Deteksi Transfer Fraud pada Sistem Pembayaran dengan Graph Neural Network (GNN)

Proposal Hackathon Bank Indonesia 2024

Tim ”JN and GNN”

Jens Naki

Juni 2024

Ringkasan Eksekutif

- Proyek ini dirancang untuk mengikuti event Hackathon BI 2024, khususnya untuk menyelesaikan Problem Statement Nomor 3: Risk Management and Customer Protection.
- Proyek ini diharapkan dapat melakukan identifikasi dan pencegahan transaksi transfer yang bersifat fraud, sebelum transaksi tersebut terjadi. Implementasi yang berhasil dari proyek ini akan berdampak pada minimalisasi risiko fraud dari aktivitas transfer nasabah.
- Konsep Artificial Intelligence / Machine Learning yang digunakan pada proyek ini adalah Graph Neural Network (GNN). GNN adalah sebuah Neural Network khusus untuk data tipe graph.
- Pilot analysis telah dilakukan dengan melakukan pengujian model GNN pada dataset Bitcoin Elliptic Dataset. Dataset bersifat publicly available namun sifatnya anonymized, sehingga kerahasiaan address dan transaksi Bitcoin blockchain terjaga. Hasil pengujian disertakan sebagai Lampiran dari proposal ini.

Tim “JN and GNN”

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Peran dalam tim	:	Data Scientist
Keahlian dan pengalaman relevan	:	• Peserta OSN Informatika SMA tingkat nasional tahun 2008 • Mengikuti Diklat Pengolahan Data menggunakan Python yang diselenggarakan Pusdiklat Keuangan Umum Kemenkeu • Mempelajari Machine Learning di Digitalent Scholarship Kominfo • Saat ini studi Master of Data Science di The University of Adelaide, Australia
Link portofolio	:	https://github.com/jensdavion/Hackathon_BI

Tujuan / Sasaran Proyek

Tujuan utama
Dengan Graph Neutral Network (GNN), transaksi transfer antar rekening yang bersifat fraud dapat diidentifikasi dan dicegah secara real time, sebelum transaksi selesai dilakukan.

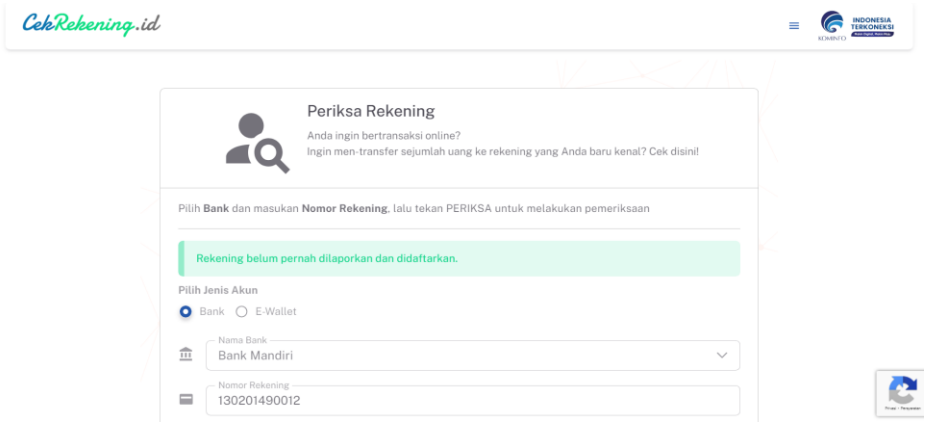
Sasaran terukur:
Ada banyak pengukuran untuk menilai keberhasilan proyek ini, antara lain:
- Waktu proses per transaksi, diharapkan tetap cepat,
- Total transaksi transfer fraud dicegah.
- Total nominal transaksi transfer fraud dicegah.
- Rata-rata nominal fraud dicegah per transaksi.
- Total transaksi fraud yang masih terjadi (misal database cekrekening.id Kemenkominfo).
- Total nominal transaksi fraud yang masih terjadi.
- Rata-rata nominal fraud terjadi per transaksi
- Rasio transaksi fraud dicegah dibanding transaksi terjadi
- Rasio nominal fraud dicegah disbanding nominal fraud terjadi

Dampak
Proyek ini bermanfaat bagi masyarakat luas, karena usaha pencegahan transaksi transfer fraud dapat meminimalisasi risiko kerugian, dibandingkan jika korban fraud harus melaporkan kepada pihak Bank setelah transaksi terjadi.

Rumusan Masalah

Masalah
Perlunya sistem untuk identifikasi transaksi transfer antar rekening yang kemungkinan bersifat fraud, misalnya pencurian identitas, skema ponzi, pembayaran ransomware, dan tindakan penipuan lainnya.

Solusi saat ini:
- Tidak ditemukan referensi cara bank-bank di Indonesia mendeteksi transaksi mencurigakan.
- Berdasarkan pengalaman pribadi, belum pernah mengalami transaksi transfer antar rekening yang dicurigai pihak bank, termasuk transfer valas ke luar negeri.
- Masyarakat dapat melakukan pengecekan daftar rekening ke database CekRekening.id milik Kemenkominfo. Kelemahan solusi ini, yaitu masyarakat harus mengalami kerugian akibat *fraud* terlebih dulu. Selain itu, ada kemungkinan korban fraud tidak melaporkan, misalnya kurang paham teknologi, atau bahkan tidak tahu kalau ada layanan CekRekening.id.



Gambar di samping adalah tampilan CekRekening.id, jika rekening yang diperiksa belum pernah didaftarkan atau dilaporkan.
Sumber: cekrekening.id

Metode/Mekanisme ML

Rancangan Pipeline Proyek

START

Nasabah inisiasi transaksi transfer

GRAPH (PyTorch)

- Konversi data ke bentuk graph data
- Split data untuk training, validation, dan test.

TRAINING (PyTorch Geometric)

- Running model yang cocok untuk large scale data, GraphSAGE.
- PyG memiliki fitur distributed training untuk memecah training ke beberapa mesin/GPU secara bersama.
- Dengan model GraphSAGE, distributed training PyG, dan optimalisasi PyG, running selesai dalam hitungan detik.

OUTPUT

- Cek hasil prediksi
- Jika transaksi nasabah diprediksi fraud, berikan peringatan dan konfirmasi apakah nasabah ingin melanjutkan transaksi

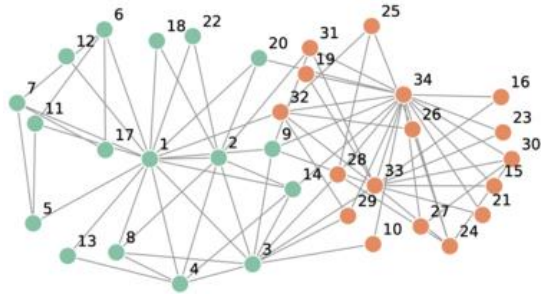
PyTorch

PyG

Metode/Mekanisme ML

Graph Data

Graph adalah sebuah struktur di mana terdapat sejumlah Node yang dihubungkan oleh sejumlah Edge. Gambar berikut adalah graph dari Zachary's karate club, sering digunakan untuk pengenalan graph. Nodes adalah anggota 2 klub karate berbeda, sementara garis edge menggambarkan hubungan pertemanan (node 1 berteman dengan nomor 32, meskipun keduanya beda klub).



Zachary's karate club
Sumber: Wikipedia

Transaksi transfer antar rekening secara intuitif dapat kita gambarkan sebagai graph. Misalnya nomor rekening sebagai node, dan nominal yang ditransfer sebagai edge.

Node dan Edge Features

Feature pada node dan edge adalah informasi tambahan terkait node dan edge itu sendiri. Misalnya, pada Zachary's karate club, node adalah anggota klub, feature dapat ditambahkan, misalnya: umur, tinggi dan berat badan.

Metode/Mekanisme ML

Graph Neural Network

GNN merupakan jenis neural network pada machine learning, khusus untuk data berbentuk graph. GNN digunakan untuk menyelesaikan beberapa jenis masalah, yaitu:

- Node classification, untuk prediksi label node, misalnya prediksi mana node fraud dan non fraud di sebuah payment network.
- Link prediction, untuk prediksi potensial hubungan antar node. Contoh use case: recommend system di Netflix.
- Graph classification, untuk prediksi bentuk graph secara keseluruhan, misalnya prediksi molekul di Biologi.

Permasalahan pada proyek ini masuk ke dalam jenis node classification.

