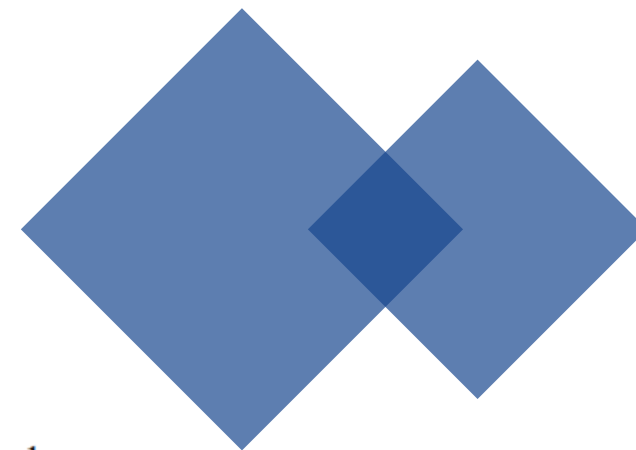


# FC-STGNN

Fully-Connected Spatial-  
Temporal Graph for Multivariate  
Time Series Data



**Yucheng Wang<sup>1,2</sup>, Yuecong Xu<sup>2</sup>, Jianfei Yang<sup>1</sup>,  
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<sup>1</sup>Nanyang Technological University, Singapore

<sup>2</sup>Institute for Infocomm Research, A\*STAR, Singapore

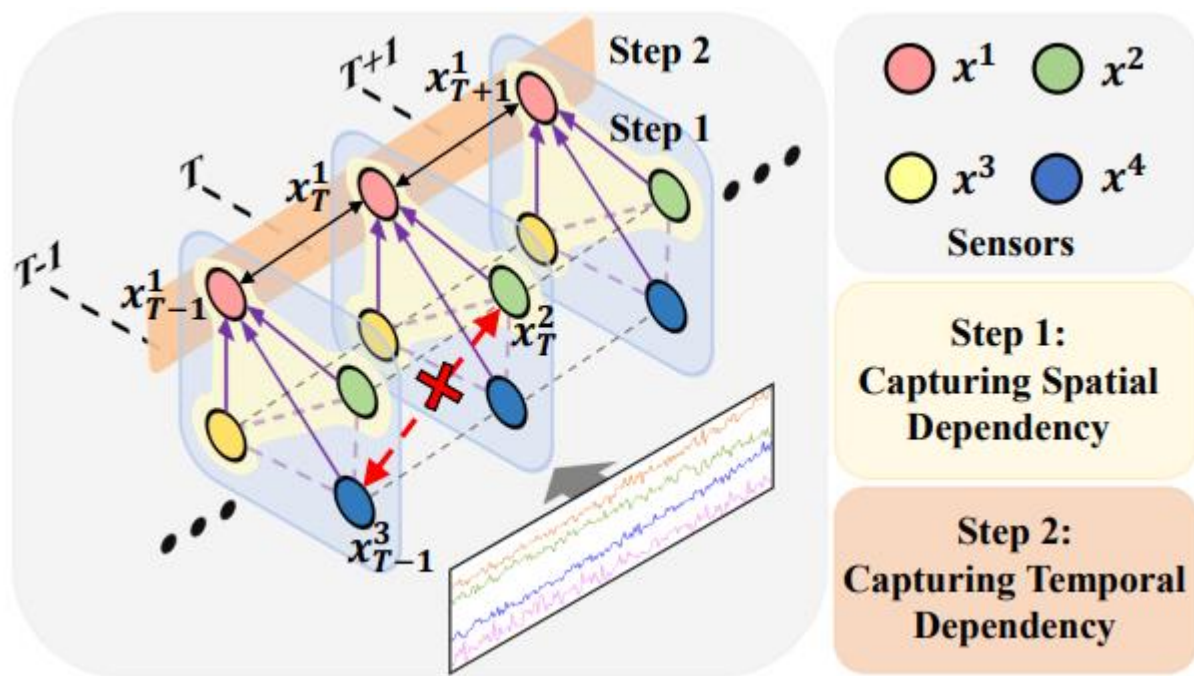
<sup>3</sup>Centre for Frontier AI Research, A\*STAR, Singapore

24.1.3

Presented by Yyyq



- **MTS**序列 → 序列属性和多源属性 → 表现出时空依赖性
- **DEDT**之间的相关性: Different sEnsors at Different Timestamps





