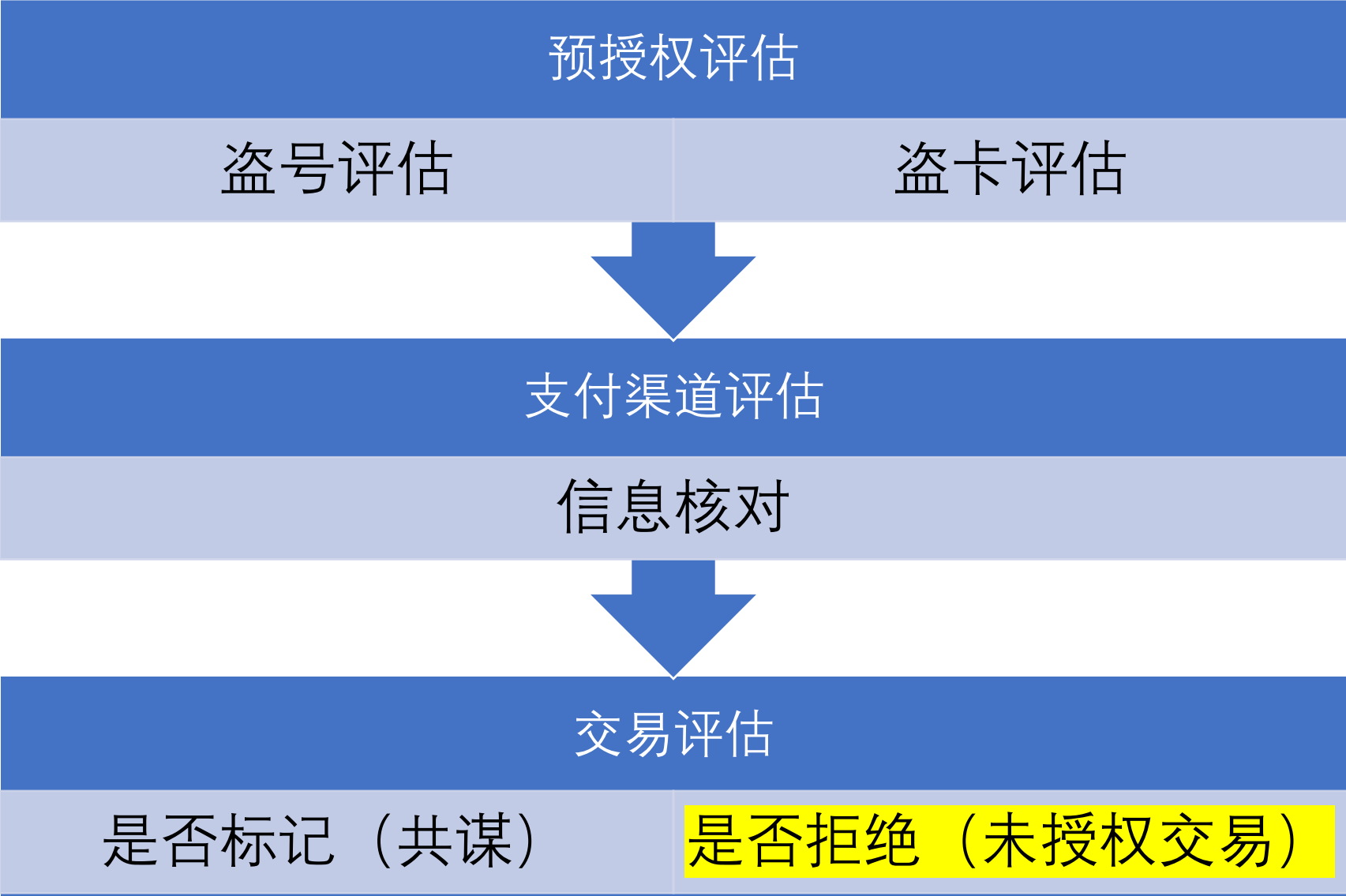


Risk in Marketplace





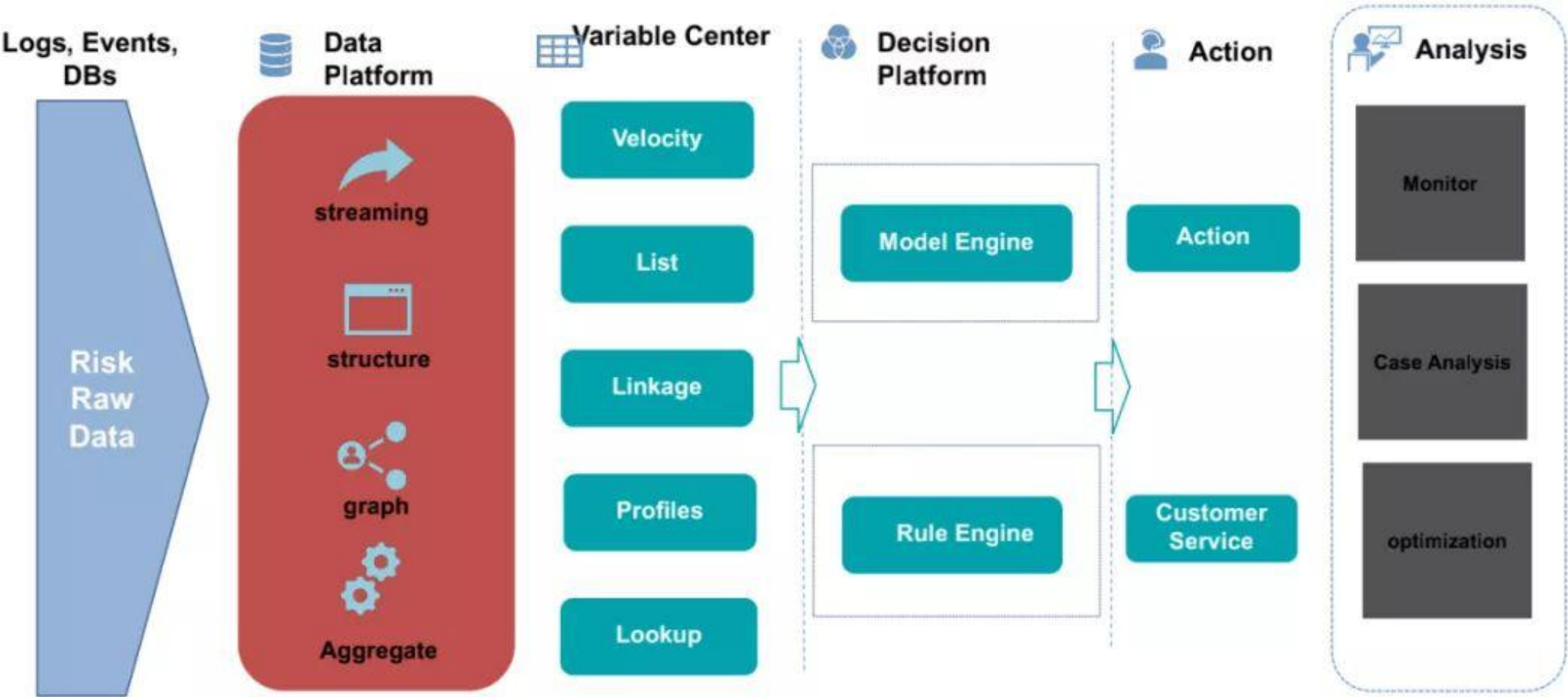
实时交易反欺诈场景介绍





实时交易反欺诈场景介绍

Transaction Risk Platforms



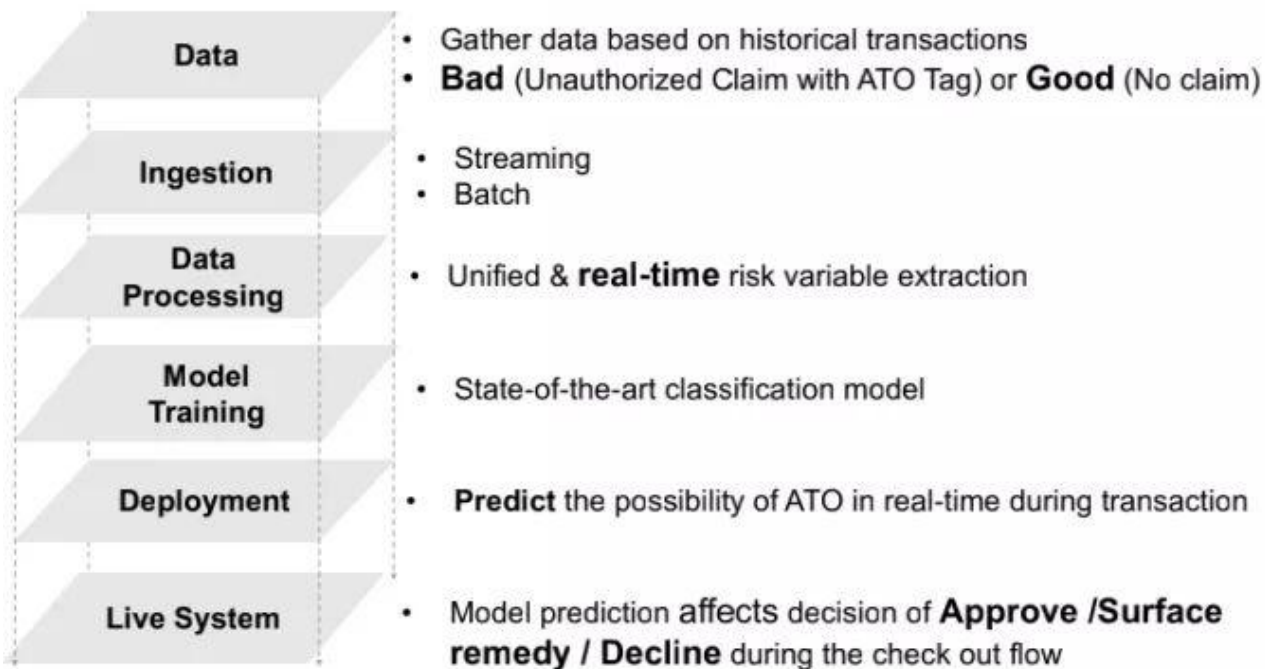


实时交易反欺诈场景介绍

Real-time Risk Evaluation: Supervised Machine-learned Models for Account Takeover

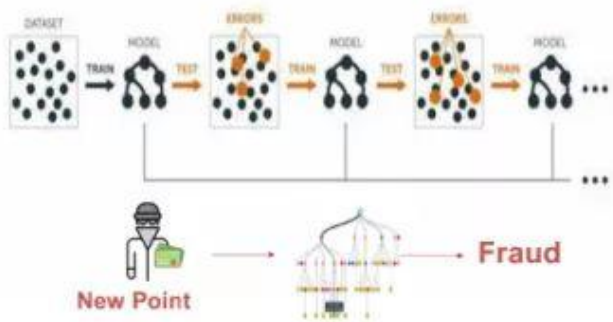
What is Account Takeover (ATO)?