Model GNN

Dalam 5 tahun terakhir, bermunculan banyak model GNN baru, dengan fitur masing-masing. Pytorch Geometric melakukan penambahan model GNN baru secara berkala, berdasarkan paper-paper internasional yang dirilis.

Pada proyek, rencana model yang akan digunakan adalah GraphSAGE. Model ini memungkinkan model untuk running hanya pada sebagian sample, karena fitur-fitur dari node sekitar telah diagregasi ke node sekitar. SAGE = SAmple and aggreGatE.

Pada pilot analysis yang disertakan bersama proposal ini, model yang digunakan terhadap dataset adalah GAT dan GATv2. Kedua model ini termasuk model yang paling sederhana

Dataset yang digunakan

Dataset yang digunakan adalah Bitcoin Elliptic Dataset, sifatnya publicly available sehingga bisa diunduh oleh siapa saja. (https://www.kaggle.com/code/smlopezza/elliptic-data-set-eda-graphs-random-forest).

Deskripsi

Dataset adalah anonymized data transaksi dari Bitcoin blockchain. Transaksi yang diketahui licit atau bukan fraud adalah transaksi yang melibatkan entitas yang sudah diketahui bukan fraud (crypto exchange, wallet provider, miner, dll.). Sementara transaksi yang dilabeli illicit atau fraud adalah transaksi yang melibatkan entitas yang melakukan fraud (scam, malware, organisasi teroris, ransomware, dll.). Dataset telah

Nodes dan Edges

Node pada graph merepresentasikan sebuah transaksi bitcoin(bukan alamat bitcoin). Edge hanya menunjukkan bahwa ada aliran bitcoin antara 2 node yang terhubung. Graph terdiri dari 203.769 nodes dan 234.355 edges. 2% (4.545 nodes) dilabeli class1 (illicit atau fraud). 21% (42.019 nodes) dilabeli class2 (licit atau nonfraud). Sisanya tidak dilabeli alias unknown.

Features

Terdapat 166 features pada setiap node. Informasi asli features dirahasiakan. Dataset hanya memberi informasi bahwa 94 features di awal berasal dari transaksi itu sendiri (time step atau time period, transaction fee, dll). 72 features berikutnya adalah feature-feature untuk agregasi node dengan node sekitarnya.

Tools dan teknologi yang digunakan

Pada implementasi proyek ini, tools yang diperkirakan akan digunakan adalah sebagai berikut:
Hardware:
- Server untuk menyimpan graph data dan model.
- Device dengan GPU yang mendukung untuk running model.

Software:
- Jupyter Notebook
- Python
- Pytorch dan Pytorch Geometric

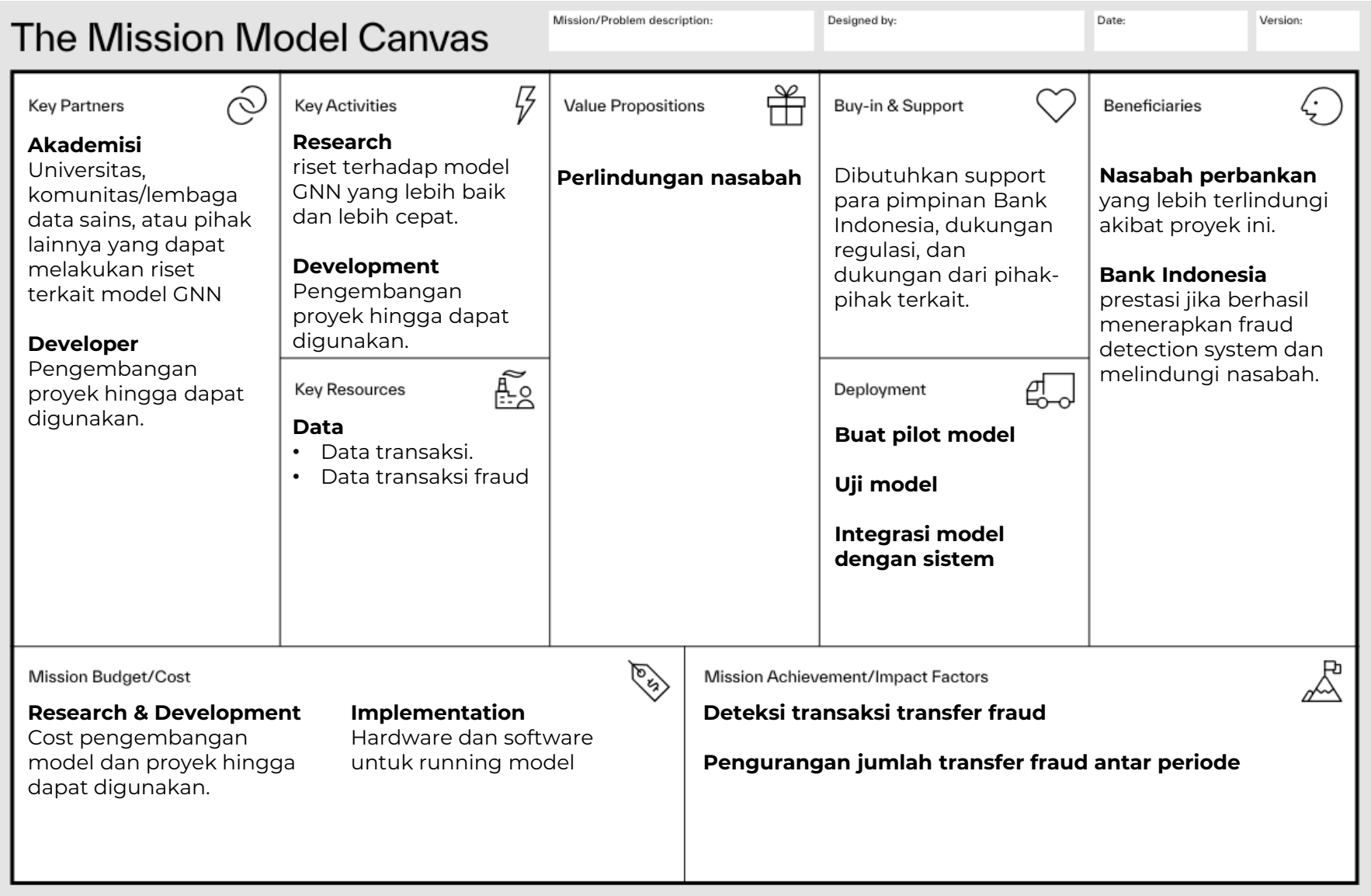
Pada pilot analysis, tools yang digunakan disesuaikan dengan kondisi, dijelaskan lebih lanjut pada bagian rancangan pilot analysis.

Bisnis model dan keberlanjutan

Mission Model Canvas
Alexander Osterwalder, designer template Business Model Canvas (BMC), pada tahun 2016 meluncurkan Mission Model Canvas (MMC). Tujuan MMC adalah mengakomodasi kebutuhan BMC bagi organisasi yang tujuannya bukan untuk mendapatkan uang, namun untuk memenuhi misi tertentu.

Perbedaan BMC dan MMC
Ada 5 perubahan yang dilakukan dari BMC ke MMC, yaitu:
- Revenue Streams diubah menjadi Mission Achievement.
- Customer Segments diubah menjadi Beneficiaries.
- Cost Structure diubah menjadi Mission Cost/Budget.
- Channel diubah menjadi Deployment.
- Customer Relationship diubah menjadi Buy-in/Support.

Bisnis model dan keberlanjutan



The Mission Model Canvas

Mission/Problem description:	Designed by:	Date:	Version:

Key Partners

Akademisi
Universitas, komunitas/lembaga data sains, atau pihak lainnya yang dapat melakukan riset terkait model GNN

Developer
Pengembangan proyek hingga dapat digunakan.

Key Activities

Research
riset terhadap model GNN yang lebih baik dan lebih cepat.

Development
Pengembangan proyek hingga dapat digunakan.

Key Resources

Data
- Data transaksi.
- Data transaksi fraud

Value Propositions

Perlindungan nasabah

Buy-in & Support

Dibutuhkan support para pimpinan Bank Indonesia, dukungan regulasi, dan dukungan dari pihak-pihak terkait.

Deployment

Buat pilot model

Uji model

Integrasi model dengan sistem

Beneficiaries

Nasabah perbankan
yang lebih terlindungi akibat proyek ini.

Bank Indonesia
prestasi jika berhasil menerapkan fraud detection system dan melindungi nasabah.

Mission Budget/Cost

Research & Development
Cost pengembangan model dan proyek hingga dapat digunakan.