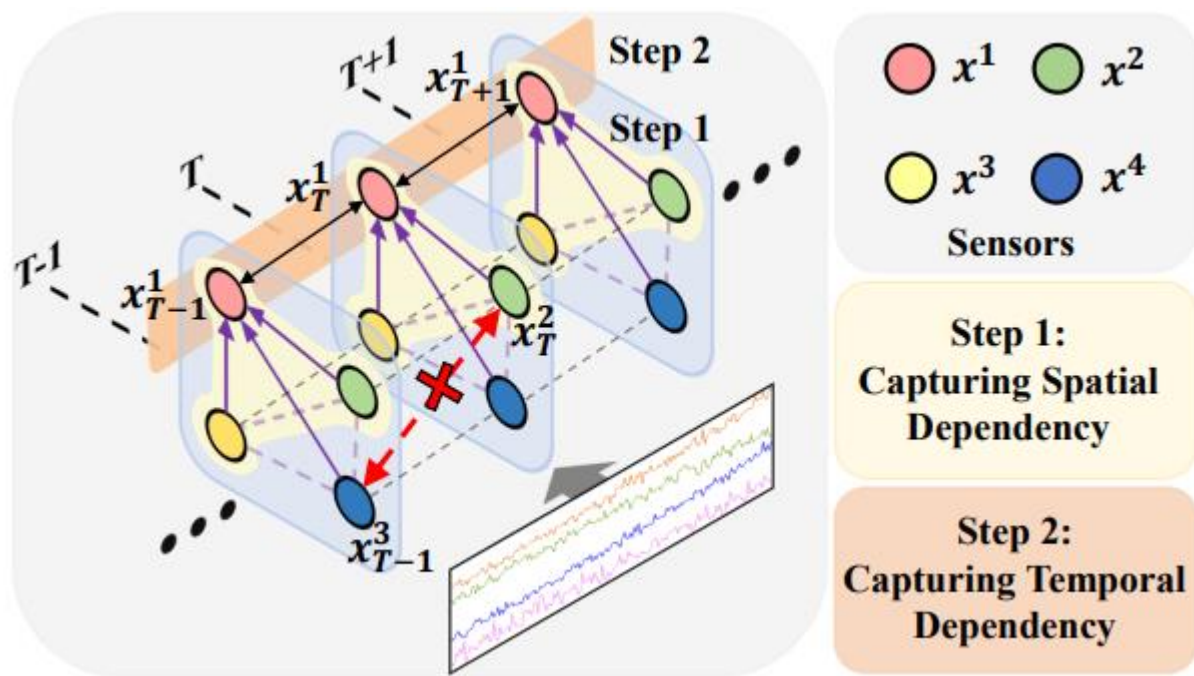
### ➤ Sensor—传感器（对应Multivariate）

- 它不同于路网中的固定传感器所体现出的图拓扑关系，可以理解为能够获取不同特征的传感器
- 比如：温/湿度传感器、速度/加速度传感器、功率传感器等等.....
- 不同于路网，这些固定传感器之间是没有原始连接关系的，但它们之间在时序上又存在着一定相关性

### ➤ Timestamp—时间戳

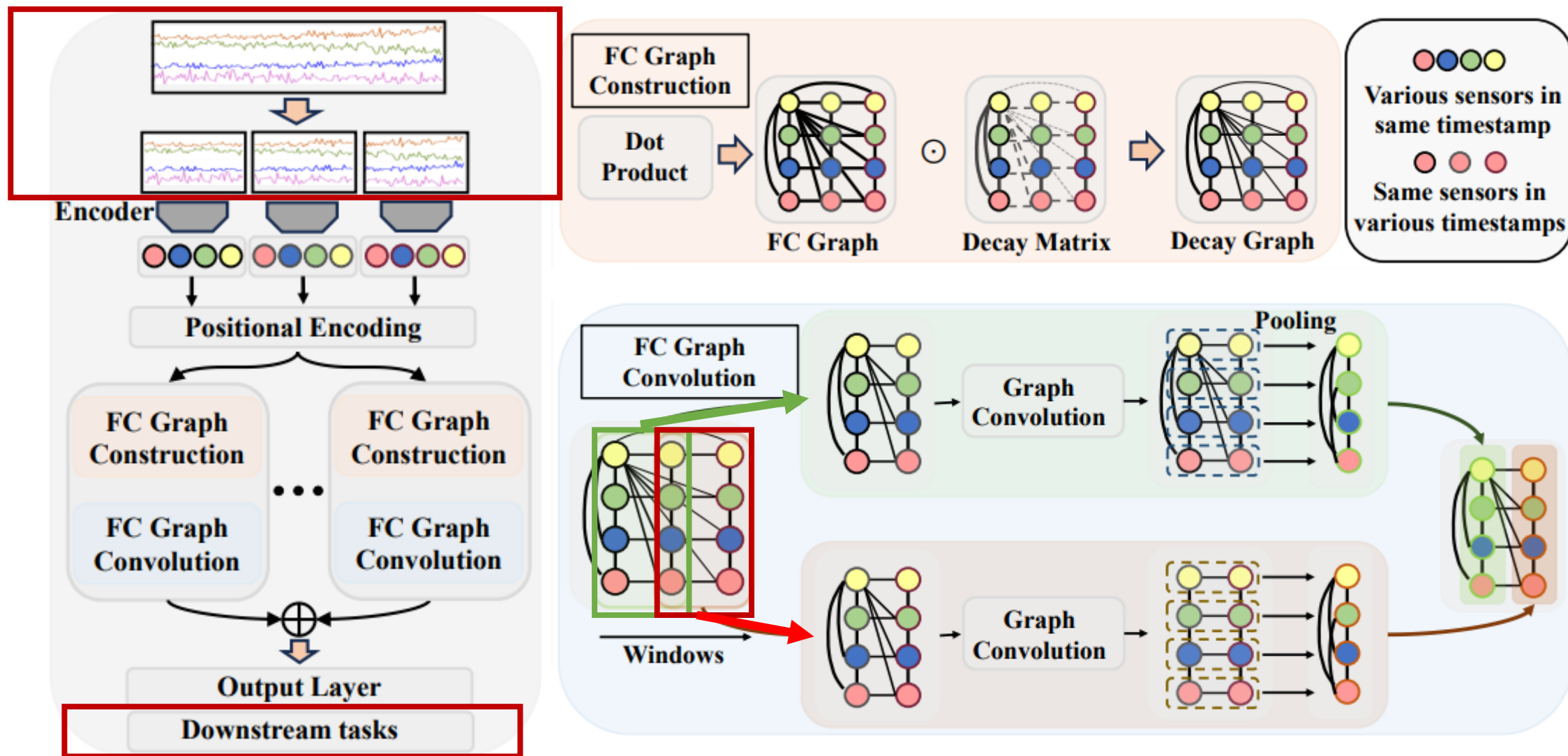
- 不同于Time Step时间步：按照时间长度聚合得到值
- 更符合于“时刻”的概念

- **MTS**序列 → 序列属性和多源属性 → 表现出时空依赖性
- **DFDT**之间的相关性: Different sEnsors at Different Timestamps
- 提取有效表征, 服务于不同的下游任务



