Conditional Forecasting of Margin Calls Using Dynamic Graph Neural Networks

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EPFL

Plan of the talk

1. Motivation
2. Dynamic Graph Neural Networks (DGNNs)
3. Problem formulation
4. Proposed method
5. Results

Motivation - Policy

- Despite regulatory efforts[1], **derivatives markets** have seen recurrent episodes of **instability** in recent years (e.g. the Nasdaq Clearing member failure, the COVID-19 "dash for cash" in March 2020, nickel market volatility in March 2022, the European energy crisis, and the UK gilt market turmoil in October 2022).

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- **Recent advances in systemic risk data collection** have enabled real-time mapping of margin calls[3], but current approaches remain largely *ex post*, underscoring the need for a **network forecasting** framework.

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Research question: Can we forecast margin calls in stressed derivatives markets, by leveraging available transaction-level historical data?

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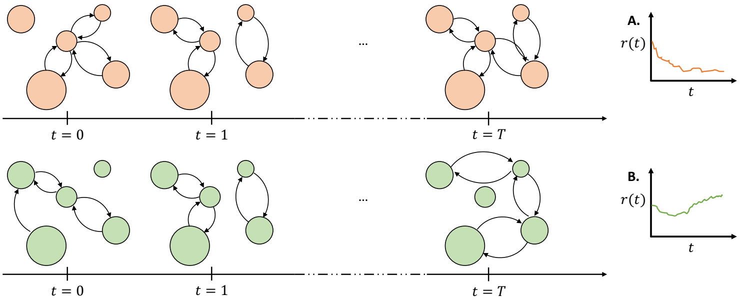
- Recent systemic risk events in the derivatives market are due to **feedback loops** arising from the **dynamic** and **adaptive** behavior of the market participants.



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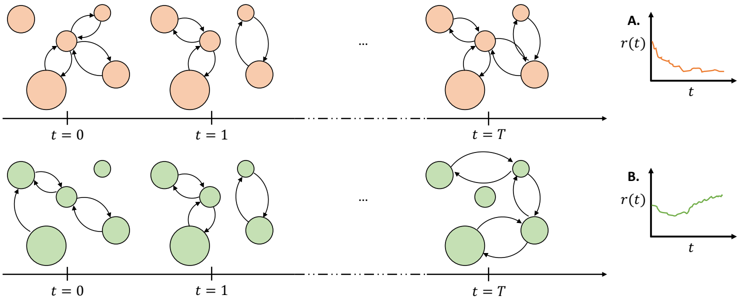

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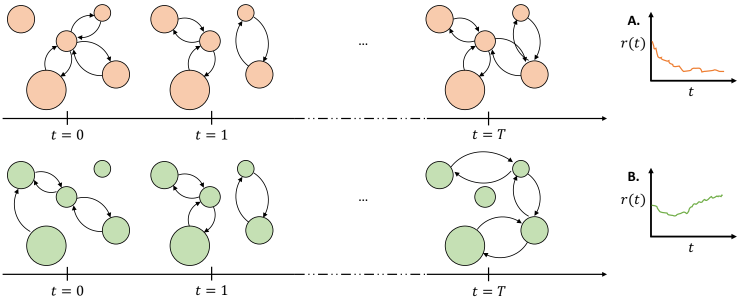


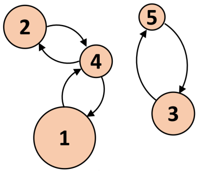
- But research on insolvency and illiquidity cascades has focused so far only on *static* financial networks.
- **Research question:** Can we develop a **Dynamic Graph Neural Network (DGNN)** method to **solve** m**-steps ahead forecasting problems** in **dynamic** financial networks,
conditionally on macro-economic stress test scenarios?

Dynamic Graph Neural Networks (DGNNs)

Graph Neural Networks (GNN)

Let $\mathcal{G} = (V, X, E)$ be a graph:

- $V = \{1, \dots, N\}$ set of vertices,
- $X \in \mathbb{R}^{N \times C}$ node features,
- $E = \{(i, j)$ if there is an edge from i to $j\}$.



Goal: solve a non-linear **node regression** task, $Y = f(X) \in \mathbb{R}^N$, by exploiting the graph structure (because we know that the nodes' behavior can impact their neighbors).

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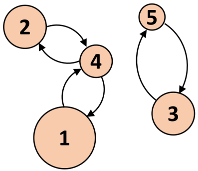

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A **Graph Convolutional Network (GCN)** by [Kipf and Welling, 2017] consists of ℓ layers that recursively aggregate information from all nodes that are at most ℓ edges away ($\ell \leq$ diameter(G)):

$$\begin{cases} h^{(1)} &= \sigma(A\, X\, W^{(1)}) \\ h^{(2)} &= \sigma(A\, h^{(1)}\, W^{(2)}) \\ \vdots & \\ h^{(\ell)} &= \sigma(A\, h^{(\ell-1)}\, W^{(\ell)}) =: \mathrm{GCN}^{(\ell)}(A, X) \in \mathbb{R}^{N \times P} \end{cases}$$

where $A \in \mathbb{R}^{N \times N}$ is the adjacency matrix and σ is an element-wise non-linearity.