Implementation
Hardware dan software untuk running model

Mission Achievement/Impact Factors

Deteksi transaksi transfer fraud

Pengurangan jumlah transfer fraud antar periode

Rancangan pilot analysis

Pilot analysis

Pilot analysis dilakukan dengan menerapkan model pada dataset awal, untuk menguji apakah model dapat diaplikasikan pada dataset yang sesungguhnya. Analisis telah selesai dilakukan dan disertakan sebagai Lampiran pada proposal ini. Ada beberapa perbedaan dari pilot analysis dengan rencana penerapannya pada proyek, selengkapnya dijelaskan pada tabel di bawah ini:

Nomor	Aspek	Pilot Analysis	Implementasi Proyek
1	Dataset	Bitcoin Elliptic	Data transfer bank
2	Dataset size	203rb nodes & 234.355 edges	Jumlah nodes dan edges transaksi perbankan diperkirakan sangat besar
3	Model	GNN model GAT, model melihat graph secara keseluruhan, tidak cocok untuk data skala besar.	GNN model GraphSAGE, model ini dapat running dengan sampling Sebagian graph saja, sehingga cocok untuk data skala besar.
4	Device	Device pribadi	Machine sesuai standar industri

Rancangan pilot analysis

Hasil pilot analysis

Performance metrics dari model GAT dan GATv2 pada dataset menunjukkan hasil sebagai berikut:

Nomor	Metric	GAT	GATv2
1	f1micro	0.9782	0.9761
2	accuracy	0.9782	0.9761
3	f1macro	0.9326	0.9276
4	auc-roc	0.9788	0.9812
5	recall	0.8458	0.8583
6	precision	0.9111	0.8788

Penutup

Implementasi proyek ini pada Sistem Pembayaran Bank Indonesia diharapkan dapat menjadi sebuah early warning system, yang melindungi nasabah dari tindakan transfer fraud jenis apapun.

Model ini juga dapat diimplementasikan untuk use case lain, misalnya identifikasi circle atau pihak-pihak yang terlibat dalam sebuah aktivitas pencucian uang.

Referensi

- Elliptic website. www.elliptic.co.
- Kementerian Komunikasi dan Informatika. CekRekening.id. https://cekrekening.id/

- Alex Osterwalder. (2016). The Mission Model Canvas: an adapted The Business Model Canvas for mission driver organizations. https://www.strategyzer.com/library/the-mission-model-canvas-an-adapted-business-model-canvas-for-mission-driven-organizations.
- Anthony Taing. (2022). Fraud detection with Graph Attention Networks. https://medium.com/stanford-cs224w/fraud-detection-with-gat-edac49bda1a0.
- Brody, S., Alon, U., & Yahav, E. (2021). How attentive are graph attention networks?. arXiv preprint arXiv:2105.14491.
- Hamilton, W., Ying, Z., & Leskovec, J. (2017). Inductive representation learning on large graphs. Advances in neural information processing systems, 30.
- Weber, M., Domeniconi, G., Chen, J., Weidele, D. K. I., Bellei, C., Robinson, T., & Leiserson, C. E. (2019). Anti-money laundering in bitcoin: Experimenting with graph convolutional networks for financial forensics. arXiv preprint arXiv:1908.02591.
- Veličković, P., Cucurull, G., Casanova, A., Romero, A., Lio, P., & Bengio, Y. (2017). Graph attention networks. arXiv preprint arXiv:1710.10903.

- Pytorch documentation. https://pytorch.org/docs/stable/index.html
- Pytorch Geometric documentation. https://pytorch-geometric.readthedocs.io/en/latest/

Lampiran

Notebook code pilot analysis dan hasilnya dapat dibaca mulai halaman selanjutnya.

Deteksi Transfer Fraud pada Sistem Pembayaran dengan Graph Neural Network (GNN)

Pilot Analysis dalam rangka Hackathon Bank Indonesia 2024

Oleh : Tim JN and GNN - Jens Naki

1. Dengan GNN, diharapkan Bank Indonesia dapat mendeteksi aktivitas transfer fraud antar rekening dalam jaringan.
2. Pilot analysis dilakukan untuk menguji model sebelum diimplementasikan pada dataset yang sebenarnya.
3. Anonymized dataset yang digunakan adalah Elliptic Bitcoin Dataset (https://www.kaggle.com/datasets/ellipticco/elliptic-data-set). Dataset ini berisi informasi transfer Bitcoin antar alamat pada periode waktu tertentu. Sebagian transfer telah teridentifikasi sebagai fraud / illicit entities (penipuan, malware, organisasi teroris, ransomware, skema Ponzi, dll.). Sebagian transfer telah teridentifikasi sebagai non fraud / licit entities (Bitcoin exchange, wallet provider, miner, dll).
4. Model GNN yang digunakan adalah GAT dan GATv2 prebuilt dari Pytorch Geometric.
5. Code pada notebook ini dimodifikasi dari code Anthony Taing, Stanford CS224W GraphML Tutorials (https://medium.com/stanford-cs224w/fraud-detection-with-gat-edac49bda1a0).

Referensi:

1. Elliptic website, www.elliptic.co.
2. Anti-Money Laundering in Bitcoin: Experimenting with Graph Convolutional Networks for Financial Forensics, arXiv:1908.02591, 2019.
3. M. Weber G. Domeniconi J. Chen D. K. I. Weidele C. Bellei, T. Robinson, C. E. Leiserson, https://www.kaggle.com/ellipticco/elliptic-data-set, 2019.
4. Graph Attention Networks, Petar Veličković and Guillem Cucurull and Arantxa Casanova and Adriana Romero and Pietro Liò and Yoshua Bengio, arXiv:1710.10903, 2018.
5. PyG documentation: pytorch-geometric.readthedocs.io/en/latest/
6. https://medium.com/stanford-cs224w/fraud-detection-with-gat-edac49bda1a0

Instalasi package yang dibutuhkan:

1. Pytorch : https://pytorch.org/get-started/locally/
2. Pytorch Geometric: https://pytorch-geometric.readthedocs.io/en/latest/install/installation.html

In [20]:
```
import torch
```

In [21]:
```
import torch_geometric
```

In [22]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

from torch.nn import Linear, LayerNorm, ReLU, Dropout
```

```
import torch.nn.functional as F
from torch_geometric.data import Data, DataLoader
from sklearn.metrics import accuracy_score,f1_score,roc_auc_score, precision_score, recall_score, confusion_matrix

import scipy.sparse as sp

import warnings
warnings.filterwarnings("ignore")
import pandas as pd
from sklearn.model_selection import train_test_split

import torch.nn.functional as F
from sklearn.metrics import roc_auc_score
from torch.nn import Linear
from torch_geometric.nn import GATConv,GATv2Conv
```

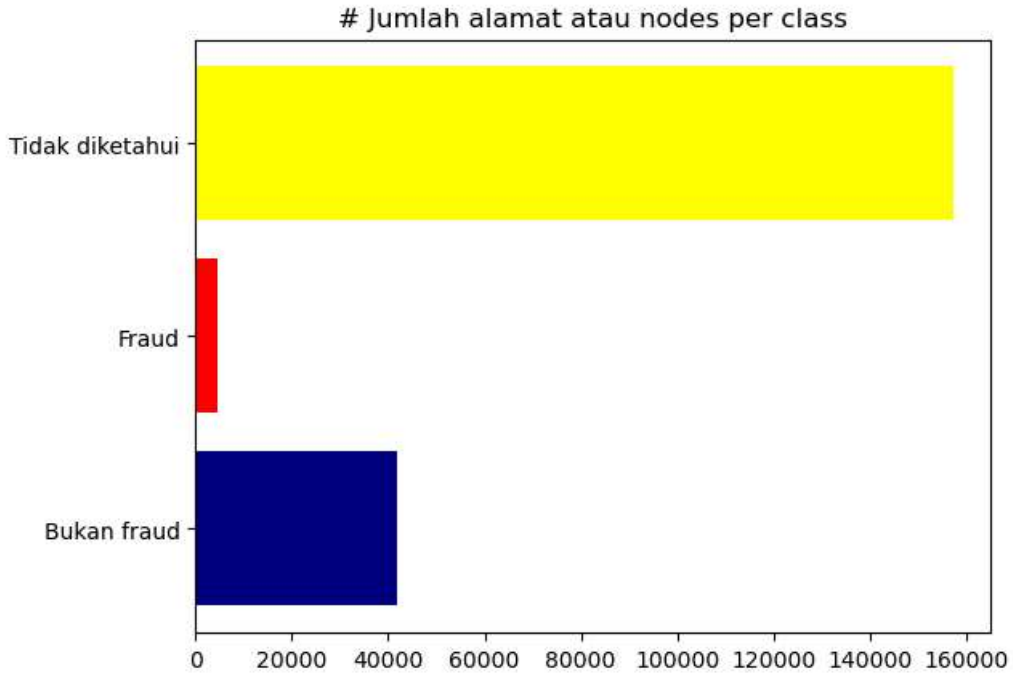
In [23]:
```
#Download data ke folder kita, menggunakan datasets dari Pytorch Geometric
#bisa juga didownload manual dari https://www.kaggle.com/datasets/ellipticco/elliptic-data-set