## 02

## Overview



## 03

## 算法实现: FC图构建

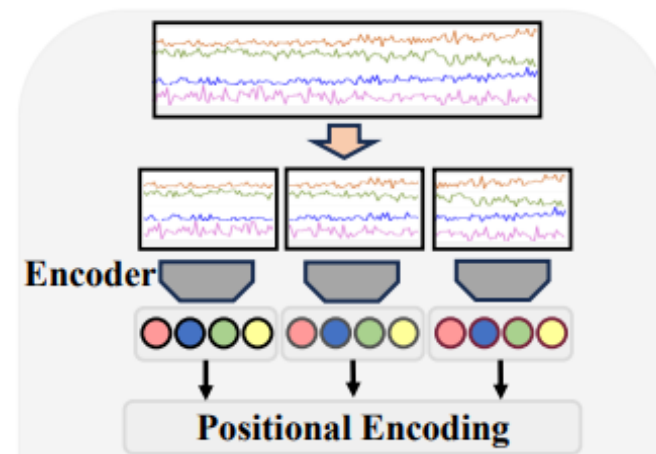
## ➤ 数据准备:

## • MTS数据分割

$$X \in \mathbb{R}^{N \times L} \rightarrow \{X_t\}_{t=1}^{\hat{L}} \begin{cases} \text{patch size } f \\ X_t = \{x_{t,i}\}_{i=1}^N, \quad X_t \in \mathbb{R}^{N \times f} \\ \hat{L} = \lfloor \frac{L}{f} \rfloor \end{cases}$$

## • Sensor-level特征: Encoder + Positional Encoding

$$z_{t,i} = f_p(t) + x'_{t,i} \begin{cases} f_p(t)^{(m)} := \begin{cases} \sin(\omega_k \cdot t) & \text{if } m = 2k, \\ \cos(\omega_k \cdot t) & \text{if } m = 2k + 1. \end{cases} \\ x'_{t,i} = f_c(x_{t,i} | W_c) \end{cases}$$