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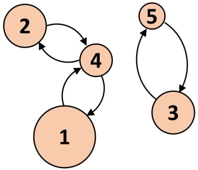

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The **hidden variables** $h^{(\ell)}$ extracted by the model can be used solve the regression task, i.e. $Y \approx \tilde{f}(h^{(\ell)})$, where $\tilde{f}$ may even be linear.

Dynamic Graph Neural Networks (DGNNs)

For dynamic graphs, $\mathcal{G}_t = (V_t, X_t, E_t)$, we must use a DGNN, for instance the **GC-LSTM** model[4]:

- extracts h_t from the graph $\mathcal{G}_t$ at time t using a Graph Convolutional Network (GCN) (spatial dimension),
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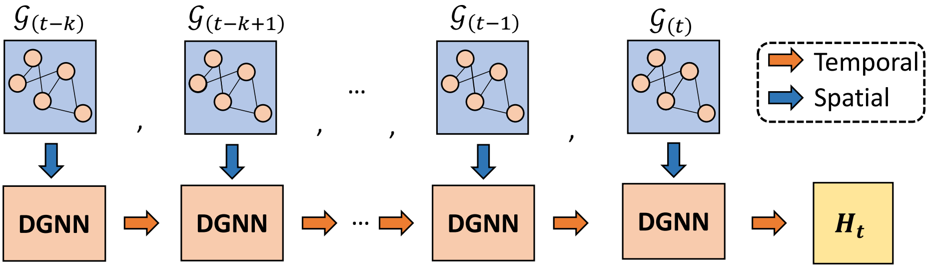

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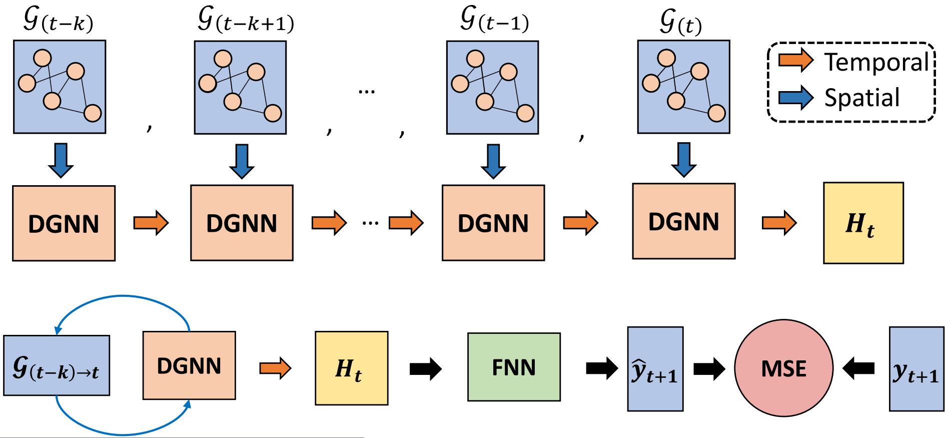

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Problem: we want to forecast margin calls in a network of heterogeneous market participants that dynamically exchange Interest Rate Swaps[5] (IRS).

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Let $(\Omega, \mathcal{A}, (\mathcal{A}_t)_{t\geq 0}, \mathbb{Q})$ be a filtered probability space[6] and let $r(t)$ be a **reference rate** with Cox-Ingersoll-Ross (CIR) dynamics:

$$\begin{cases} dr(t) = \kappa(\theta - r(t))dt + \sigma\sqrt{r(t)}dW_t, \\ r(0) \in \mathbb{R}_+. \end{cases}$$

We denote the **bond price** by $p(t, T)$ and the corresponding **daily term structure** by $R(t, T)$.

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Then the **value of an Interest Rate Swap** on the reference rate $r(t)$ at time t is:

$$V(t) = \delta N \left(p(t,T)\left(1 + K(T - t_0)\right) - \prod_{t_i \in (t_0, t] \cap \mathcal{T}} \left(1 + r(t_i)(t_i - t_{i-1})\right) \right),$$

where N is the notional, t_0 the start date, T the maturity, K the fixed interest rate, and $\delta \in \{-1, +1\}$.