from torch_geometric.datasets import EllipticBitcoinDataset
dataset = EllipticBitcoinDataset(root="")
```

In [24]:
```
df_feature = pd.read_csv("./raw/elliptic_txs_features.csv",header=None)
df_edges = pd.read_csv("./raw/elliptic_txs_edgelist.csv")
df_classes =  pd.read_csv("./raw/elliptic_txs_classes.csv")
```

In [25]:
```
#Ubah format string jadi angka 0:Bukan fraud, 1:Fraud, 2:Tidak diketahui
df_classes["class"] = df_classes["class"].map({"unknown":2, "1":1, "2":0})
```

In [27]:
```
#Visualisasi proporsi transaksi NonFraud
group_class = df_classes.groupby("class").count()
plt.title ("# Jumlah alamat atau nodes per class")
plt.barh(["Bukan fraud","Fraud","Tidak diketahui"], group_class["txId"].values, color=["navy","red", "yellow"])
```

Out[27]:
```
<BarContainer object of 3 artists>
```



In [28]:
```
df_feature.head()
```

Out[28]:

	0	1	2	3	4	5	6	7	8	9	...	157	158	159	160	161	162	
0	230425980	1	-0.171469	-0.184668	-1.201369	-0.121970	-0.043875	-0.113002	-0.061584	-0.162097	...	-0.562153	-0.600999	1.461330	1.461369	0.018279	-0.087490	-0.13
1	5530458	1	-0.171484	-0.184668	-1.201369	-0.121970	-0.043875	-0.113002	-0.061584	-0.162112	...	0.947382	0.673103	-0.979074	-0.978556	0.018279	-0.087490	-0.13
2	232022460	1	-0.172107	-0.184668	-1.201369	-0.121970	-0.043875	-0.113002	-0.061584	-0.162749	...	0.670883	0.439728	-0.979074	-0.978556	-0.098889	-0.106715	-0.13
3	232438397	1	0.163054	1.963790	-0.646376	12.409294	-0.063725	9.782742	12.414558	-0.163645	...	-0.577099	-0.613614	0.241128	0.241406	1.072793	0.085530	-0.13
4	230460314	1	1.011523	-0.081127	-1.201369	1.153668	0.333276	1.312656	-0.061584	-0.163523	...	-0.511871	-0.400422	0.517257	0.579382	0.018279	0.277775	0.32

5 rows × 167 columns

In [29]:
```
df_edges.head()
```

Out[29]:

	txId1	txId2
0	230425980	5530458
1	232022460	232438397
2	230460314	230459870
3	230333930	230595899
4	232013274	232029206

In [30]:
```
df_classes.head()
```

Out[30]:

	txId	class
0	230425980	2
1	5530458	2
2	232022460	2
3	232438397	0
4	230460314	2

In [31]:
```
# Penggabungan features dengan classes
df_merge = df_feature.merge(df_classes, how="left", right_on="txId", left_on=0)
df_merge = df_merge.sort_values(0).reset_index(drop=True)
df_merge.head()
```

Out[31]:

	0	1	2	3	4	5	6	7	8	9	...	159	160	161	162	163	164	165
0	1076	48	-0.168500	0.270909	-0.091383	-0.046932	-0.043875	-0.029140	-0.061584	-0.163591	...	1.461330	1.461369	0.018279	0.470019	1.216796	1.151607	1.519700
1	2534	6	-0.170834	-0.131425	1.018602	0.028105	0.055376	0.054722	-0.061584	-0.163572	...	0.955101	0.459257	-0.098889	-0.087490	-0.099080	-0.122137	-0.379970
2	3181	34	1.305212	-0.210553	-1.756361	-0.121970	97.300650	-0.113002	-0.061584	1.348765	...	0.059948	0.113967	-0.098889	1.969527	0.037532	-0.131010	0.006994
3	3321	1	-0.169615	-0.184668	-1.201369	-0.121970	-0.043875	-0.113002	-0.061584	-0.160199	...	0.241128	0.241406	-0.098889	-0.087490	-0.084674	-0.140597	1.519700
4	3889	48	-0.086232	-0.101835	-0.646376	-0.121970	17.046997	-0.113002	-0.061584	-0.074885	...	0.082065	0.114773	-0.098889	8.948005	1.024948	-0.009570	-0.080708

5 rows × 169 columns

In [32]:
```
#setup mapping trans ID ke node ID
nodes = df_merge[0].values

map_id = {j:i for i,j in enumerate(nodes)} #mapping nodes ke index
```

```
#Membuat edge dataframe yang trans ID nya telah dimap ke nodeID

edges = df_edges.copy()
edges.txId1 = edges.txId1.map(map_id) #get nodes idx1 from edges list and filtered data
edges.txId2 = edges.txId2.map(map_id)

edges = edges.astype(int)

edge_index = np.array(edges.values).T #convert into an array
edge_index = torch.tensor(edge_index, dtype=torch.long).contiguous() #create tensor

print(f"shape of edge index is {edge_index.shape}")
edge_index
```

```
shape of edge index is torch.Size([2, 234355])
```

Out[32]:
```
tensor([[138670, 141325, 139232,  ..., 100420,  54833, 101159],
        [  4142, 142201, 139223,  ..., 100419,  81951, 101163]])
```

In [33]:
```
#Membuat weights tensor dengan bentuk yang sama dengan edge_index
weights = torch.tensor([1] * edge_index.shape[1], dtype=torch.double)
```

In [34]:
```
#Define labels
labels = df_merge["class"].values
print("labels", np.unique(labels))
labels
```

```
labels [0 1 2]
```

Out[34]:
```
array([2, 0, 0, ..., 2, 2, 2], dtype=int64)
```

In [35]:
```
#Passing node features ke model

node_features = df_merge.drop(["txId"], axis=1).copy()
print("unique=",node_features["class"].unique())

#mempertahankan IDs yang sudah diketahui dan tidak
classified_idx = node_features["class"].loc[node_features["class"]!=2].index
unclassified_idx = node_features["class"].loc[node_features["class"]==2].index

#filter label fraud dan nonfraud
classified_fraud_idx = node_features["class"].loc[node_features["class"]==1].index
classified_nonfraud_idx = node_features["class"].loc[node_features["class"]==0].index

#Drop kolom yang tidak dibutuhkan, 0 = transID, 1 = time period, class = labels
node_features = node_features.drop(columns = [0,1,"class"])

#Konvert tensor
node_features_t = torch.tensor(np.array(node_features.values, dtype=np.double), dtype=torch.double)
node_features_t
```