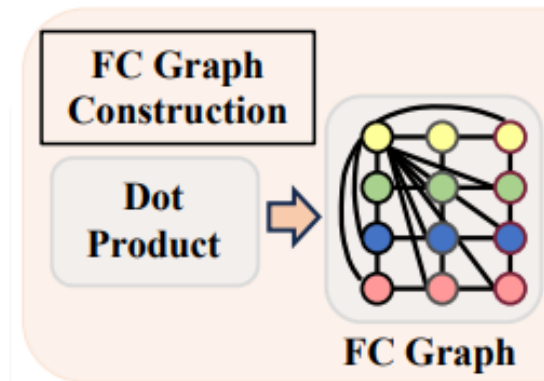
## 03



## 算法实现：FC图构建

## ➤ 添加DEDT相关性：

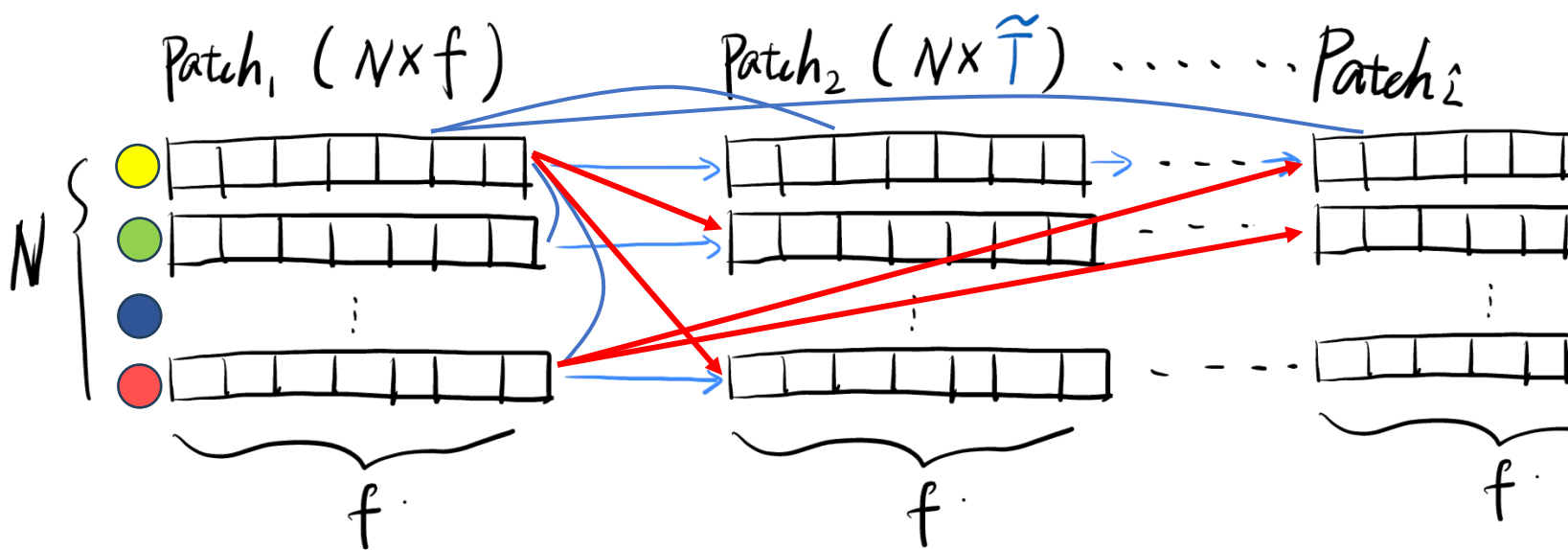
Sensor之间的相关性：用点积计算 不同patch、不同传感器 之间的相似度





## 03

## 算法实现: FC图构建

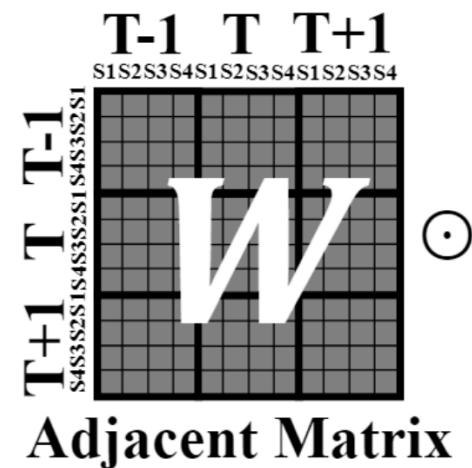
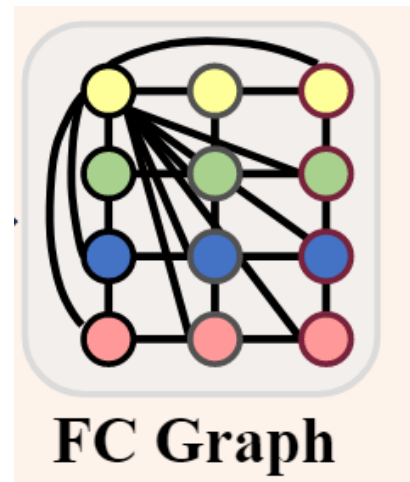
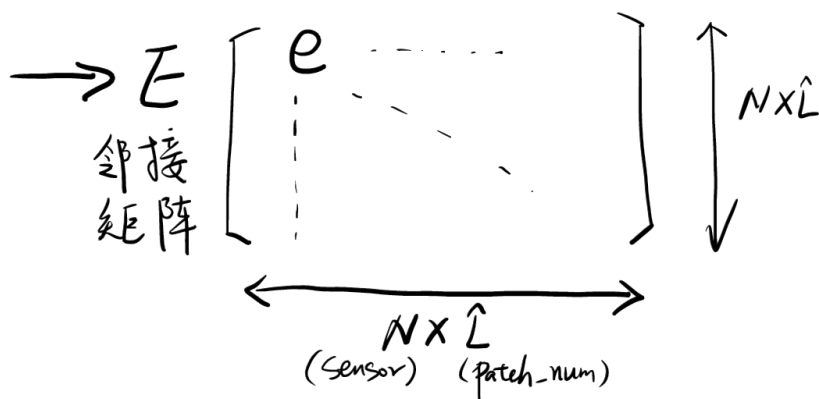


$$z_{t,v} : Q$$

$$z_{r,j} : K$$

$$\rightarrow \text{Softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)$$

$$e = \text{Similarity Score}$$





## 03

## 算法实现: FC图构建

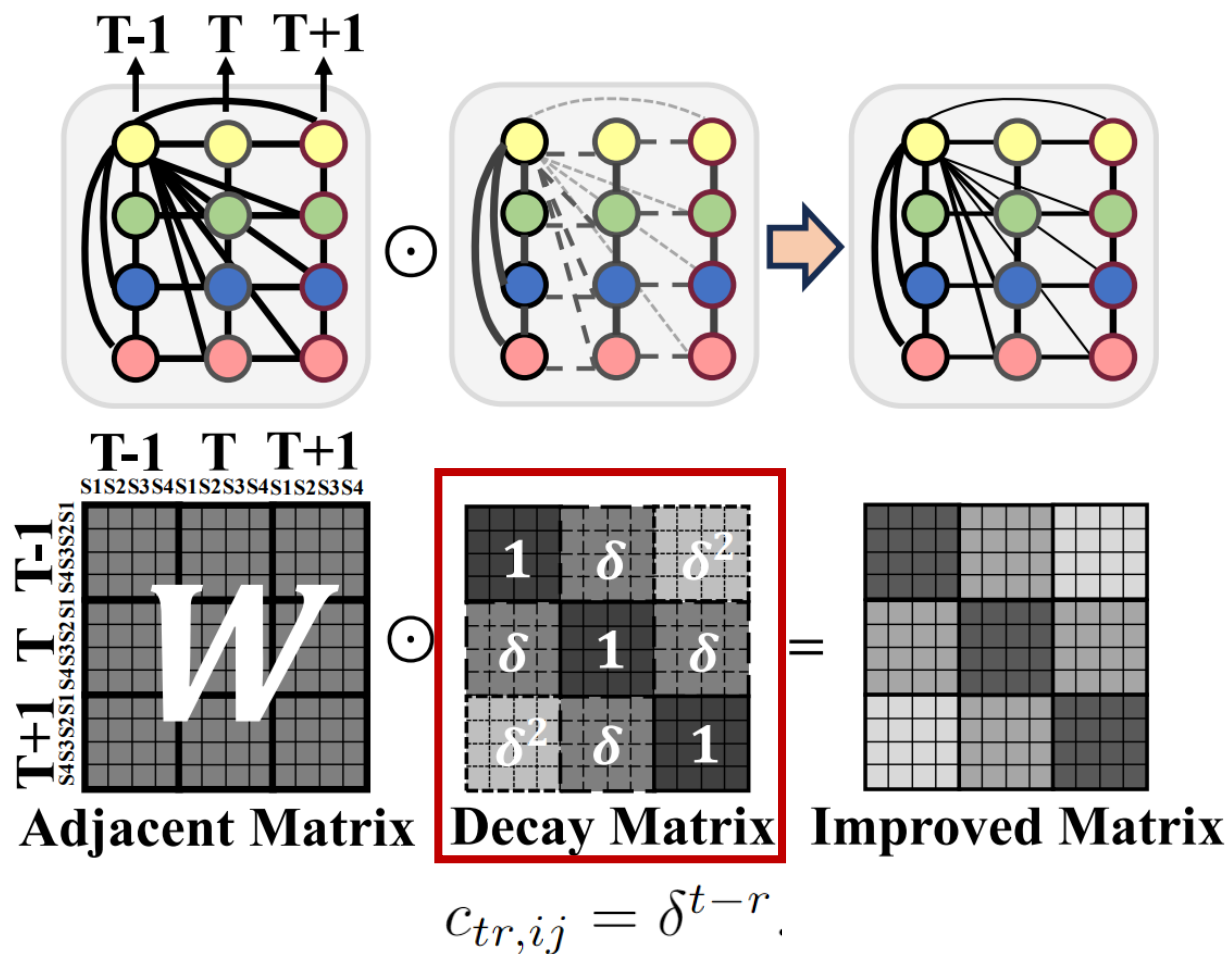
## ➤ 添加衰减矩阵:

衰减指数 $\delta$  (0,1)