- Account takeover fraud is a form of identity theft in which the fraudster gets access to a victim's eBay accounts
- A successful account takeover attack leads to fraudulent transactions and unauthorized shopping from the victim's compromised account



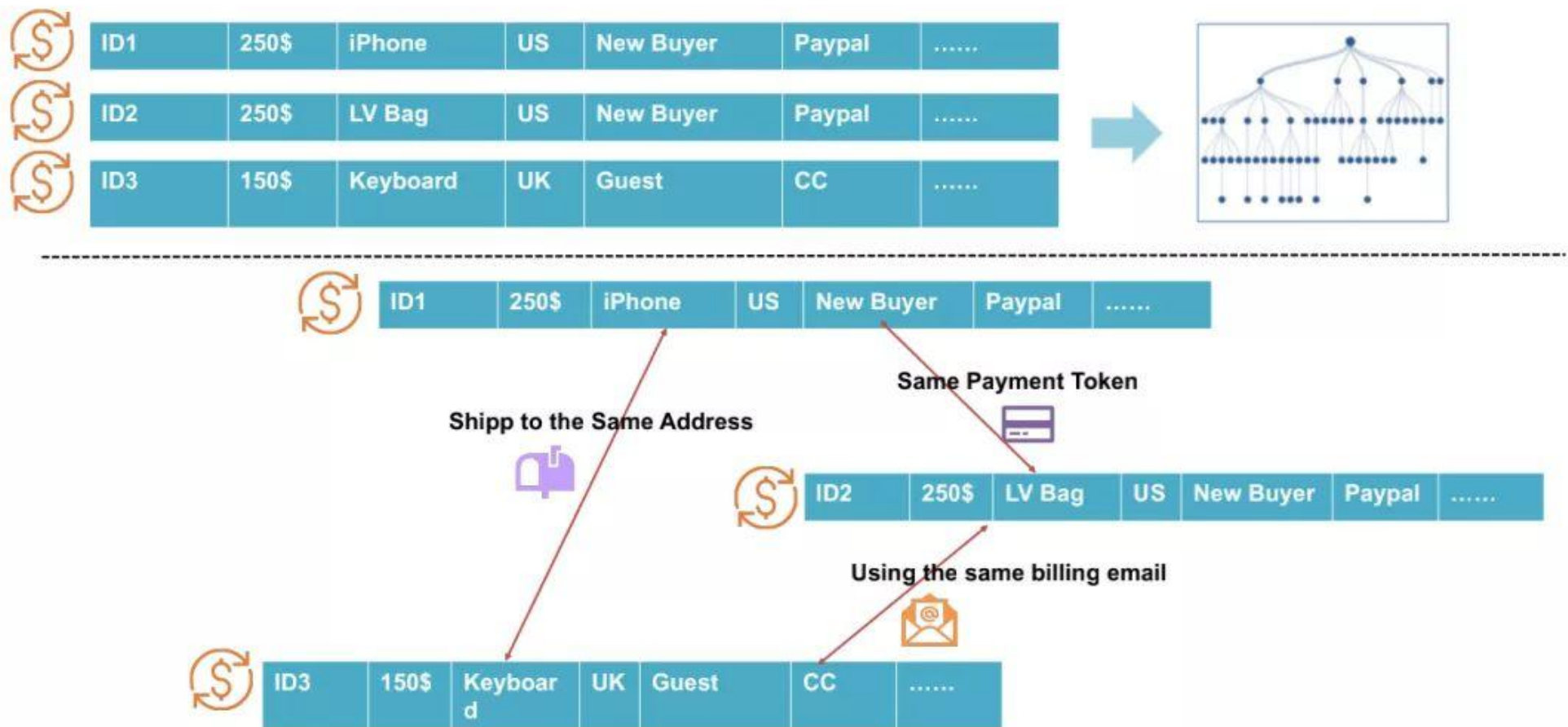
Supervised Machine Learning

- Treat accounts/sample independently
- Capture known risk issue with good performance