```
unique= [2 0 1]
```

Out[35]:
```
tensor([[-0.1685,  0.2709, -0.0914,  ...,  1.1516,  1.5197,  1.5214],
        [-0.1708, -0.1314,  1.0186,  ..., -0.1221, -0.3800, -0.3793],
        [ 1.3052, -0.2106, -1.7564,  ..., -0.1310,  0.0070,  0.0178],
        ...,
        [-0.1727, -0.1588, -1.2014,  ..., -0.2698, -0.1206, -0.1198],
        [-0.1727, -0.1588, -1.2014,  ..., -0.2698, -0.1206, -0.1198],
        [-0.1433, -0.1588, -1.2014,  ..., -0.0975, -0.1206, -0.1198]],
       dtype=torch.float64)
```

In [36]:
```
# Melihat hasil node_features
node_features
```

Out[36]:

	2	3	4	5	6	7	8	9	10	11	...	157	158	159	160	161	
0	-0.168500	0.270909	-0.091383	-0.046932	-0.043875	-0.029140	-0.061584	-0.163591	-0.164980	-0.009283	...	0.073047	-0.039637	1.461330	1.461369	0.018279	0.47(
1	-0.170834	-0.131425	1.018602	0.028105	0.055376	0.054722	-0.061584	-0.163572	-0.167757	-0.038545	...	1.228858	0.379357	0.955101	0.459257	-0.098889	-0.08
2	1.305212	-0.210553	-1.756361	-0.121970	97.300650	-0.113002	-0.061584	1.348765	1.321754	-0.049707	...	1.348450	1.590664	0.059948	0.113967	-0.098889	1.96
3	-0.169615	-0.184668	-1.201369	-0.121970	-0.043875	-0.113002	-0.061584	-0.160199	-0.166062	-0.049707	...	-0.577099	-0.500080	0.241128	0.241406	-0.098889	-0.08
4	-0.086232	-0.101835	-0.646376	-0.121970	17.046997	-0.113002	-0.061584	-0.074885	-0.081943	-0.049707	...	0.501062	0.362510	0.082065	0.114773	-0.098889	8.94
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
203764	-0.172978	-0.172527	0.463609	-0.121970	-0.043875	-0.113002	-0.061584	-0.163640	-0.169455	-0.049707	...	-0.577099	-0.600999	0.241128	0.241406	0.018279	-0.08
203765	-0.172669	-0.158783	-1.201369	-0.121970	-0.063725	-0.113002	-0.061584	-0.163323	-0.169142	-0.049707	...	-0.577099	-0.626229	0.241128	0.241406	-0.216057	-0.12
203766	-0.172669	-0.158783	-1.201369	-0.121970	-0.063725	-0.113002	-0.061584	-0.163323	-0.169142	-0.049707	...	-0.577099	-0.626229	0.241128	0.241406	-0.216057	-0.12
203767	-0.172669	-0.158783	-1.201369	-0.121970	-0.063725	-0.113002	-0.061584	-0.163323	-0.169142	-0.049707	...	-0.577099	-0.626229	0.241128	0.241406	-0.216057	-0.12
203768	-0.143292	-0.158783	-1.201369	-0.121970	-0.043875	-0.113002	-0.061584	-0.133266	-0.139507	-0.049707	...	-0.577099	-0.613614	0.241128	0.241406	0.018279	-0.08

203769 rows × 165 columns

In [37]:
```
#membuat data training dengan test size = 15%
train_idx, valid_idx = train_test_split(classified_idx.values, test_size=0.15)
lentrain = len(train_idx)
lenvalid = len(valid_idx)
print(f"train_idx size {lentrain}")
print(f"test_idx size {lenvalid}")
```

```
train_idx size 39579
test_idx size 6985
```

In [38]:
```
#membuat Pytorch Geometric dataset
data_train = Data(x=node_features_t, edge_index=edge_index, edge_attr=weights,
                  y=torch.tensor(labels, dtype=torch.double))
```

```
#masukan train dan valid idx
data_train.train_idx = train_idx
data_train.valid_idx = valid_idx
data_train.test_idx = unclassified_idx
```

In [39]:
```
#import package yang dibutuhkan
import torch
import torch.nn as nn
import torch.nn.functional as F

import torch_geometric.nn as pyg_nn
import torch_geometric.utils as pyg_utils

from torch import Tensor
from typing import Union, Tuple, Optional
from torch_geometric.typing import (OptPairTensor, Adj, Size, NoneType, OptTensor)

from torch.nn import Parameter, Linear
from torch_geometric.nn.conv import MessagePassing
from torch_geometric.utils import remove_self_loops, add_self_loops, softmax, degree

from torch_geometric.nn import GATConv, GATv2Conv
import pickle
```

In [41]:
```
#Model GAT Prebuilt dari Pytorch Geometric

class GAT(torch.nn.Module):
    def __init__(self,input_dim, hidden_dim, output_dim,args):
        super(GAT, self).__init__()
        #use our gat message passing
        self.conv1 = GATConv(input_dim, hidden_dim, heads=args['heads'])
        self.conv2 = GATConv(args['heads'] * hidden_dim, hidden_dim, heads=args['heads'])

        self.post_mp = nn.Sequential(
            nn.Linear(args['heads'] * hidden_dim, hidden_dim), nn.Dropout(args['dropout'] ),
            nn.Linear(hidden_dim, output_dim))

    def forward(self, data, adj=None):
        x, edge_index = data.x, data.edge_index
        # Layer 1
        x = self.conv1(x, edge_index)
        x = F.dropout(F.relu(x), p=args['dropout'], training=self.training)
        # Layer 2
        x = self.conv2(x, edge_index)
        x = F.dropout(F.relu(x), p=args['dropout'], training=self.training)
        # MLP output
        x = self.post_mp(x)
        return F.sigmoid(x)
```

In [42]:
```
#Model GATv2 dari Pytorch Geometric
class GATv2(torch.nn.Module):
    def __init__(self,input_dim, hidden_dim, output_dim,args):
        super(GATv2, self).__init__()
        #use our gat message passing
        self.conv1 = GATv2Conv(input_dim, hidden_dim, heads=args['heads'])
        self.conv2 = GATv2Conv(args['heads'] * hidden_dim, hidden_dim, heads=args['heads'])

        self.post_mp = nn.Sequential(
            nn.Linear(args['heads'] * hidden_dim, hidden_dim), nn.Dropout(args['dropout'] ),
            nn.Linear(hidden_dim, output_dim))

    def forward(self, data, adj=None):
        x, edge_index = data.x, data.edge_index
        # Layer 1
        x = self.conv1(x, edge_index)
        x = F.dropout(F.relu(x), p=args['dropout'], training=self.training)
        # Layer 2
        x = self.conv2(x, edge_index)
        x = F.dropout(F.relu(x), p=args['dropout'], training=self.training)
        # MLP output
        x = self.post_mp(x)
        return F.sigmoid(x)
```

In [49]:
```
#Model Training
class GnnTrainer(object):

  def __init__(self, model):
    self.model = model
    self.metric_manager = MetricManager(modes=["train", "val"])

  def train(self, data_train, optimizer, criterion, scheduler, args):

    self.data_train = data_train
    for epoch in range(args['epochs']):
        self.model.train()
        optimizer.zero_grad()
        out = self.model(data_train)

        out = out.reshape((data_train.x.shape[0]))
        loss = criterion(out[data_train.train_idx], data_train.y[data_train.train_idx])
        ## Metric calculations
        # train data
        target_labels = data_train.y.detach().cpu().numpy()[data_train.train_idx]
        pred_scores = out.detach().cpu().numpy()[data_train.train_idx]
        train_acc, train_f1,train_f1macro, train_aucroc, train_recall, train_precision, train_cm = self.metric_manager.store_metrics("train", pred_scores, target_


        ## Training Step
        loss.backward()
```

```
        optimizer.step()

        # validation data
        self.model.eval()
        target_labels = data_train.y.detach().cpu().numpy()[data_train.valid_idx]
        pred_scores = out.detach().cpu().numpy()[data_train.valid_idx]
        val_acc, val_f1,val_f1macro, val_aucroc, val_recall, val_precision, val_cm = self.metric_manager.store_metrics("val", pred_scores, target_labels)

        if epoch%5 == 0:
          print("epoch: {} - loss: {:.4f} - accuracy train: {:.4f} -accuracy valid: {:.4f}  - val roc: {:.4f}  - val f1micro: {:.4f}".format(epoch, loss.item(), t

  # To predict labels
  def predict(self, data=None, unclassified_only=True, threshold=0.5):
    # evaluate model:
    self.model.eval()
    if data is not None:
      self.data_train = data

    out = self.model(self.data_train)
    out = out.reshape((self.data_train.x.shape[0]))

    if unclassified_only:
      pred_scores = out.detach().cpu().numpy()[self.data_train.test_idx]
    else:
      pred_scores = out.detach().cpu().numpy()

    pred_labels = pred_scores > threshold

    return {"pred_scores":pred_scores, "pred_labels":pred_labels}

  # To save metrics
  def save_metrics(self, save_name, path="./save/"):
    file_to_store = open(path + save_name, "wb")
    pickle.dump(self.metric_manager, file_to_store)
    file_to_store.close()

  # To save model
  def save_model(self, save_name, path="./save/"):
    torch.save(self.model.state_dict(), path + save_name)
```

In [50]:

```
#Metric Manager
class MetricManager(object):
  def __init__(self, modes=["train", "val"]):

    self.output = {}

    for mode in modes:
      self.output[mode] = {}
      self.output[mode]["accuracy"] = []
      self.output[mode]["f1micro"] = []
      self.output[mode]["f1macro"] = []
```

```
      self.output[mode]["aucroc"] = []
      #new
      self.output[mode]["precision"] = []
      self.output[mode]["recall"] = []
      self.output[mode]["cm"] = []

  def store_metrics(self, mode, pred_scores, target_labels, threshold=0.5):