同一个patch内为1

相邻  $\delta^1$ 

隔几步就几次方

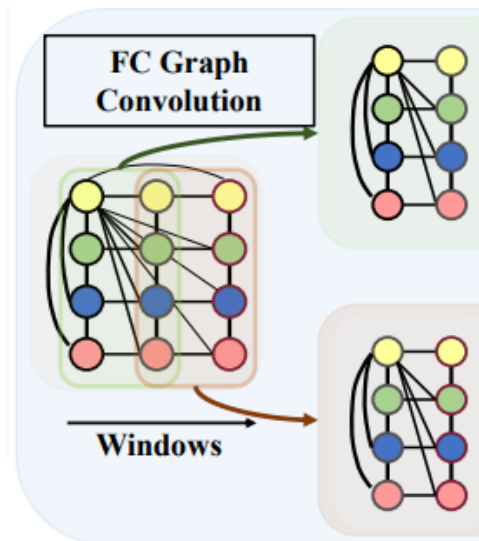
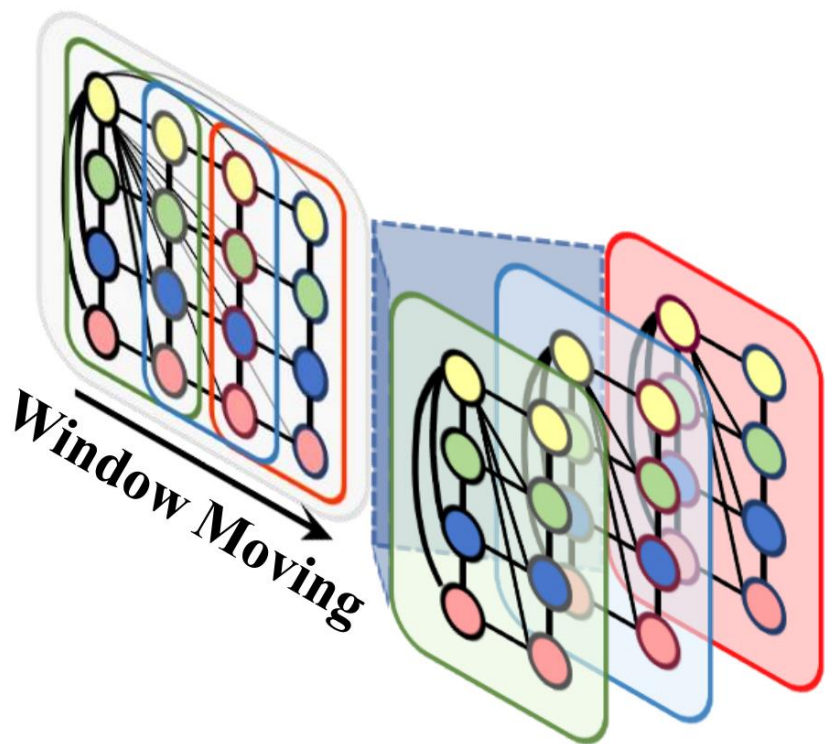


## 03



## 算法实现：FC图卷积

- 移动窗口：捕获局部的时间依赖  
窗口大小为2，步幅为1



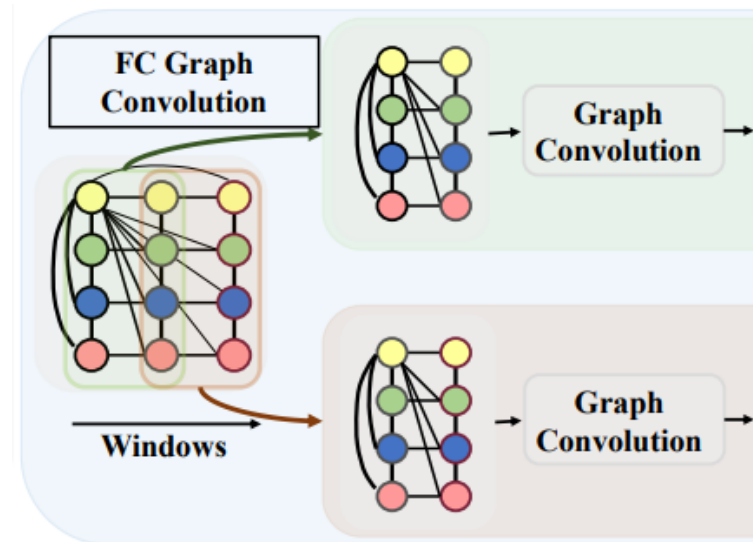
## 03

## 算法实现: FC图卷积

- 消息传递神经网络(MPNN): 传播和更新
  - 传播阶段: 相邻节点传播到中心节点
  - 更新阶段: 非线性函数更新特征 (ReLU)
- 中心节点:
  - 一个窗口包含M个patch, 每个patch又包括N个sensor
  - 中心 → 窗口中心 → 窗口中多个时序的中心

$$h_{t,i}^l = \sum_{r=w-\frac{M}{2}}^{w+\frac{M}{2}} \sum_{j=1}^N z_{r,j}^l e_{tr,ij}^l \cdot \begin{cases} \left\{ \left\{ z_{r,j}^l \right\}_{j=1}^N \right\}_{r=w-\frac{M}{2}}^{w+\frac{M}{2}} \\ \left\{ \left\{ e_{tr,ij}^l \right\}_{j=1}^N \right\}_{r=w-\frac{M}{2}}^{w+\frac{M}{2}} \end{cases} \quad \checkmark$$