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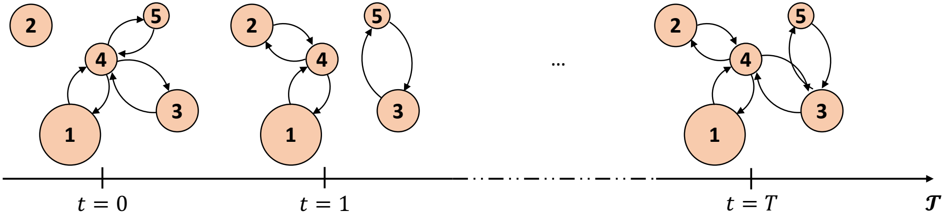
Problem formulation - Network dynamics



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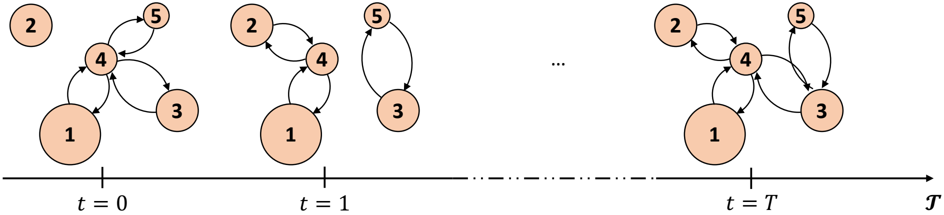

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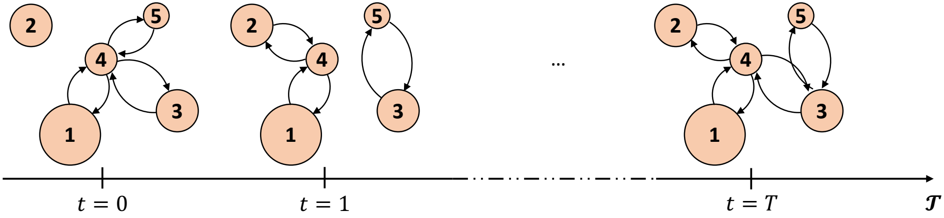

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- **edges** $(i, j) \in E_t$ represent IRS contracts and follow a point process $\left(t_k^{(i,j)}, N_k^{(i,j)}, K_k^{(i,j)}, T_k^{(i,j)}, \delta_k^{(i,j)}\right)_{k\in\mathbb{N}}$ with intensity conditional on $r(t)$ and X_t:

$$\lambda_t^{(i,j)}(r(t), x_i(t), x_j(t)) = \gamma \cdot \exp\{\eta + (\theta + \beta \cdot g(x_i(t), x_j(t)))\, r(t)\}, \quad g(x_i(t), x_j(t)) = \begin{cases} +1 & \text{(hub-private)} \\ 1/3 & \text{(hub-hub)} \\ -1 & \text{(private-private)} \end{cases}$$

Problem formulation

Forecasting target:

At time t_l, for each counterparty i, we want to forecast its total m-**steps ahead variation margin**:

$$M^{(i)}(t_{l+m}) := \sum_{j \in \mathcal{N}_i(t)} \sum_{k \in \mathbb{N}} V_k^{(i,j)}(t_{l+m}) - (1 + r(t_{l+m})\Delta t) V_k^{(i,j)}(t_{l+m-1}),$$

<u>conditionally on a future trajectory of the reference rate $r(t)$</u>.

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A successful forecasting method must take into account:

- the valuation of **existing contracts** (by time t_l):

$$\mathcal{H}_t = \sigma\left((t_k, N_k, K_k, T_k, \delta_k),\ k \in \mathbb{N} \text{ such that } t_k \leq t\right)$$

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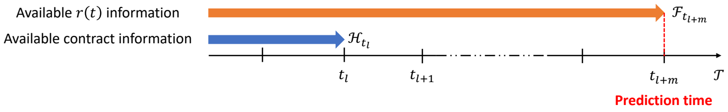

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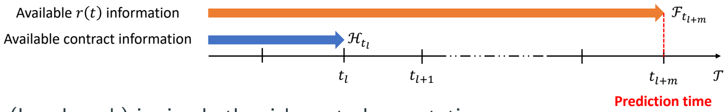


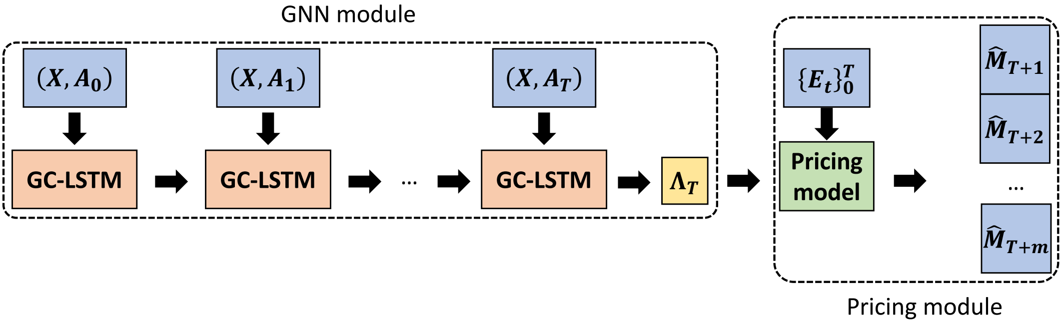
The **ground truth** (benchmark) is simply the risk-neutral expectation:

$$\prod_{t_i \in (t_l, t_{l+m}] \cap \mathcal{T}} (1 + r(t_i)\Delta t)^{-1} \mathbb{E}^{\mathbb{Q}}\left[M(t_{l+m}) \mid \mathcal{F}_{t_{l+m}} \vee \mathcal{H}_{t_l}\right].$$