    # calculate metrics
    pred_labels = pred_scores > threshold
    accuracy = accuracy_score(target_labels, pred_labels)
    f1micro = f1_score(target_labels, pred_labels,average='micro')
    f1macro = f1_score(target_labels, pred_labels,average='macro')
    aucroc = roc_auc_score(target_labels, pred_scores)
    #new
    recall = recall_score(target_labels, pred_labels)
    precision = precision_score(target_labels, pred_labels)
    cm = confusion_matrix(target_labels, pred_labels)

    # Collect results
    self.output[mode]["accuracy"].append(accuracy)
    self.output[mode]["f1micro"].append(f1micro)
    self.output[mode]["f1macro"].append(f1macro)
    self.output[mode]["aucroc"].append(aucroc)
    #new
    self.output[mode]["recall"].append(recall)
    self.output[mode]["precision"].append(precision)
    self.output[mode]["cm"].append(cm)

    return accuracy, f1micro,f1macro, aucroc,recall,precision,cm

  # Get best results
  def get_best(self, metric, mode="val"):

    # Get best results index
    best_results = {}
    i = np.array(self.output[mode][metric]).argmax()

    # Output
    for m in self.output[mode].keys():
      best_results[m] = self.output[mode][m][i]

    return best_results
```

In [51]:

```
# Setting training argument
args={"epochs":100,
      'lr':0.01,
      'weight_decay':1e-5,
      'prebuild':True,
      'heads':2,
      'hidden_dim': 128,
```

```
      'dropout': 0.5
      }

device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
```

In [55]:
```
# Model selector GAT atau GATv2
net = "GAT"

if net == "GAT":
    if args['prebuild']==True:
      model = GAT(data_train.num_node_features, args['hidden_dim'], 1, args)
      print("Prebuilt GAT from PyG ")
elif net == "GATv2":
    # args['heads'] = 1
    if args['prebuild']==True:
      model = GATv2(data_train.num_node_features, args['hidden_dim'], 1, args)
      print("Prebuilt GATv2 from PyG ")

model.double().to(device)
```

```
Prebuilt GAT from PyG
```

Out[55]:
```
GAT(
  (conv1): GATConv(165, 128, heads=2)
  (conv2): GATConv(256, 128, heads=2)
  (post_mp): Sequential(
    (0): Linear(in_features=256, out_features=128, bias=True)
    (1): Dropout(p=0.5, inplace=False)
    (2): Linear(in_features=128, out_features=1, bias=True)
  )
)
```

In [33]:
```
#Running Model GAT
data_train = data_train.to(device)

# Setup training settings
optimizer = torch.optim.Adam(model.parameters(), lr=args['lr'], weight_decay=args['weight_decay'])
scheduler = torch.optim.lr_scheduler.ReduceLROnPlateau(optimizer, 'min')
criterion = torch.nn.BCELoss()

# Train
gnn_trainer_gat = GnnTrainer(model)
gnn_trainer_gat.train(data_train, optimizer, criterion, scheduler, args)

gnn_trainer_gat.save_metrics("GATprebuilt.results", path="./")
gnn_trainer_gat.save_model("GATprebuilt.pth", path="./")
```

```
epoch: 0 - loss: 0.0409 - accuracy train: 0.9871 -accuracy valid: 0.9770  - val roc: 0.9810  - val f1micro: 0.9770
epoch: 5 - loss: 0.0853 - accuracy train: 0.9721 -accuracy valid: 0.9721  - val roc: 0.9740  - val f1micro: 0.9721
epoch: 10 - loss: 0.0694 - accuracy train: 0.9750 -accuracy valid: 0.9741  - val roc: 0.9767  - val f1micro: 0.9741
epoch: 15 - loss: 0.0697 - accuracy train: 0.9801 -accuracy valid: 0.9761  - val roc: 0.9792  - val f1micro: 0.9761
epoch: 20 - loss: 0.0572 - accuracy train: 0.9829 -accuracy valid: 0.9765  - val roc: 0.9816  - val f1micro: 0.9765
epoch: 25 - loss: 0.0520 - accuracy train: 0.9842 -accuracy valid: 0.9768  - val roc: 0.9790  - val f1micro: 0.9768
epoch: 30 - loss: 0.0466 - accuracy train: 0.9864 -accuracy valid: 0.9791  - val roc: 0.9806  - val f1micro: 0.9791
epoch: 35 - loss: 0.0438 - accuracy train: 0.9867 -accuracy valid: 0.9780  - val roc: 0.9799  - val f1micro: 0.9780
epoch: 40 - loss: 0.0406 - accuracy train: 0.9877 -accuracy valid: 0.9791  - val roc: 0.9799  - val f1micro: 0.9791
epoch: 45 - loss: 0.0391 - accuracy train: 0.9882 -accuracy valid: 0.9778  - val roc: 0.9792  - val f1micro: 0.9778
epoch: 50 - loss: 0.0362 - accuracy train: 0.9884 -accuracy valid: 0.9784  - val roc: 0.9784  - val f1micro: 0.9784
epoch: 55 - loss: 0.0317 - accuracy train: 0.9897 -accuracy valid: 0.9778  - val roc: 0.9781  - val f1micro: 0.9778
epoch: 60 - loss: 0.0358 - accuracy train: 0.9892 -accuracy valid: 0.9791  - val roc: 0.9807  - val f1micro: 0.9791
epoch: 65 - loss: 0.0350 - accuracy train: 0.9897 -accuracy valid: 0.9781  - val roc: 0.9806  - val f1micro: 0.9781
epoch: 70 - loss: 0.0349 - accuracy train: 0.9893 -accuracy valid: 0.9782  - val roc: 0.9782  - val f1micro: 0.9782
epoch: 75 - loss: 0.0334 - accuracy train: 0.9900 -accuracy valid: 0.9787  - val roc: 0.9769  - val f1micro: 0.9787
epoch: 80 - loss: 0.0310 - accuracy train: 0.9909 -accuracy valid: 0.9778  - val roc: 0.9802  - val f1micro: 0.9778
epoch: 85 - loss: 0.0303 - accuracy train: 0.9902 -accuracy valid: 0.9784  - val roc: 0.9797  - val f1micro: 0.9784
epoch: 90 - loss: 0.0319 - accuracy train: 0.9897 -accuracy valid: 0.9791  - val roc: 0.9784  - val f1micro: 0.9791
epoch: 95 - loss: 0.0298 - accuracy train: 0.9904 -accuracy valid: 0.9787  - val roc: 0.9779  - val f1micro: 0.9787
```

In [34]:

```python
#Running model GATv2

model = GATv2(data_train.num_node_features, args['hidden_dim'], 1, args)
model.double().to(device)
# Push data to GPU
data_train = data_train.to(device)

# Setup training settings
optimizer = torch.optim.Adam(model.parameters(), lr=args['lr'], weight_decay=args['weight_decay'])
scheduler = torch.optim.lr_scheduler.ReduceLROnPlateau(optimizer, 'min')
criterion = torch.nn.BCELoss()
# Train
gnn_trainer_gatv2 = GnnTrainer(model)
gnn_trainer_gatv2.train(data_train, optimizer, criterion, scheduler, args)

gnn_trainer_gatv2.save_metrics("GATv2prebuilt.results", path="./")
gnn_trainer_gatv2.save_model("GATv2prebuilt.pth", path="./")
```