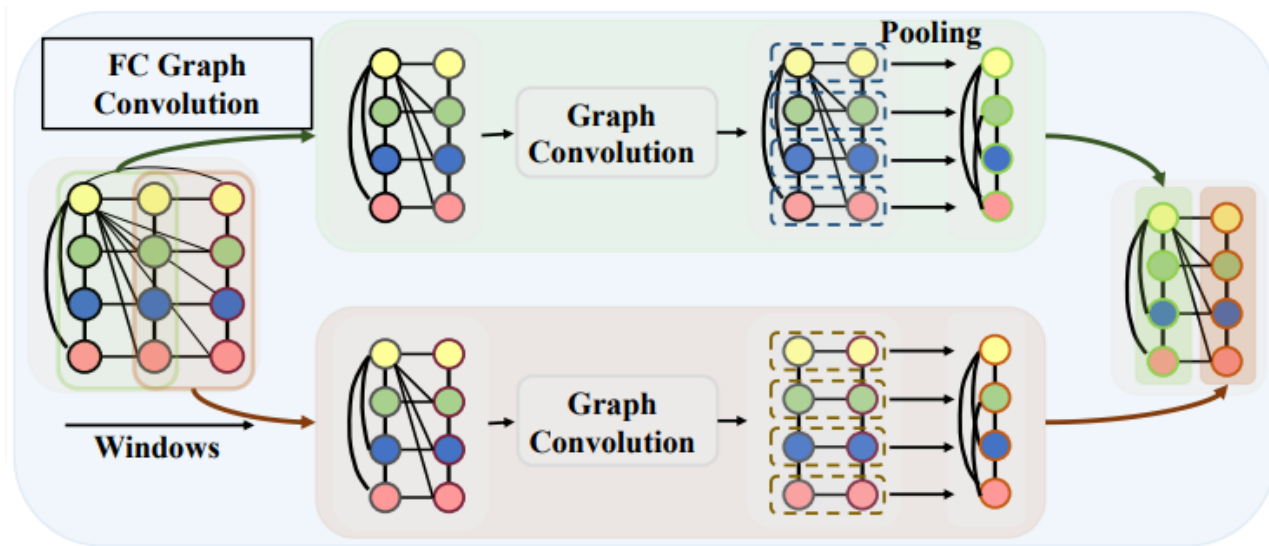
Score





➤ 池化操作

平均池化：把窗口内每个patch更新后的特征加和求平均  $/M$





C-MAPSS								UCI-HAR		ISRUC-S3	
FD001		FD002		FD003		FD004					
RMSE	Score	RMSE	Score	RMSE	Score	RMSE	Score	Accu	MF1	Accu	MF1

1、剩余使用寿命(RUL)预测：预测任务

- C-MAPSS：NASA模拟的航空发动机使用寿命（4个数据集对应不同工况和故障状态）

2、人类活动识别(HAR)：分类任务

- UCI-HAR：腰部佩戴智能手机（WALKING、WALKING\_UPSTAIRS、WALKING\_DOWNSTAIRS、SITTING、STANDING、LAYING）

3、睡眠阶段分类(SSC)：分类任务

- ISRUC-S3：健康受试者与患有睡眠障碍分类



C-MAPSS								UCI-HAR		ISRUC-S3	
FD001		FD002		FD003		FD004					
RMSE	Score	RMSE	Score	RMSE	Score	RMSE	Score	Accu	MF1	Accu	MF1

### 1、预测任务

- RMSE
- score function? : 用来判断统计模型对数据的拟合能力

### 2、分类任务

- Accuracy
- MF1: 对每一个类别计算F1值，然后对所有类别的F1值求算术平均



Models	C-MAPSS								UCI-HAR		ISRUC-S3	
	FD001		FD002		FD003		FD004					
	RMSE	Score	RMSE	Score	RMSE	Score	RMSE	Score	Accu	MF1	Accu	MF1
AConvLSTM	13.10	286	13.11	737	12.13	276	14.64	1011	86.06	85.75	72.93	69.52
DAGN	16.11	595	16.43	1242	18.05	1216	19.04	2321	89.02	88.94	55.35	50.51
InFormer	13.13	263	13.20	715	12.58	228	14.16	1023	90.23	90.23	72.15	68.67
AutoFormer	23.04	1063	16.51	1248	25.40	2034	20.31	2291	56.70	54.41	43.75	37.88
GCN	<u>12.58</u>	237	13.78	849	<u>11.92</u>	<u>218</u>	14.44	967	<u>94.79</u>	<u>94.82</u>	79.62	77.57
HAGCN	13.10	263	14.92	1086	13.46	327	14.66	880	80.79	81.08	66.59	60.20
HierCorrPool	12.64	<u>227</u>	13.23	<b>709</b>	12.30	220	<u>13.86</u>	<u>854</u>	93.81	93.79	<u>79.31</u>	<u>76.25</u>
MAGNN	12.63	246	<u>13.09</u>	<u>714</u>	12.15	253	14.30	978	90.91	90.79	68.13	64.31
Ours	<b>11.62</b>	<b>203</b>	<b>13.04</b>	738	<b>11.52</b>	<b>198</b>	<b>13.62</b>	<b>816</b>	<b>95.81</b>	<b>95.82</b>	<b>80.87</b>	<b>78.79</b>



Variants	C-MAPSS								UCI-HAR		ISRUC-S3	
	FD001		FD002		FD003		FD004					
	RMSE	Score	RMSE	Score	RMSE	Score	RMSE	Score	Accu	MF1	Accu	MF1
w/o FC GC <sup>2</sup>	12.58	237	13.78	849	11.92	218	14.44	967	94.79	94.82	79.62	77.57
w/o M&P	12.17	217	13.29	769	11.75	219	14.03	837	95.06	95.10	79.85	77.60
w/o Pooling	12.03	231	13.13	720	11.68	220	13.74	849	95.53	95.57	80.16	77.42
w/o decay	12.15	233	13.20	750	11.74	205	13.86	853	95.20	95.28	80.13	78.33
Complete	11.62	203	13.04	738	11.52	198	13.62	816	95.81	95.82	80.87	78.79
GCN	<u>12.58</u>	237	13.78	849	<u>11.92</u>	<u>218</u>	14.44	967	<u>94.79</u>	<u>94.82</u>	79.62	77.57