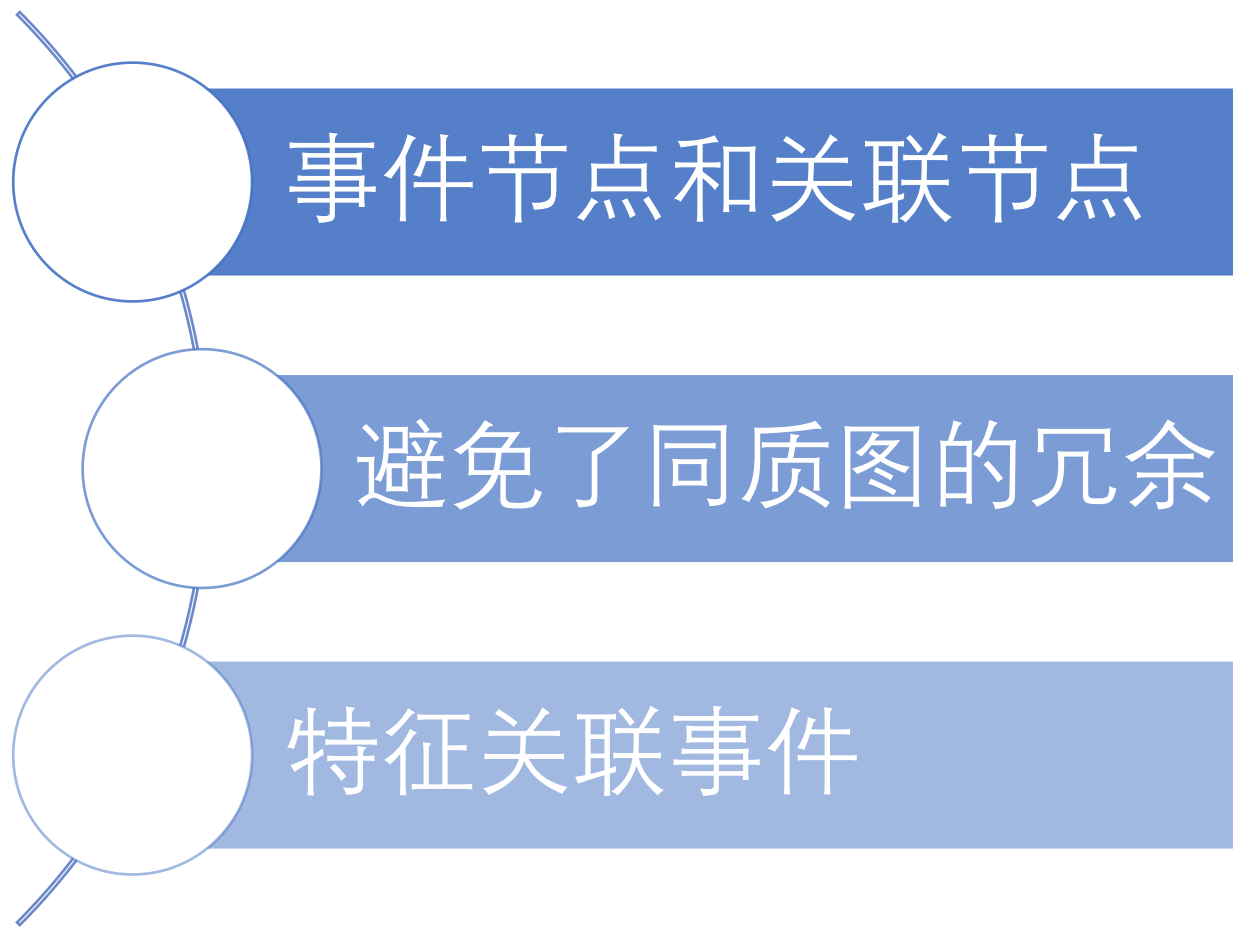
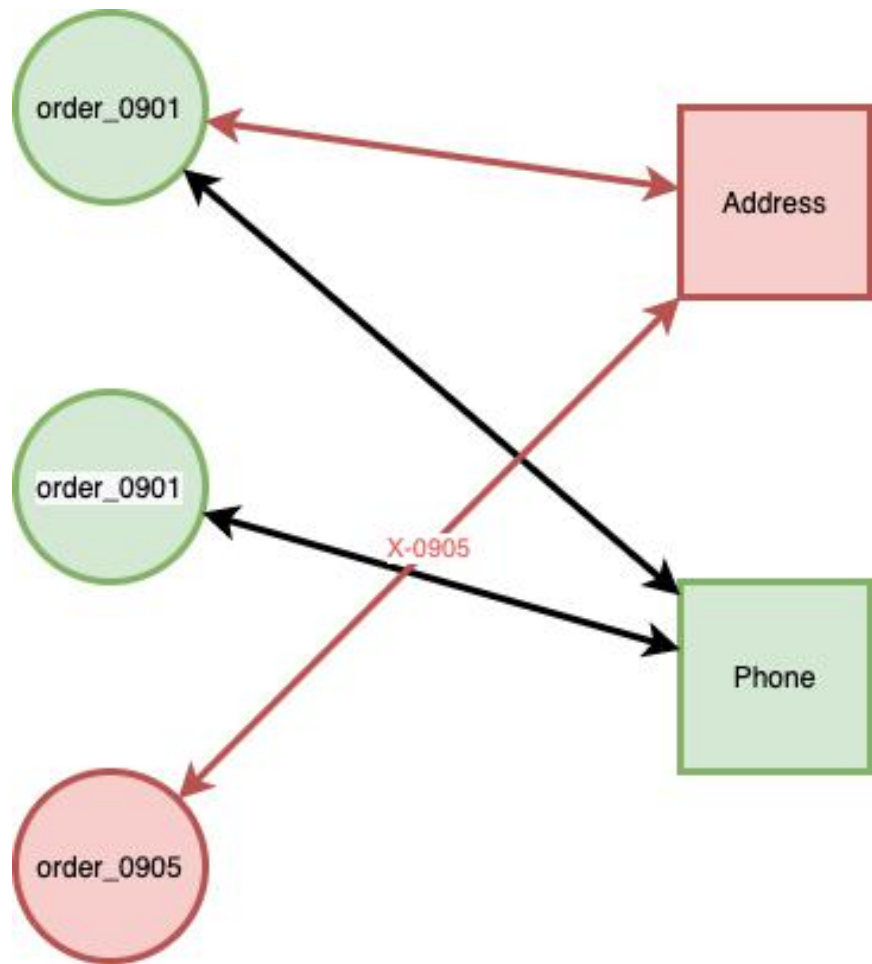


Current Machine Learning Model is not a powerful representation of context information!



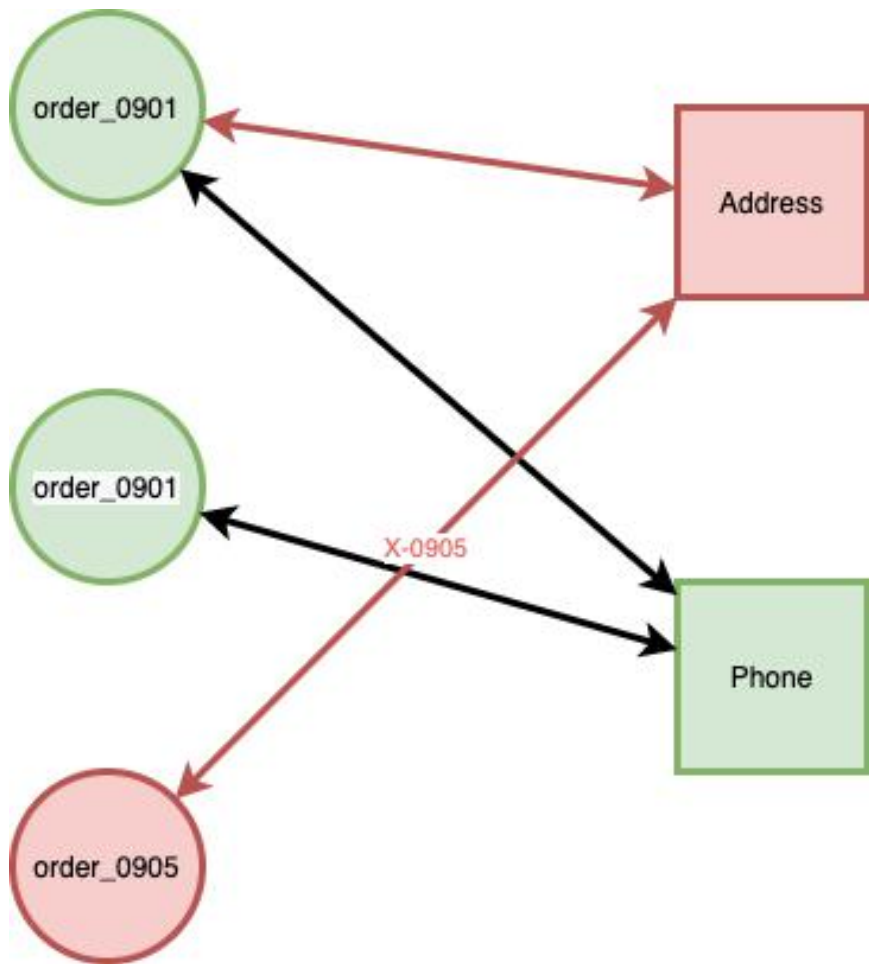


图神经网络在实时场景的挑战 – 二部图





图神经网络在实时场景的挑战 – 构图的时效性



关联节点涉及多个时间点

实例特征融合后可能有未来信息

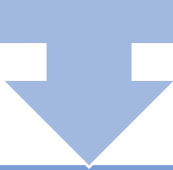
模型训练时具备推断时不可能有的“预测力”