```
epoch: 0 - loss: 0.7775 - accuracy train: 0.5748 -accuracy valid: 0.5771  - val roc: 0.4718  - val f1micro: 0.5771
epoch: 5 - loss: 0.2524 - accuracy train: 0.9014 -accuracy valid: 0.9081  - val roc: 0.8897  - val f1micro: 0.9081
epoch: 10 - loss: 0.2180 - accuracy train: 0.9014 -accuracy valid: 0.9081  - val roc: 0.9210  - val f1micro: 0.9081
epoch: 15 - loss: 0.1767 - accuracy train: 0.9013 -accuracy valid: 0.9079  - val roc: 0.9472  - val f1micro: 0.9079
epoch: 20 - loss: 0.1605 - accuracy train: 0.9014 -accuracy valid: 0.9081  - val roc: 0.9600  - val f1micro: 0.9081
epoch: 25 - loss: 0.1460 - accuracy train: 0.9032 -accuracy valid: 0.9097  - val roc: 0.9682  - val f1micro: 0.9097
epoch: 30 - loss: 0.1335 - accuracy train: 0.9529 -accuracy valid: 0.9553  - val roc: 0.9704  - val f1micro: 0.9553
epoch: 35 - loss: 0.1236 - accuracy train: 0.9676 -accuracy valid: 0.9671  - val roc: 0.9740  - val f1micro: 0.9671
epoch: 40 - loss: 0.1159 - accuracy train: 0.9718 -accuracy valid: 0.9705  - val roc: 0.9754  - val f1micro: 0.9705
epoch: 45 - loss: 0.1034 - accuracy train: 0.9742 -accuracy valid: 0.9739  - val roc: 0.9783  - val f1micro: 0.9739
epoch: 50 - loss: 0.0975 - accuracy train: 0.9758 -accuracy valid: 0.9755  - val roc: 0.9763  - val f1micro: 0.9755
epoch: 55 - loss: 0.0875 - accuracy train: 0.9780 -accuracy valid: 0.9764  - val roc: 0.9774  - val f1micro: 0.9764
epoch: 60 - loss: 0.0787 - accuracy train: 0.9800 -accuracy valid: 0.9757  - val roc: 0.9807  - val f1micro: 0.9757
epoch: 65 - loss: 0.0709 - accuracy train: 0.9811 -accuracy valid: 0.9744  - val roc: 0.9797  - val f1micro: 0.9744
epoch: 70 - loss: 0.0643 - accuracy train: 0.9818 -accuracy valid: 0.9745  - val roc: 0.9796  - val f1micro: 0.9745
epoch: 75 - loss: 0.0587 - accuracy train: 0.9828 -accuracy valid: 0.9754  - val roc: 0.9790  - val f1micro: 0.9754
epoch: 80 - loss: 0.0531 - accuracy train: 0.9833 -accuracy valid: 0.9759  - val roc: 0.9791  - val f1micro: 0.9759
epoch: 85 - loss: 0.0488 - accuracy train: 0.9852 -accuracy valid: 0.9745  - val roc: 0.9771  - val f1micro: 0.9745
epoch: 90 - loss: 0.0481 - accuracy train: 0.9860 -accuracy valid: 0.9759  - val roc: 0.9807  - val f1micro: 0.9759
epoch: 95 - loss: 0.0431 - accuracy train: 0.9865 -accuracy valid: 0.9771  - val roc: 0.9806  - val f1micro: 0.9771
```

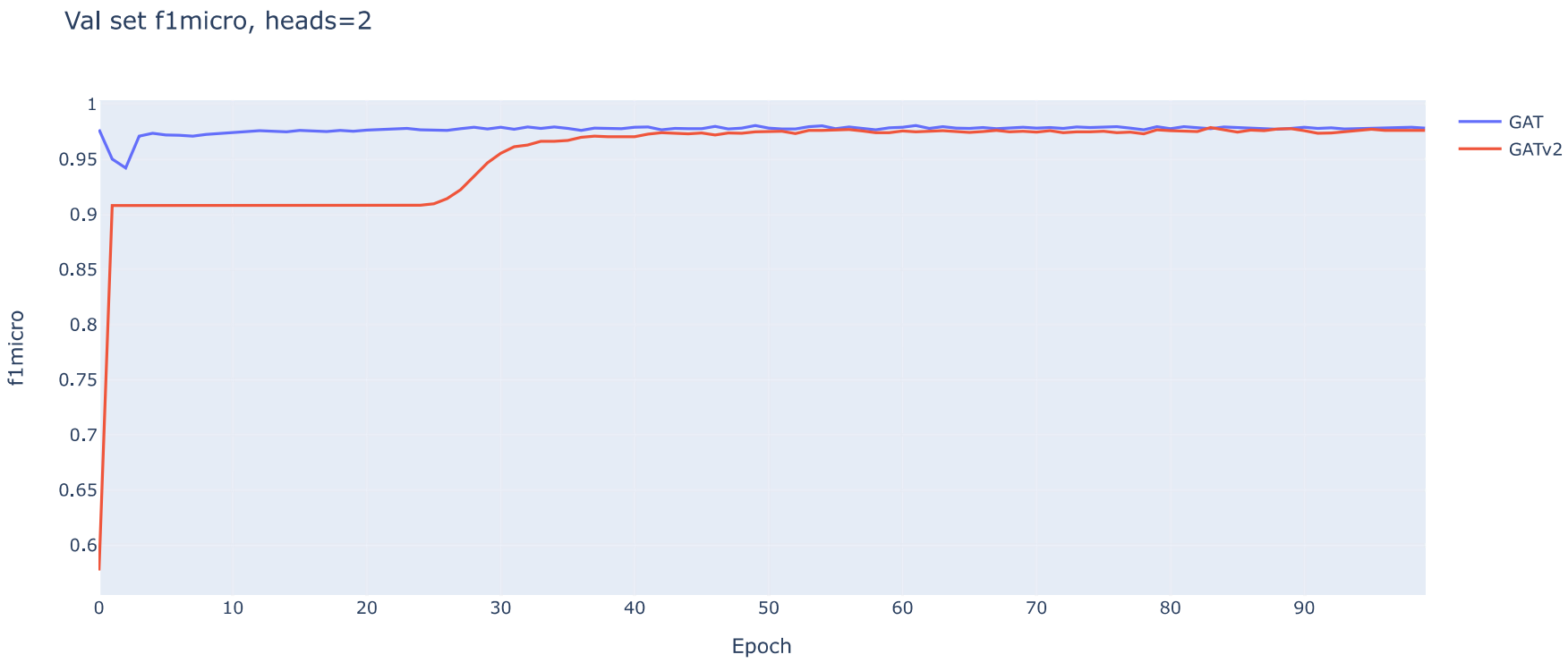
In [11]:
```
# Mengambil hasil running model yang sudah disimpan
fn="GATprebuilt.results"
mmGATprebuilt = pickle.load(open("./" + fn, "rb"))
mmGATprebuilt.get_best("aucroc")