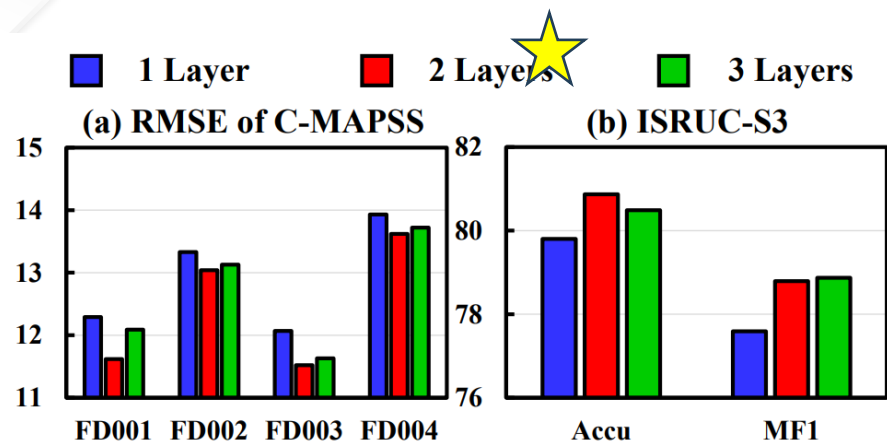


Figure 5: Sensitivity analysis for No. of parallel layers.

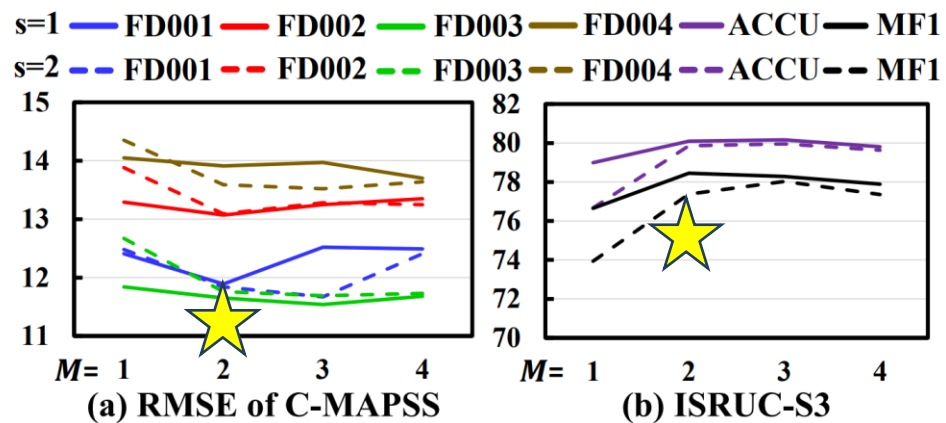


Figure 7: Sensitivity analysis for moving window sizes.

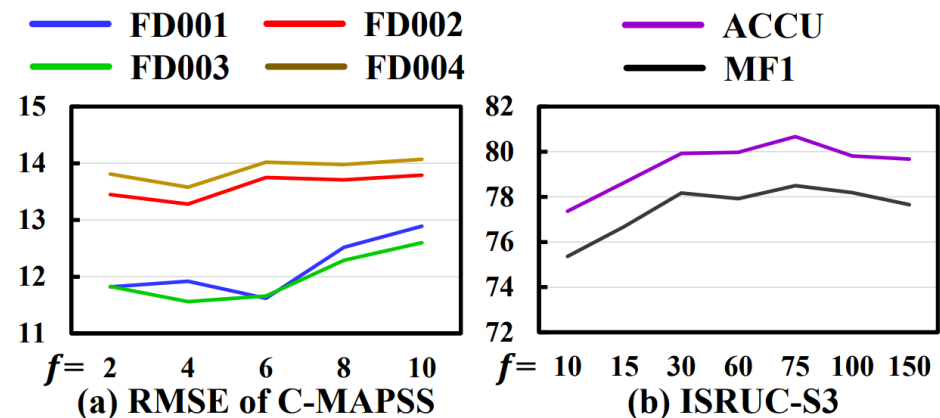


Figure 6: Sensitivity analysis for patch sizes.