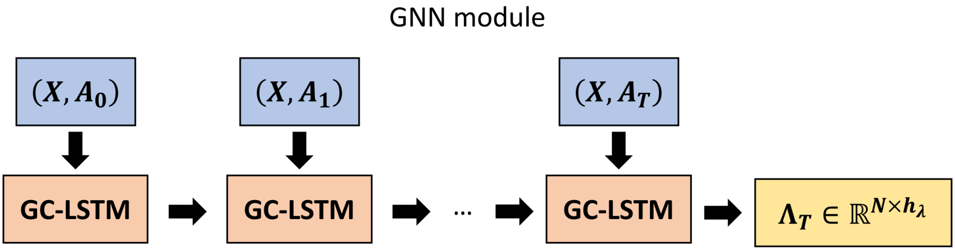
Proposed method

We propose a novel DGNN architecture to solve this conditional forecasting problem, which consists of:

- a **GNN module**,
- a **Pricing module**.

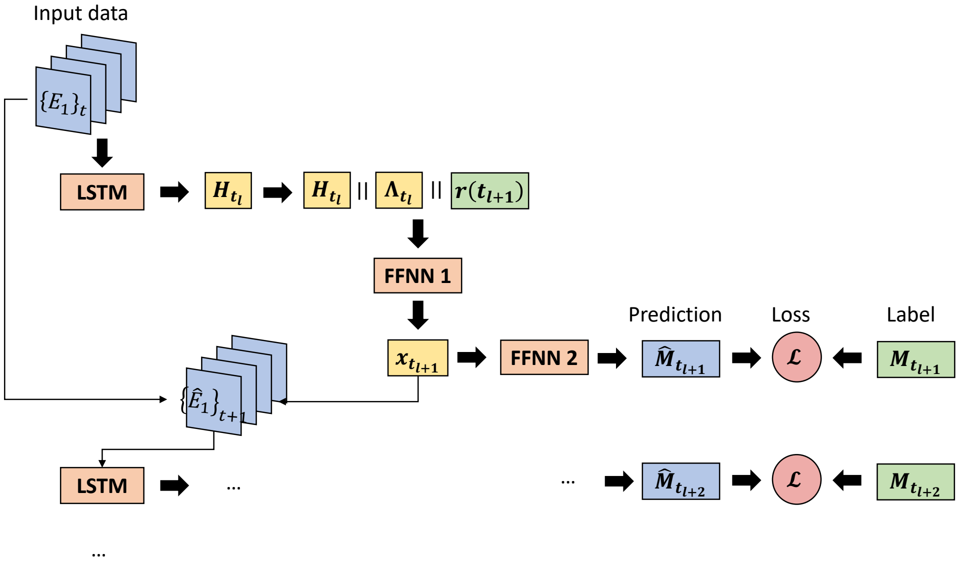


Proposed method - GNN module



- The GNN module is a standard GC-LSTM to capture the network dynamics.
- The output Λ_T is a hidden state representation of the intensity process, to model contracts in the future.