图神经网络在实时场景的挑战 – 在线推断的延迟

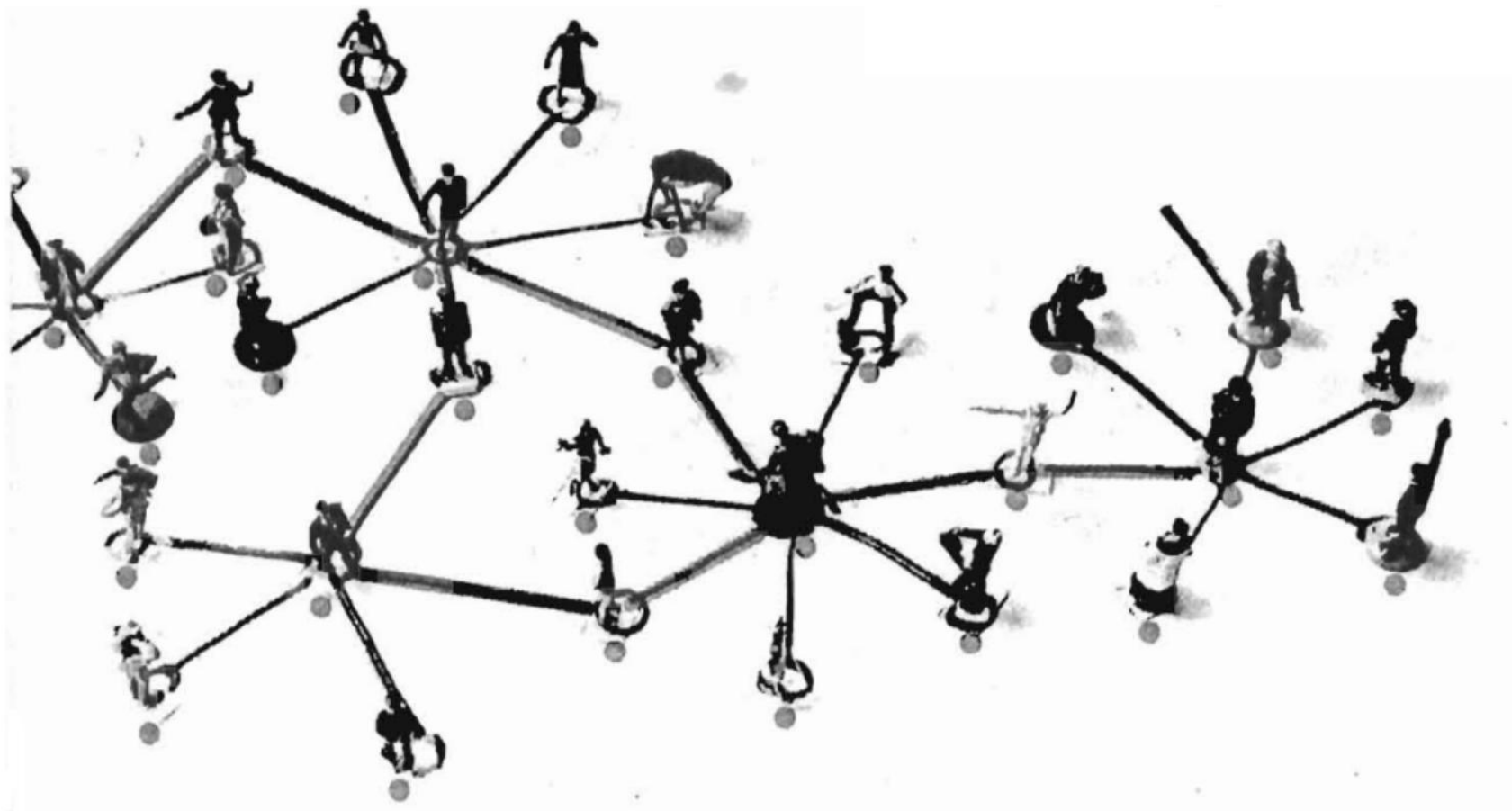
图查询延迟



关联特征的拼接



在线推断





图神经网络在实时场景的挑战 – VS GBDT

- Dataset: House insurance
 - Feature – 66 columns
 - Boolean 7
 - Integer 18
 - String 11
 - Other 7
 - Label - Resiliated
- Winner - XGBoost
 - Best metric in test
 - Efficient in Training Time
 - More Understandable

	ROC AUC	F1 score	Time (sec)
XGBoost	0.7706	0.5591	500
MLP	0.7514	0.5458	184
TabNet without pretrain	0.7579	0.5529	1464
TabNet with pretrain	0.7524	0.5484	2370