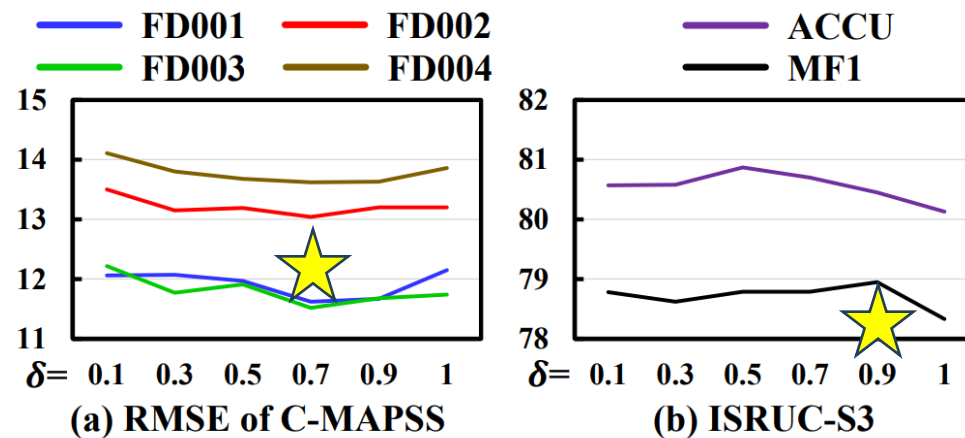


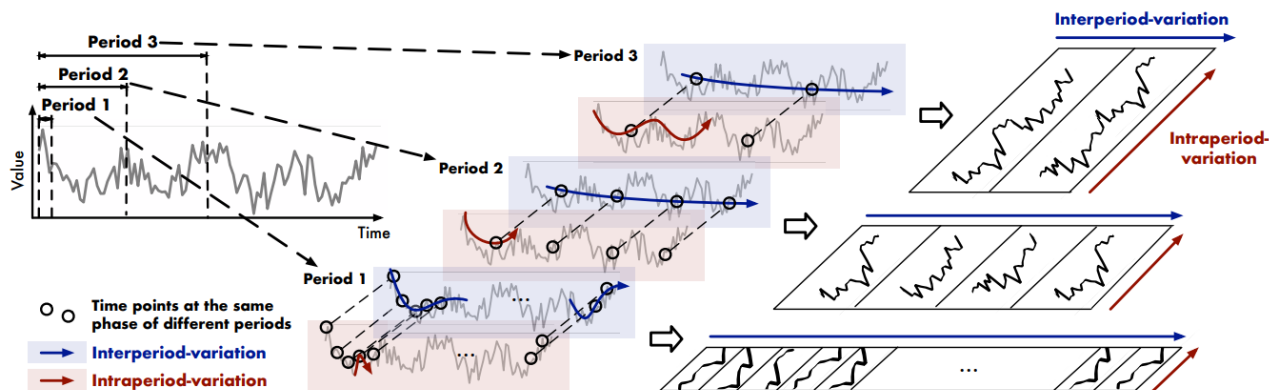
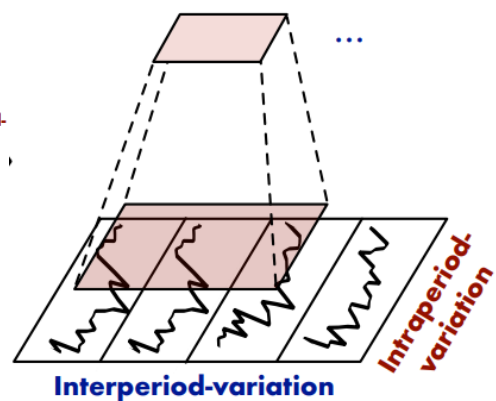
Figure 8: Sensitivity analysis for decay rates.

05



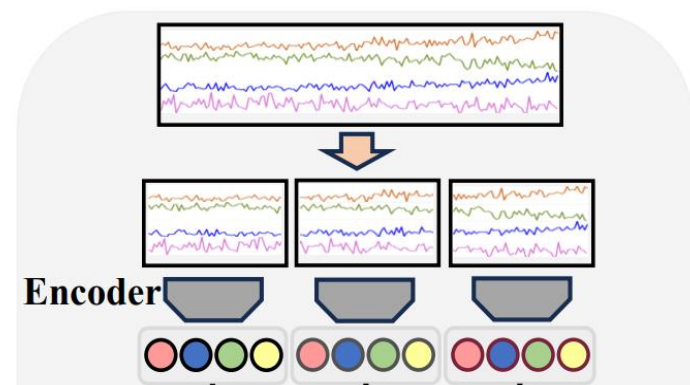
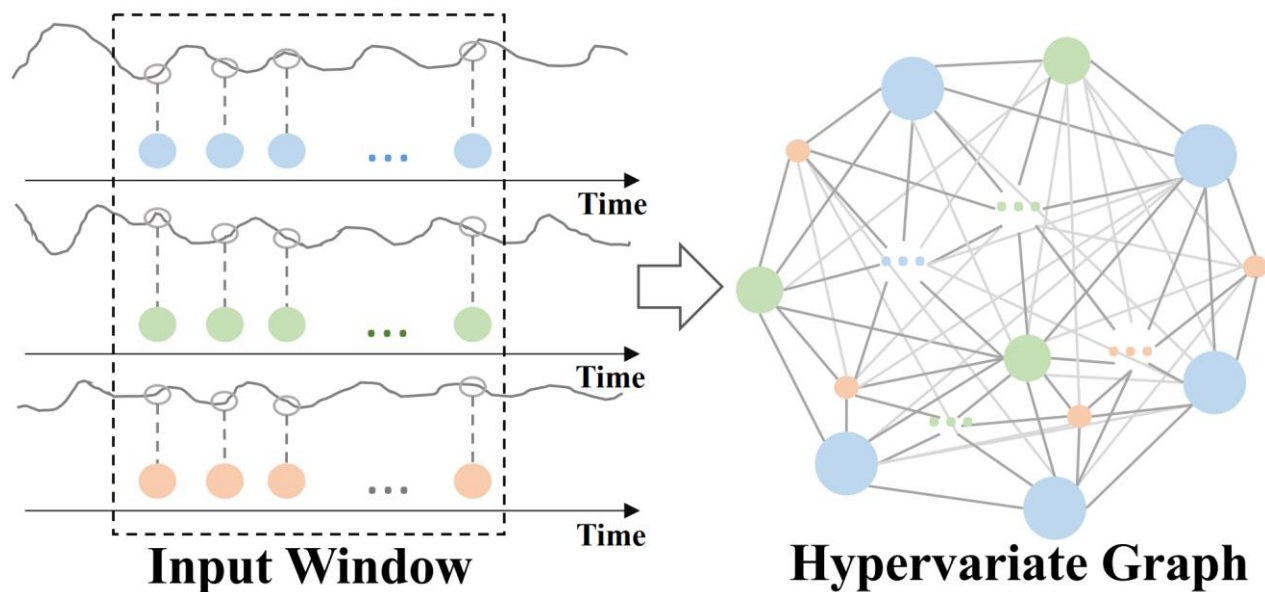
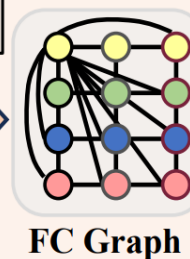
小总结

TimesNet (ICLR 2023)

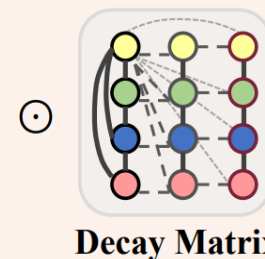
Capture Temporal 2D-variations  
by 2D Kernels

FC-STGNN(AAAI 2024)

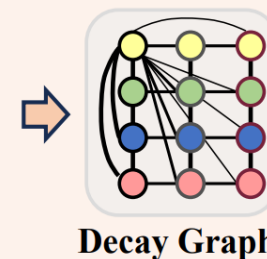
FourierGNN(NeurIPS 2023)

FC Graph  
ConstructionDot  
Product

FC Graph



Decay Matrix



Decay Graph



# 谢谢观看

MANY THANKS !



24.1.3