Proposed method - Pricing module



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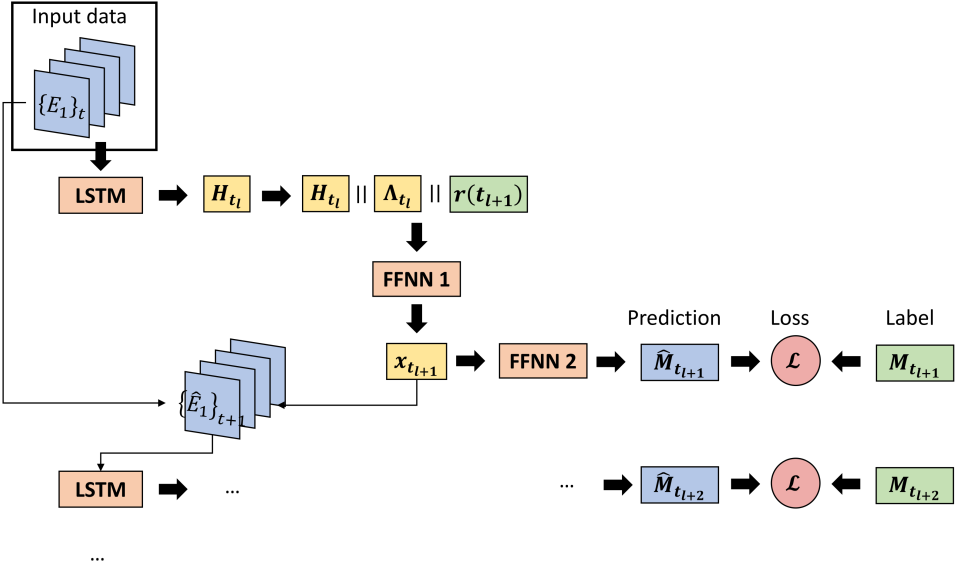
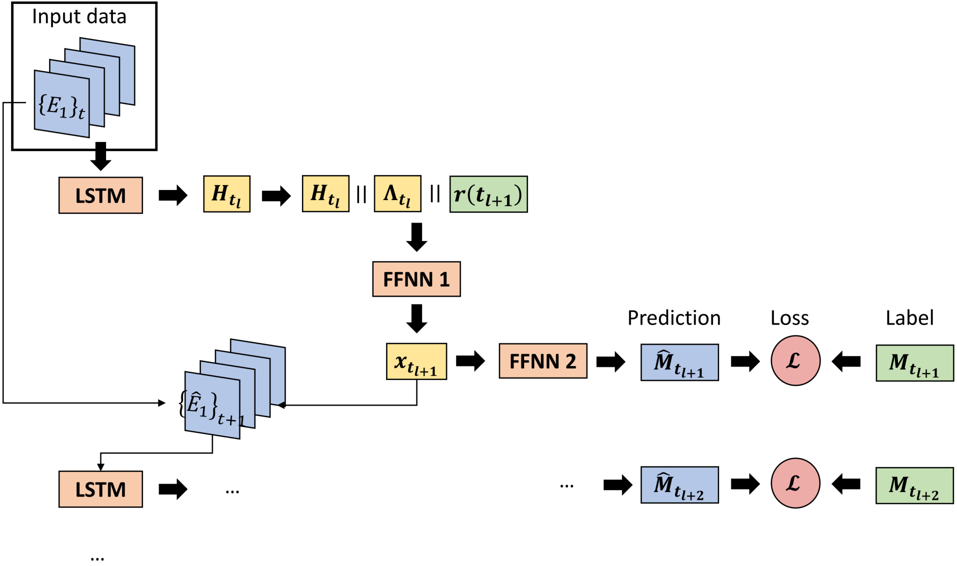
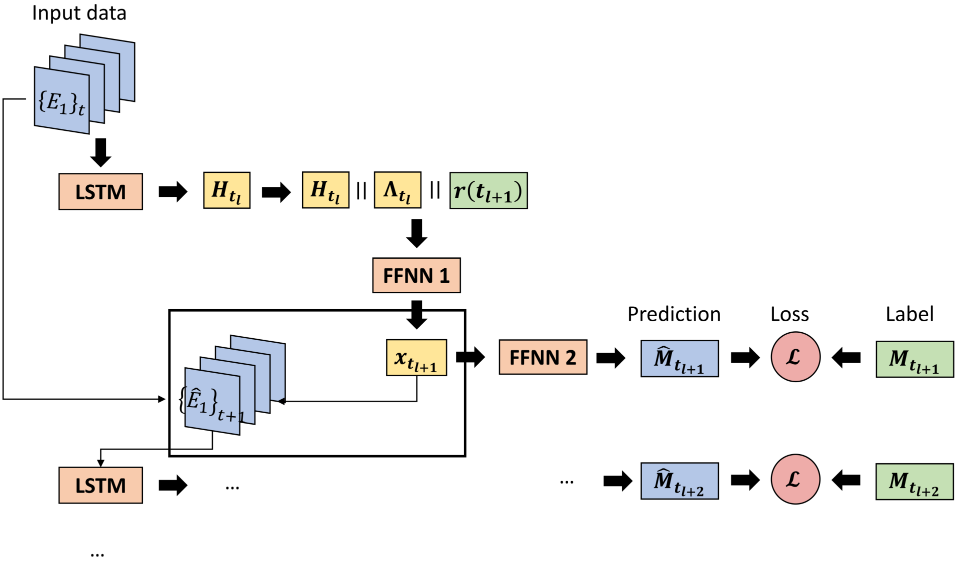