构图的时效性

- 有向动态切片图 Directed Dynamic Snapshot Graph

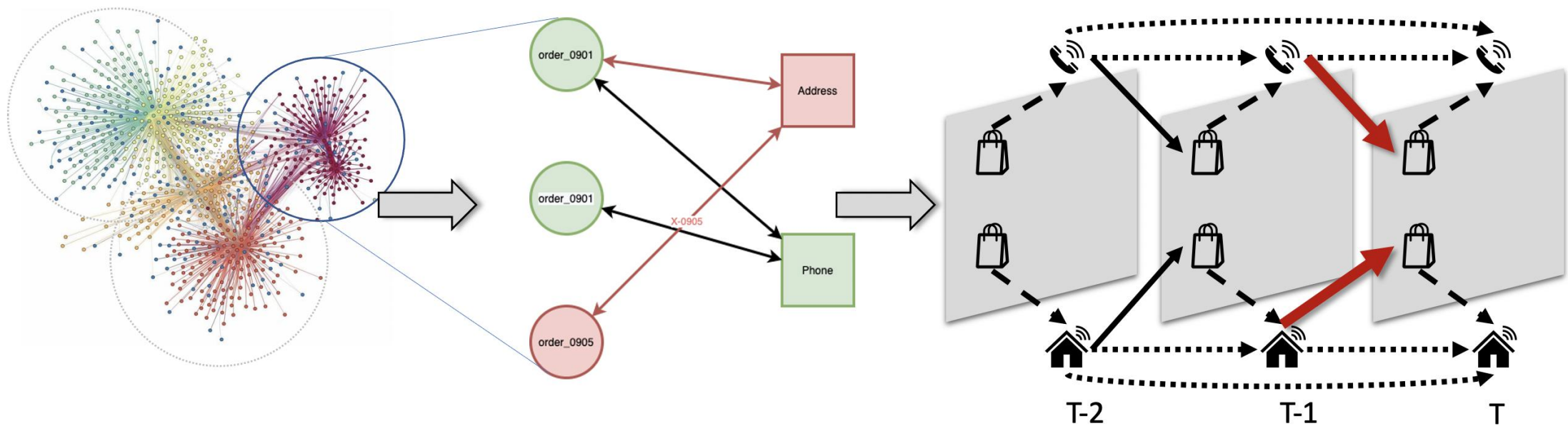
推断低延迟

- Lambda 架构的网络结构





端到端方案 – 有向动态切片图





端到端方案 – 有向动态切片图

- DDSL

Directed Dynamic Snapshot Lambda

- 运用在分区切片图上

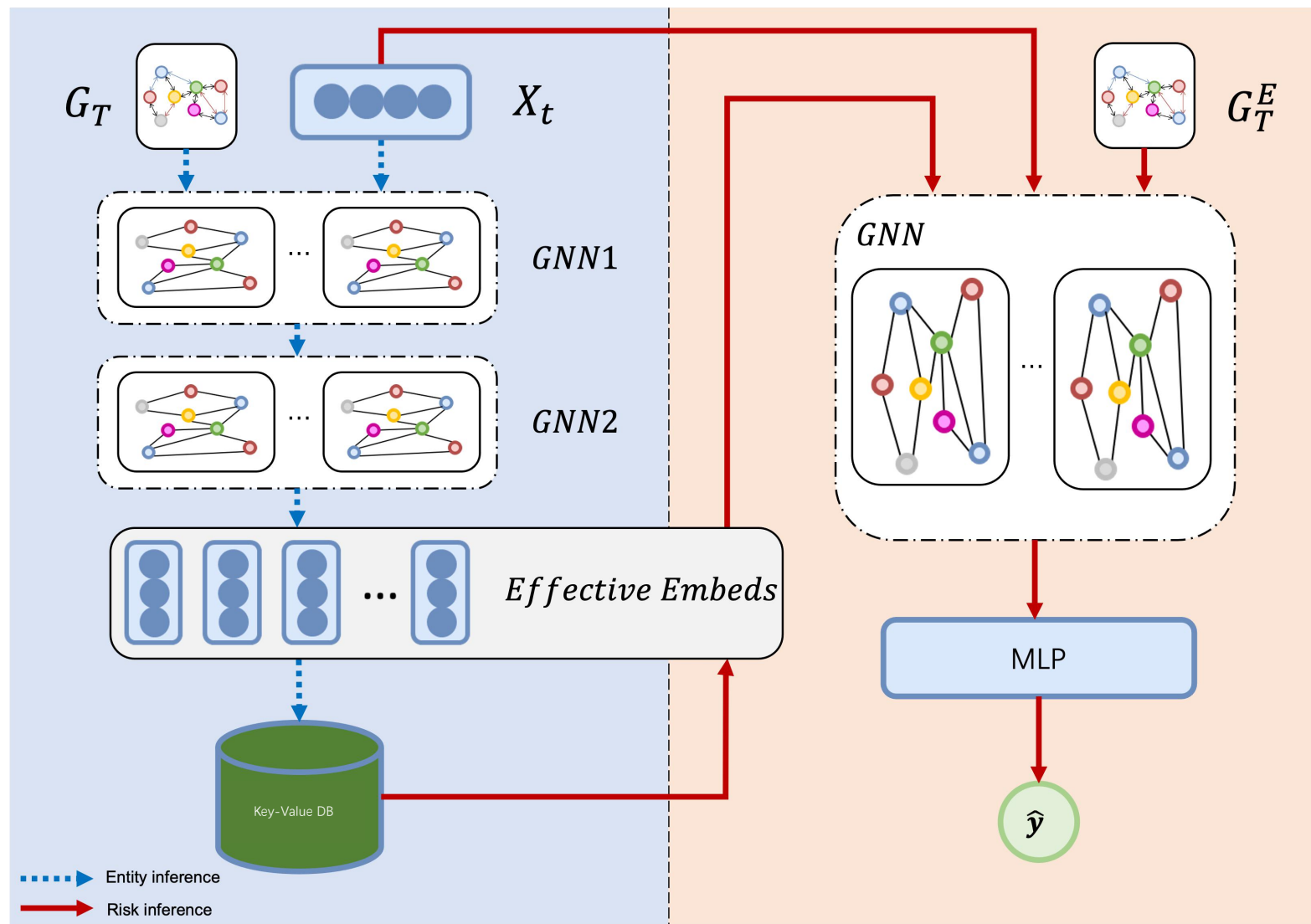
- 类ClusterGCN

- 堆叠的通用GNN层

- 类DeepGCN

- 推断的最后一跳

- 类双塔模型





离线学习

分区构图

编码学习



在线推断

实体表述

订单评估

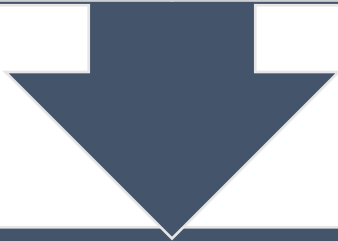




离线学习

分区构图

编码学习



在线推断

实体表述

订单评估





离线学习

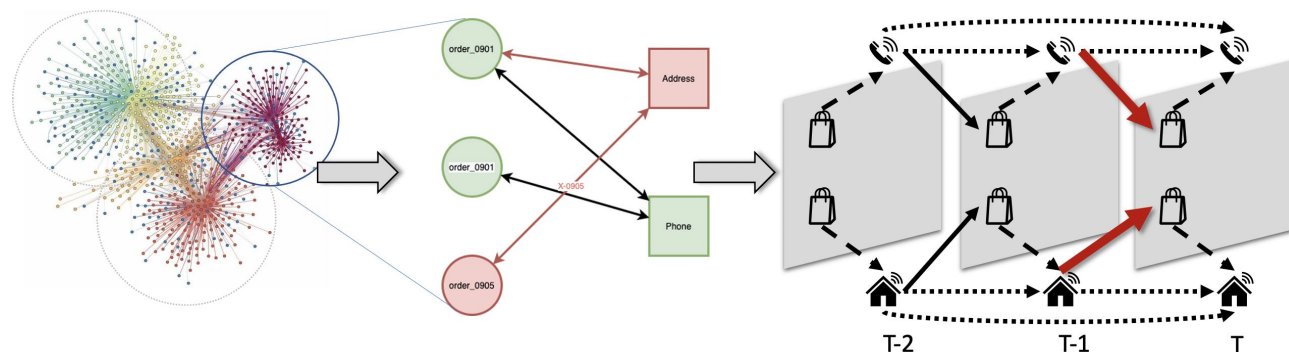
分区构图

编码学习

在线推断

实体表述

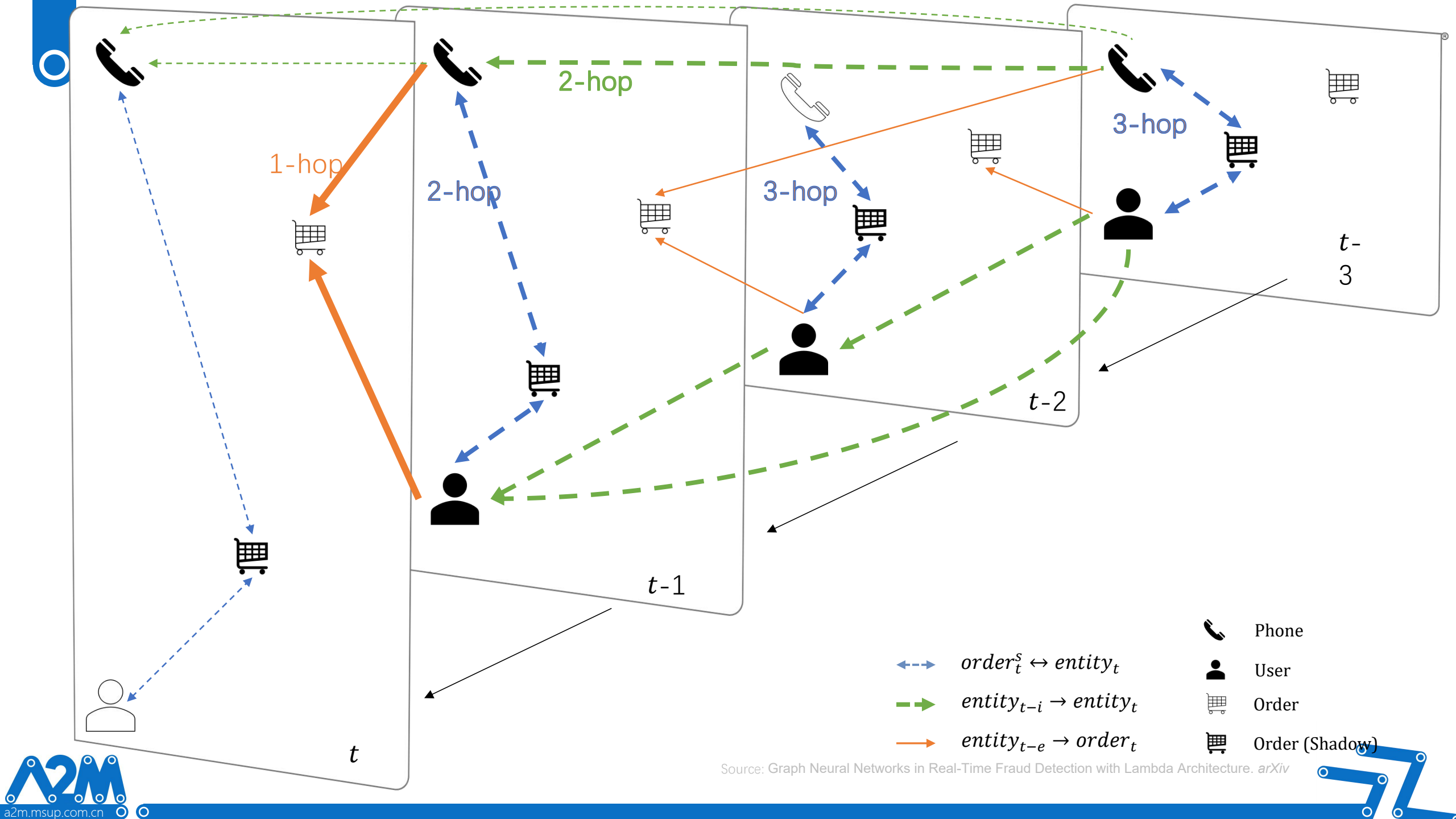
订单评估



ebaymsup[®]

- $Order_t^s \rightarrow Entity_t$
 - 实体表述
- $Entity_{t-i} \rightarrow Entity_t$
 - 实体表述
- $Entity_{t-e} \rightarrow Order_t$
 - 订单评估







离线学习

分区构图

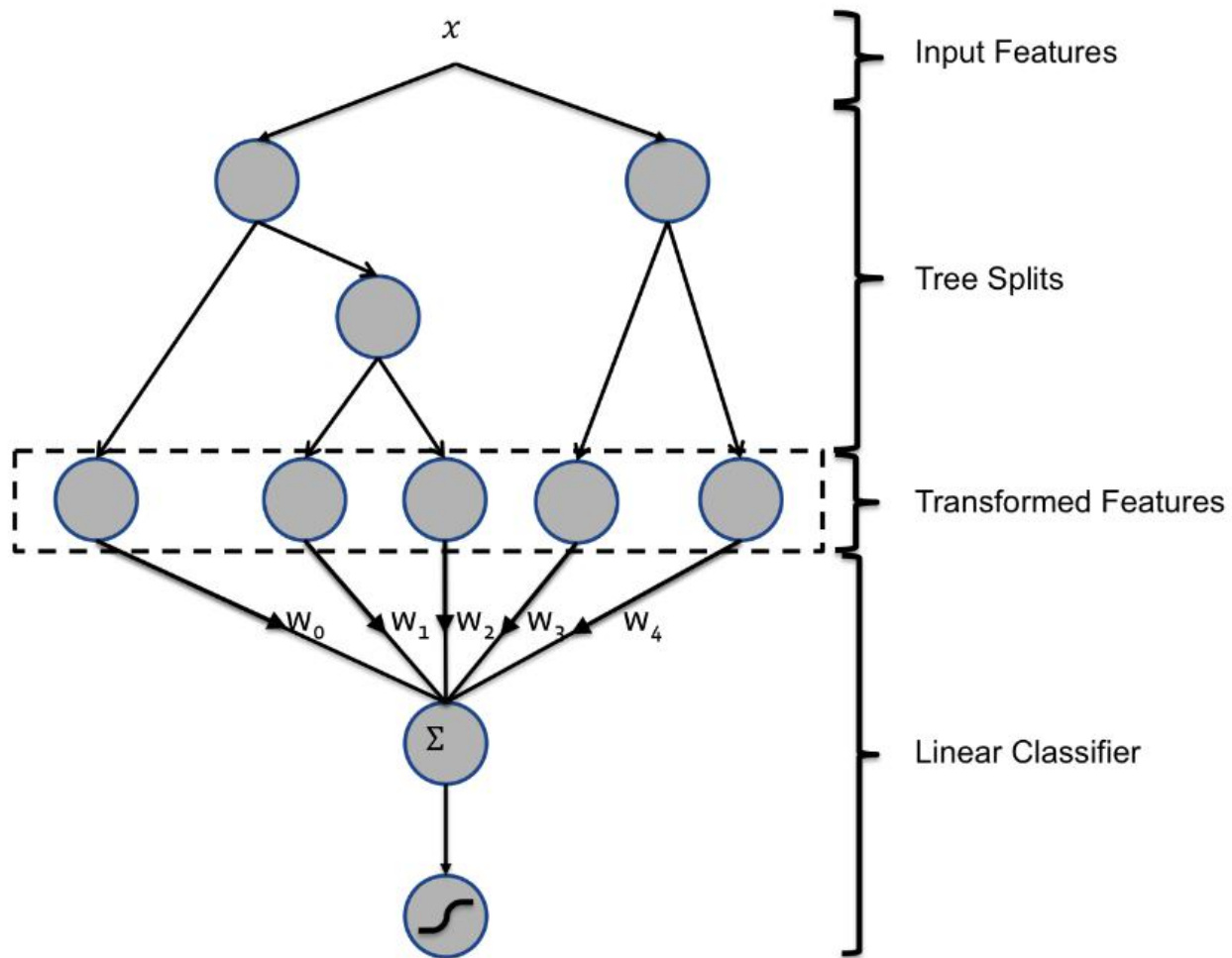
编码学习



在线推断

实体表述

订单评估





离线学习

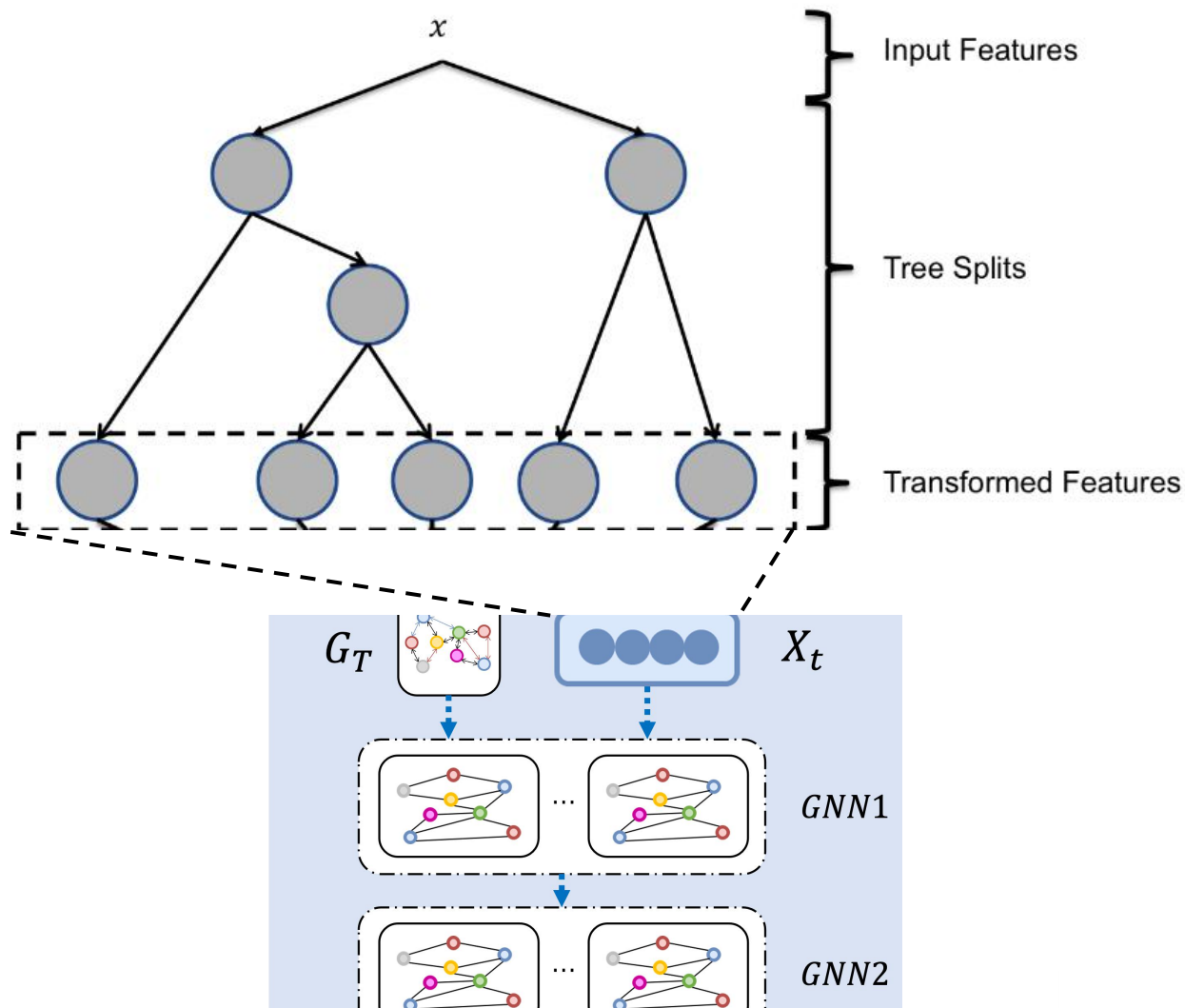