Proposed method - Pricing module - Contract matrix

$$\boxed{\{\boldsymbol{E}_t\}_{t=t_{l-k}}^{t_l}} = \underbrace{\left.\begin{array}{|c|c|c|c|}
\hline
\left[\frac{(\mathrm{T}-\mathrm{t})}{365}, p(t_0,T), p(t,T), B(t_0), B(t), \delta\right] & \dots & & \\
\hline
\left[\frac{(\mathrm{T}-\mathrm{t}-1)}{365}, p(t_0,T), p(t+1,T), B(t_0), B(t+1), \delta\right] & \dots & & \dots \\
\hline
\dots & & & \\
\hline
\left[\frac{(\mathrm{T}-\mathrm{t}-\mathrm{k})}{365}, p(t_0,T), p(t+k,T), B(t_0), B(t+k), \delta\right] & & \dots & \\
\hline
\end{array}\right\} k}_{\max_{t\in\mathcal{T}}\left(N_{active}(t)\right)\cdot 6}$$


Input data
$\{E_1\}_t$
LSTM
H_{t_l}
$H_{t_l} \,||\, \Lambda_{t_l} \,||\, r(t_{l+1})$
FFNN 1
$x_{t_{l+1}}$
FFNN 2
Prediction
$\widehat{M}_{t_{l+1}}$
Loss
$\mathcal{L}$
Label
$M_{t_{l+1}}$
$\{\hat{E}_1\}_{t+1}$
LSTM
...
...
$\widehat{M}_{t_{l+2}}$
$\mathcal{L}$
$M_{t_{l+2}}$
...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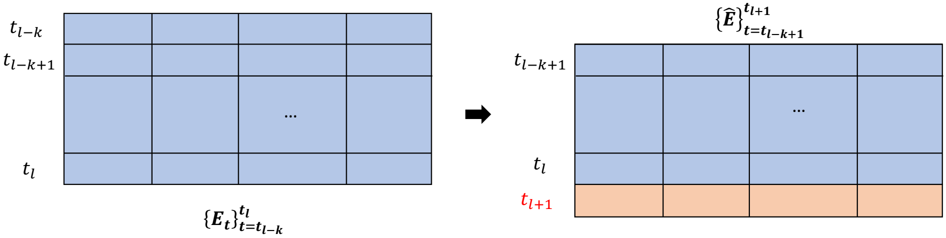
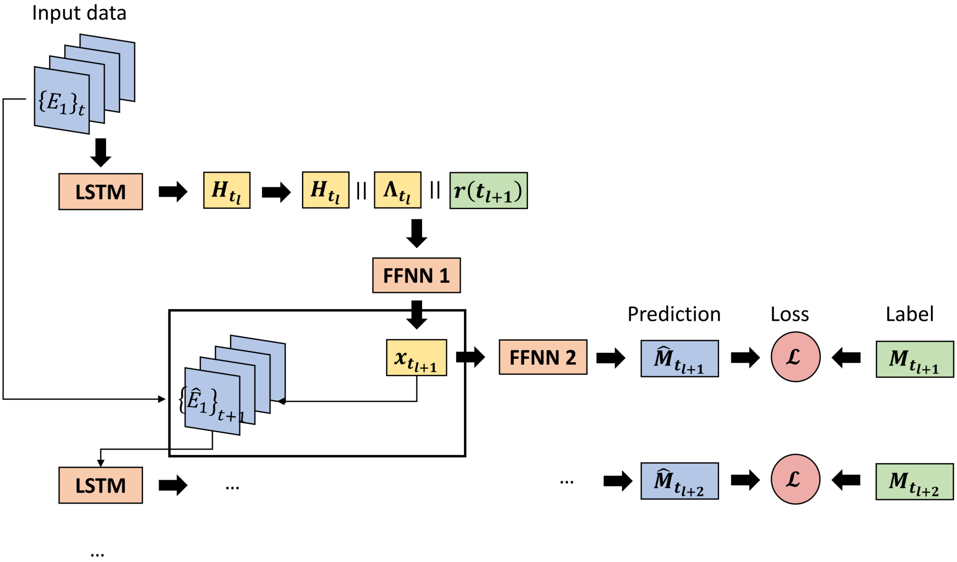
$M_{t_{l+2}}$
...