分区构图

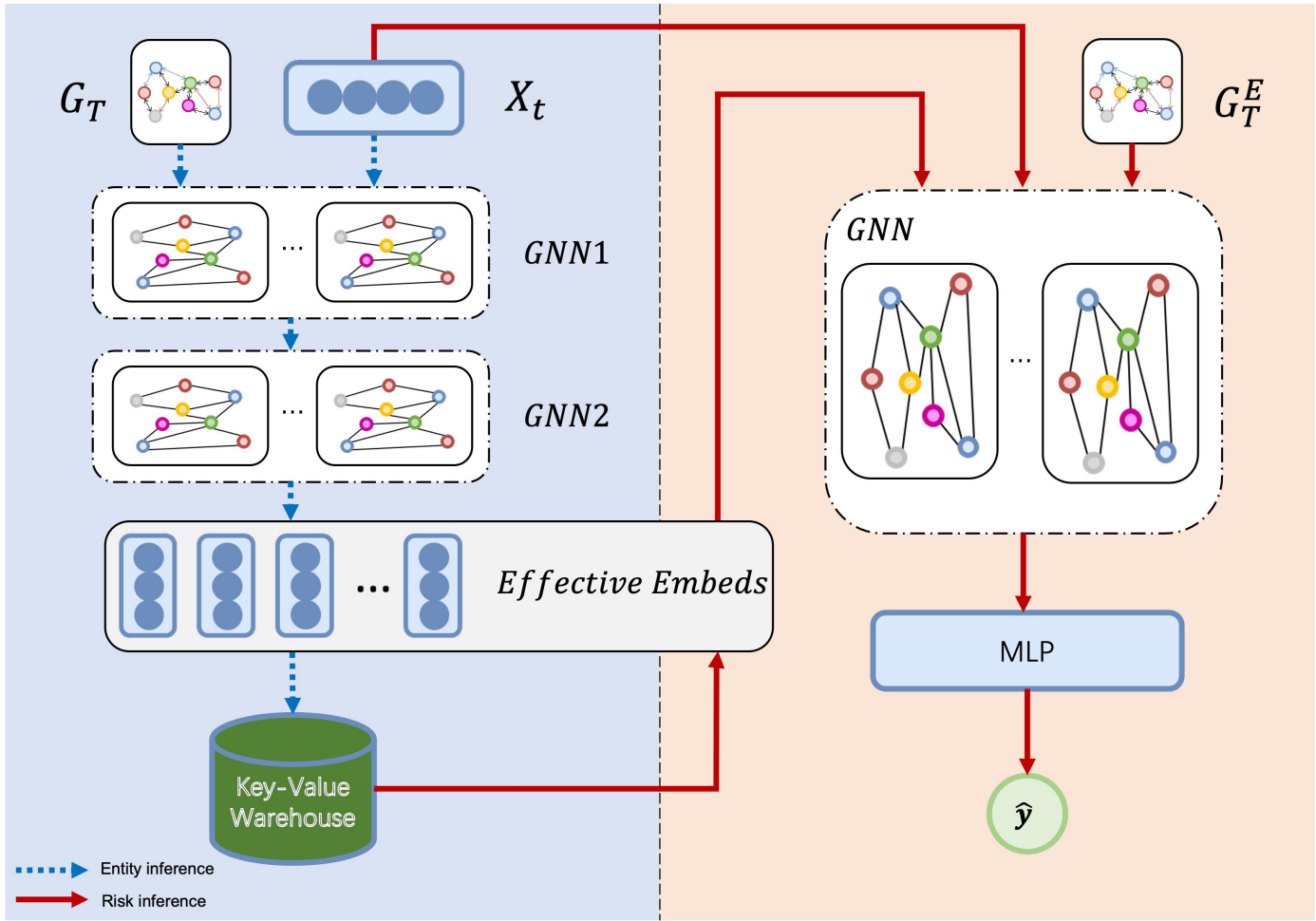
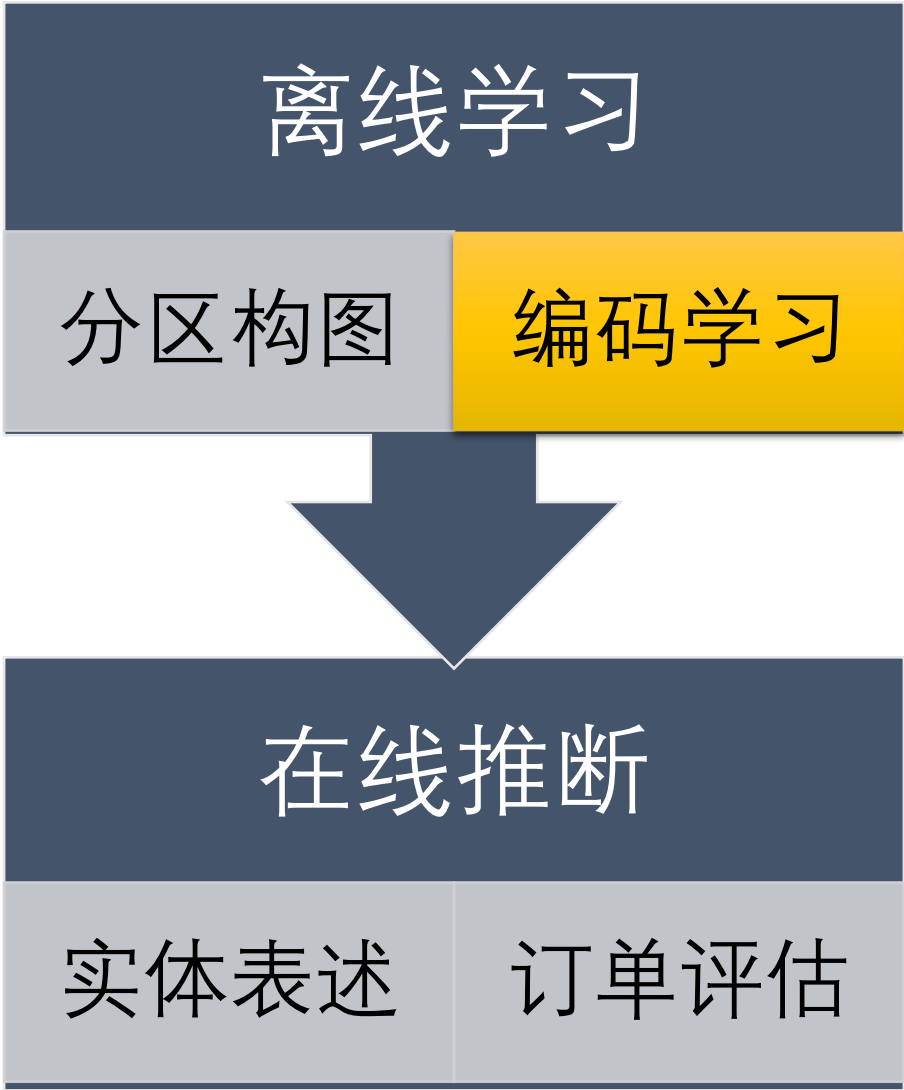
编码学习