t_{l-k}
t_{l-k+1}
...
t_l
$\{\boldsymbol{E}_t\}_{t=t_{l-k}}^{t_l}$
$\{\widehat{\boldsymbol{E}}\}_{t=t_{l-k+1}}^{t_{l+1}}$
t_{l-k+1}
...
t_l
t_{l+1}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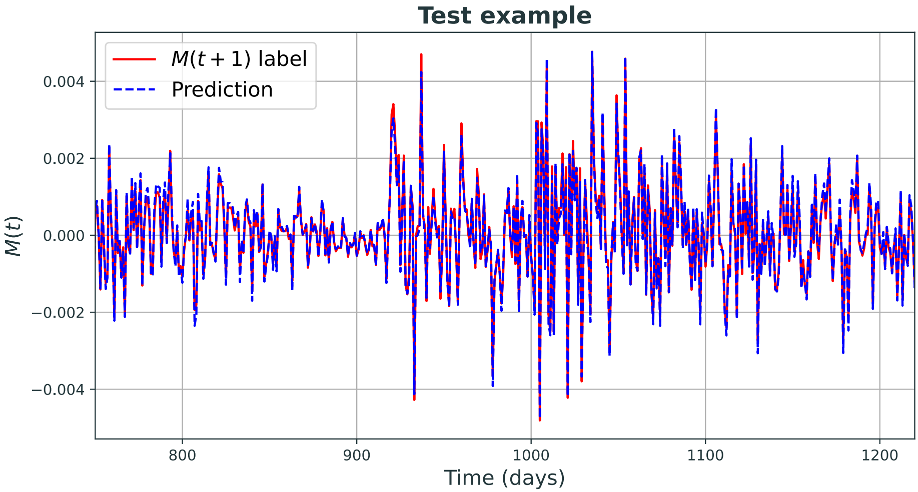
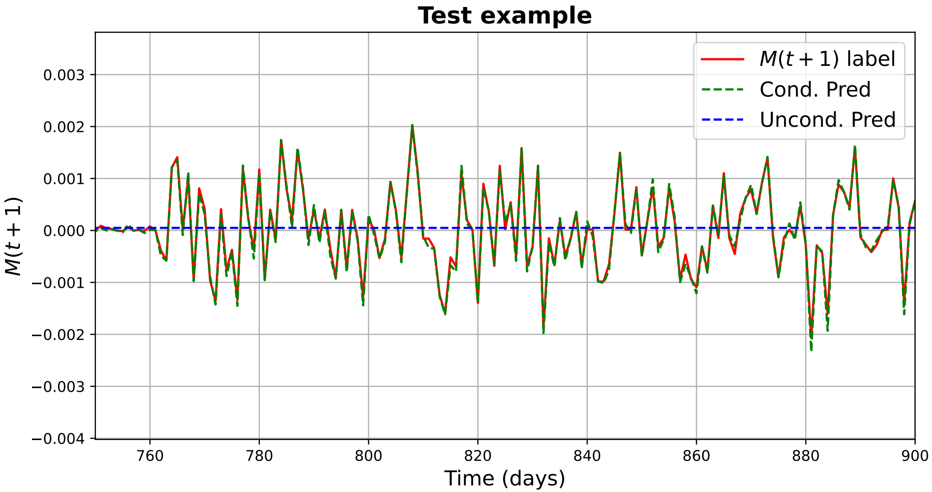
Results



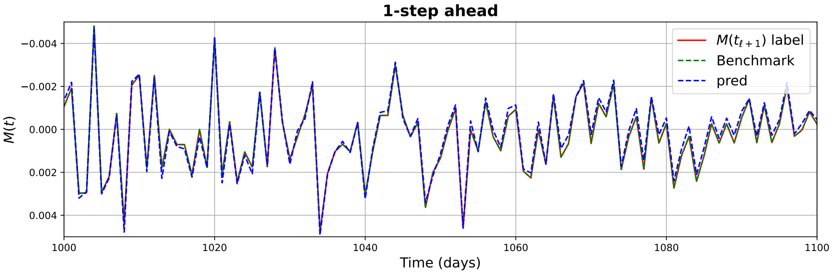
- One-step ahead stressed margin call forecast for one node in the network.

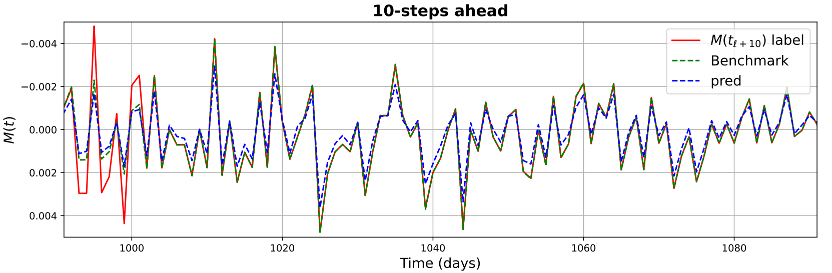
Results



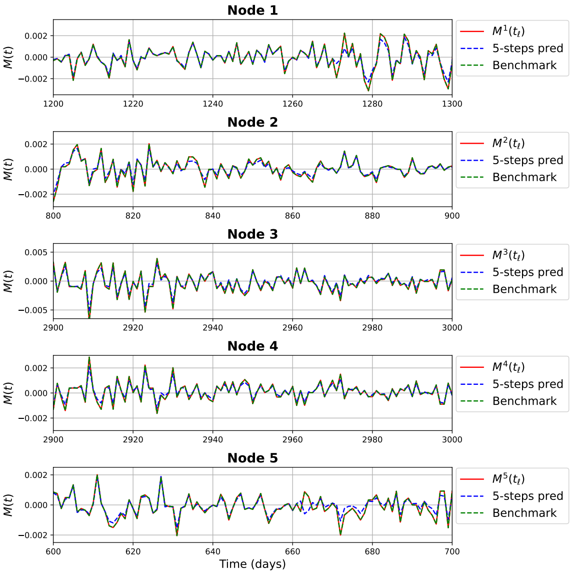
- The conditioning future interest rate trajectory (stress test scenario) is fundamental.

Results


1-step ahead
−0.004
−0.002
0.000
0.002
0.004
M(t)
1000
1020
1040
1060
1080
1100
Time (days)
$M(t_{\ell+1})$ label
Benchmark
pred


10-steps ahead
−0.004
−0.002
0.000
0.002
0.004
M(t)
1000
1020
1040
1060
1080
Time (days)
$M(t_{\ell+10})$ label
Benchmark
pred

Results



Node 1
M(t)
0.002
0.000
−0.002
1200
1220
1240
1260
1280
1300
$M^1(t_\ell)$
5-steps pred
Benchmark
Node 2
M(t)
0.002
0.000
−0.002
800
820
840
860
880
900
$M^2(t_\ell)$
5-steps pred
Benchmark
Node 3
M(t)
0.005
0.000
−0.005
2900
2920
2940
2960
2980
3000
$M^3(t_\ell)$
5-steps pred
Benchmark
Node 4
M(t)
0.002
0.000
−0.002
2900
2920
2940
2960
2980
3000
$M^4(t_\ell)$
5-steps pred
Benchmark
Node 5
M(t)
0.002
0.000
−0.002
600
620
640
660
680
700
Time (days)
$M^5(t_\ell)$
5-steps pred
Benchmark

Conclusions

Methodology:

- We introduced a **Dynamic Graph Neural Network (DGNN) model** for solving an m-steps ahead **margin call forecasting** problem in a fully dynamic network, **conditionally on stress test scenarios** (such as future trajectories of a reference rate).
- The model is modular, can be easily adapted to various derivatives markets, and produces **accurate forecasts up to a 21-day horizon**.

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Policy:

- This is a proof-of-concept work to show that **derivative transactions data could successfully be used to train machine learning models** that take into account **how the market reacts to shocks in reference interest rates** and other macro-economic variables.
- It could provide regulators and policymakers with a crucial tool to limit **pro-cyclicality** and complement **liquidity stress-testing** and **systemic risk monitoring**.

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Thank you for your attention!

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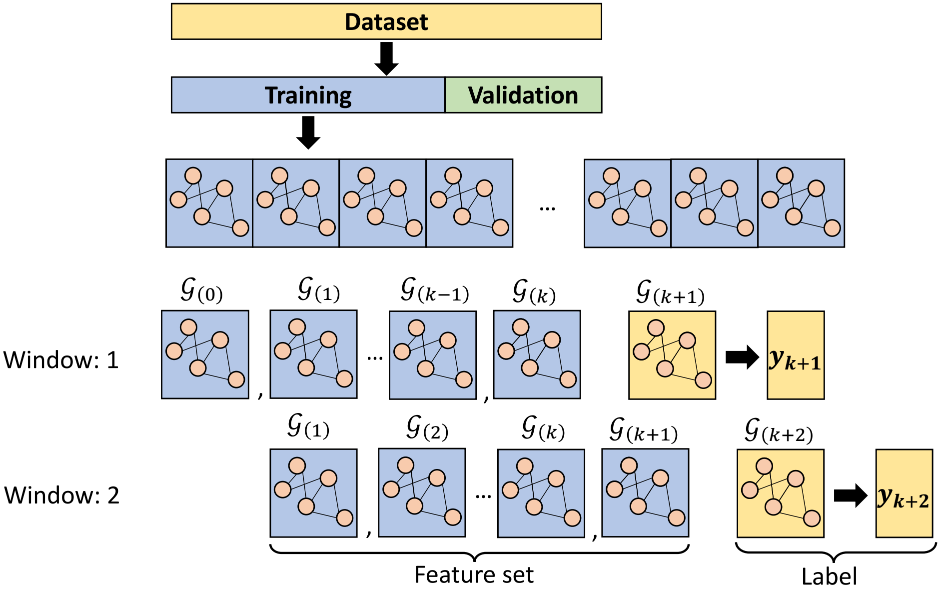
Dataset
Training
Validation
...
$\mathcal{G}_{(0)}$
$\mathcal{G}_{(1)}$
$\mathcal{G}_{(k-1)}$
$\mathcal{G}_{(k)}$
$\mathcal{G}_{(k+1)}$
Window: 1
y_{k+1}
$\mathcal{G}_{(1)}$
$\mathcal{G}_{(2)}$
$\mathcal{G}_{(k)}$
$\mathcal{G}_{(k+1)}$
$\mathcal{G}_{(k+2)}$
Window: 2
y_{k+2}
Feature set
Label