在线推断

实体表述

订单评估







离线学习

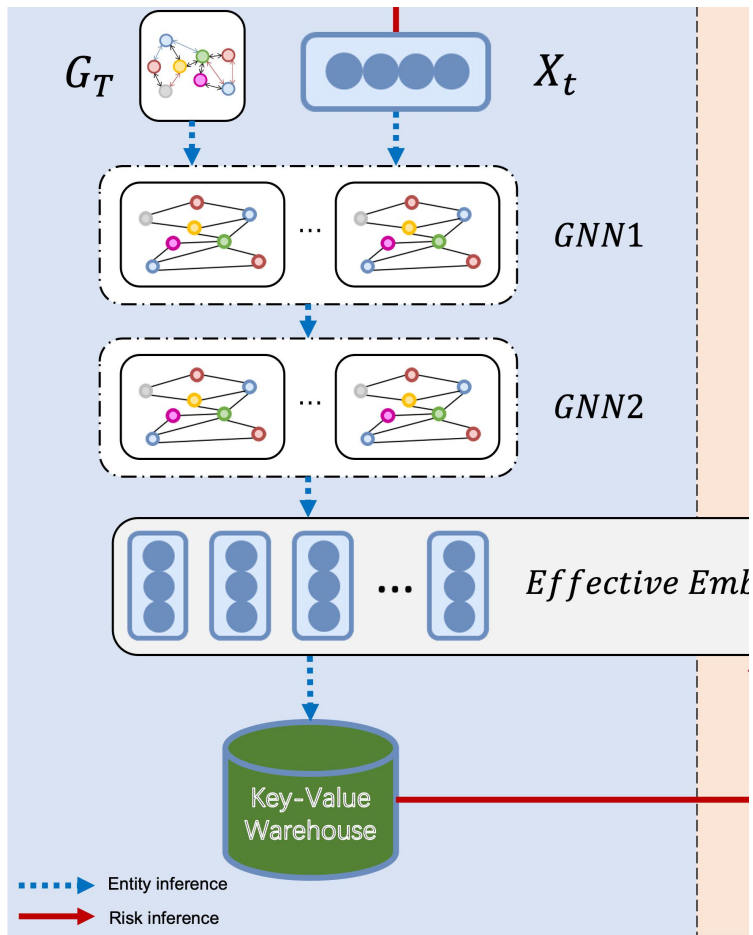
分区构图

编码学习

在线推断

实体表述

订单评估

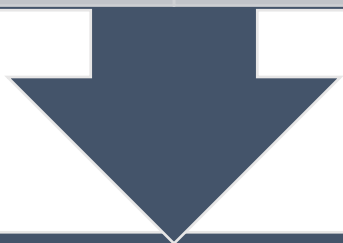




离线学习

分区构图

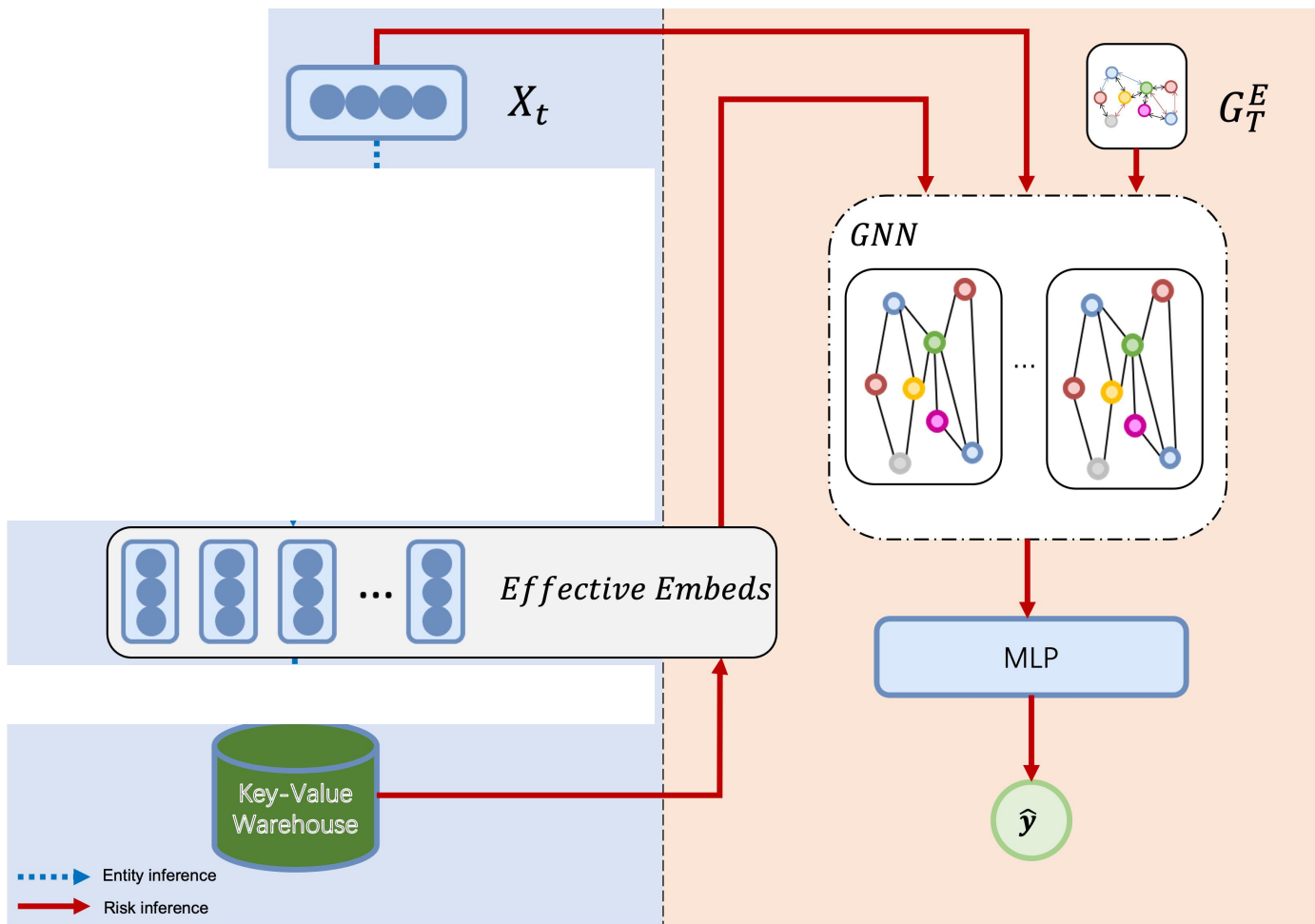
编码学习



在线推断

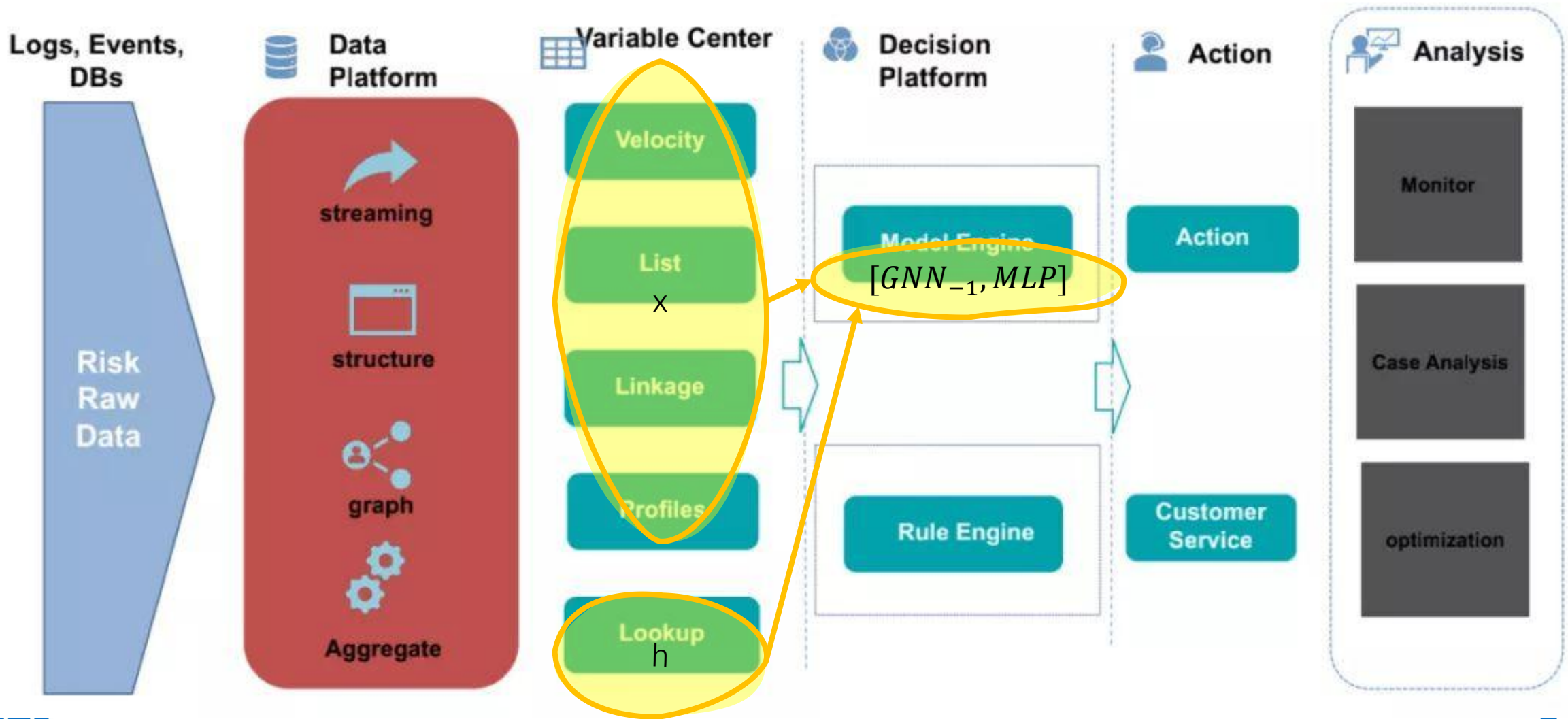
实体表述

订单评估





Transaction Risk Platforms





端到端方案 – 实验对比

交易图

- 数月交易数据构建
- 90天实体关联窗口

数据

- 训练 时间切片前80%
- 验证 时间切片中10%
- 测试 时间切片后10%

关联实体

- 账户, 电子邮箱, 设备, 收货地址, IP

交易订单节点标签分布

- 正常:异常 - 20:1





Model	Average Precision	ROC AUC
MLP	0.3917±0.0030	0.9209±0.0016
LGB	0.4081±0.0096	0.9317±0.0005
DDSL (GCN)	0.4928±0.0021	0.9428±0.0006
DDSL (GAT)	0.4796±0.0144	0.9387±0.0004

2020-11 Guest

Model	\$ Fraud Precision	\$ Fraud Recall
mlp	16.67%	12.50%
bst	16.67%	10.80%
gcg	16.67%	40.20%

2020-11 New (first payment dof < 90)

Model	\$ Fraud Precision	\$ Fraud Recall
mlp	16.67%	38.50%
bst	16.67%	51.20%
gcg	16.67%	68.99%





- 端到端的图神经网络实时反欺诈检测的方案
 - 图切分使得分布式训练和推断可行
 - 有效的实验切片构图规避未来信息
 - 高效的在线推断 $P99 < 80ms$
 - 相比GBDT有显著提升 $AP + 20\%$





- 对比引入RNN机制的TGN
- 社区分区大小对模型的影响
- 深度模型替换GBDT编码
- 图神经网络的预训练





参考资料

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5. Deep Learning vs GBDT model on tabular data, <https://www.kaggle.com/kyosukemorita/deep-learning-vs-gbdt-model-on-tabular-data/notebook>





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