fn="GATv2prebuilt.results"
mmGATv2prebuilt = pickle.load(open("./" + fn, "rb"))
mmGATv2prebuilt.get_best("aucroc")
```

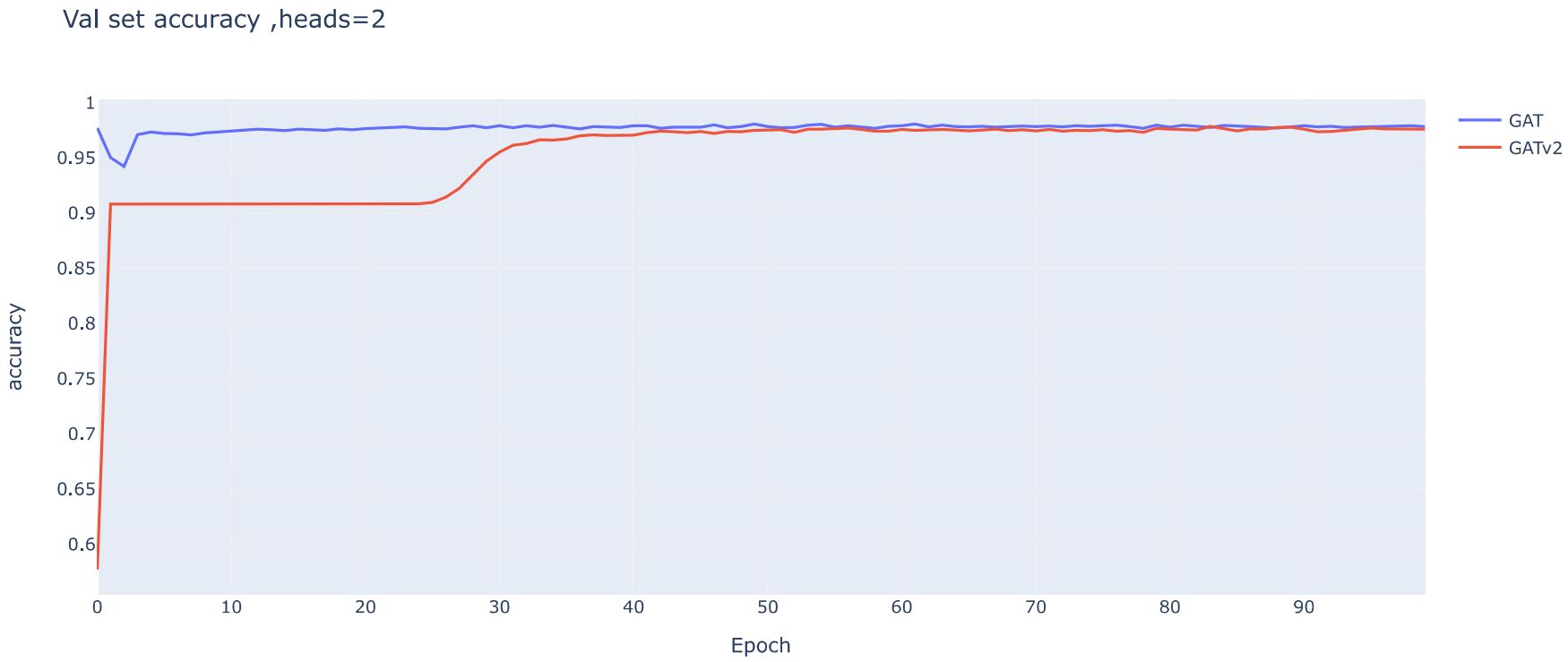
Out[11]:
```
{'accuracy': 0.9786685755189692,
 'f1micro': 0.9786685755189692,
 'f1macro': 0.9351505498088628,
 'aucroc': 0.9814292302501396,
 'precision': 0.8969404186795491,
 'recall': 0.867601246105919,
 'cm': array([[6279,   64],
        [  85,  557]], dtype=int64)}
```

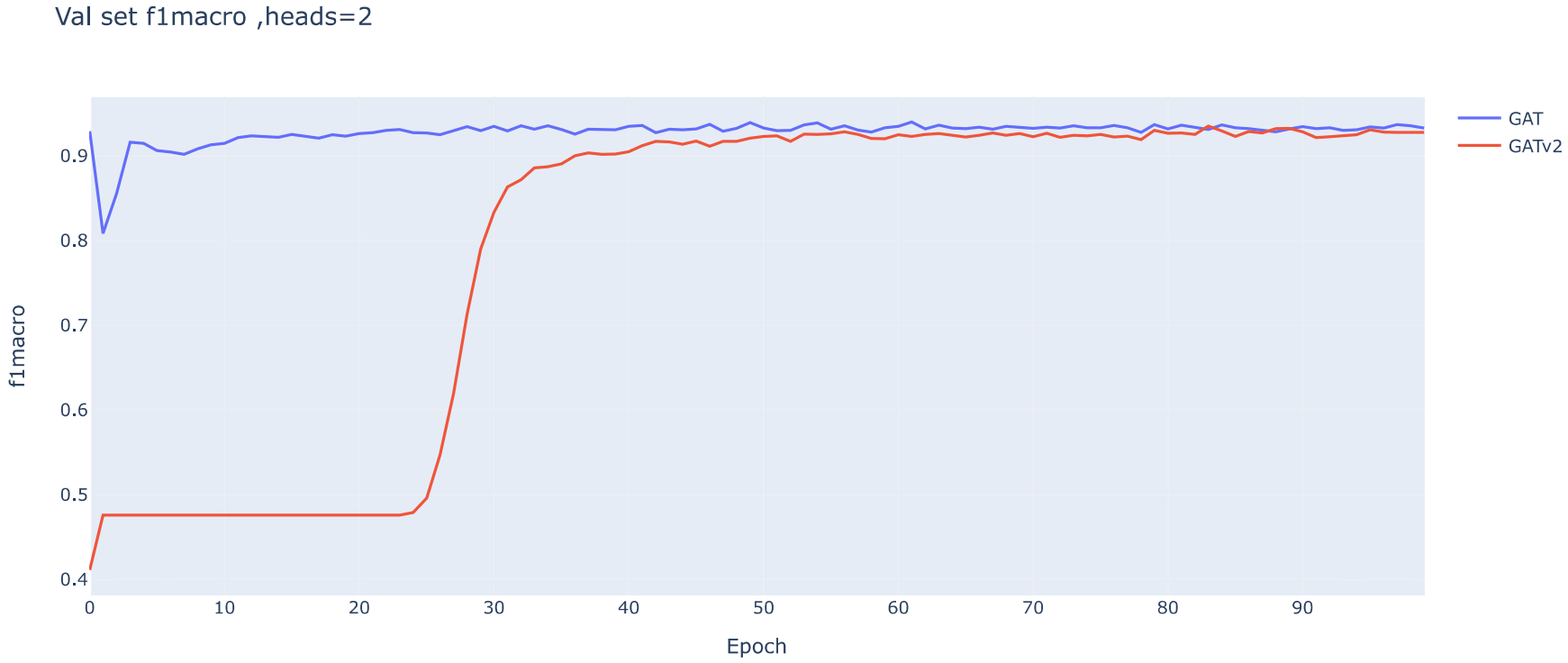
In [12]:
```
import plotly.express as px
import plotly.graph_objects as go

# Komparasi akurasi validasi
def plot_training_comp(metric_manager_list, names, metric="aucroc", version="val",title="Val set accuracy comparison"):

  fig = go.Figure()
  fig = fig.update_layout(title=title,
                          xaxis_title="Epoch",
                          yaxis_title=metric)

  for i, metric_manager in enumerate(metric_manager_list):
```

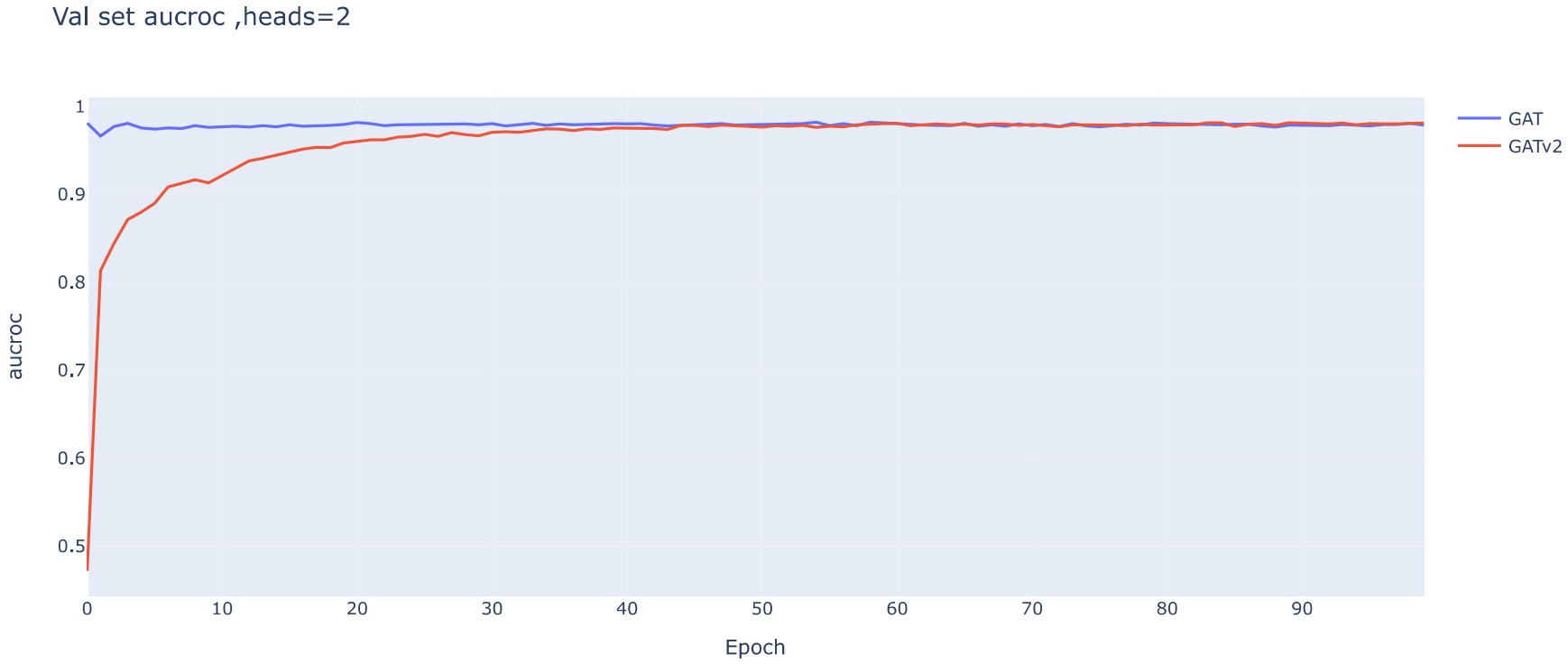
```
    epochs = np.arange(len(metric_manager.output[version][metric]))
    fig.add_trace(go.Scatter(x=epochs,
                             y=metric_manager.output[version][metric],
                             name=names[i]))
  fig.show()

# Load saved outputs
def load_results(fn):
  mm1 = pickle.load(open("./" + fn, "rb"))
  return mm1
```

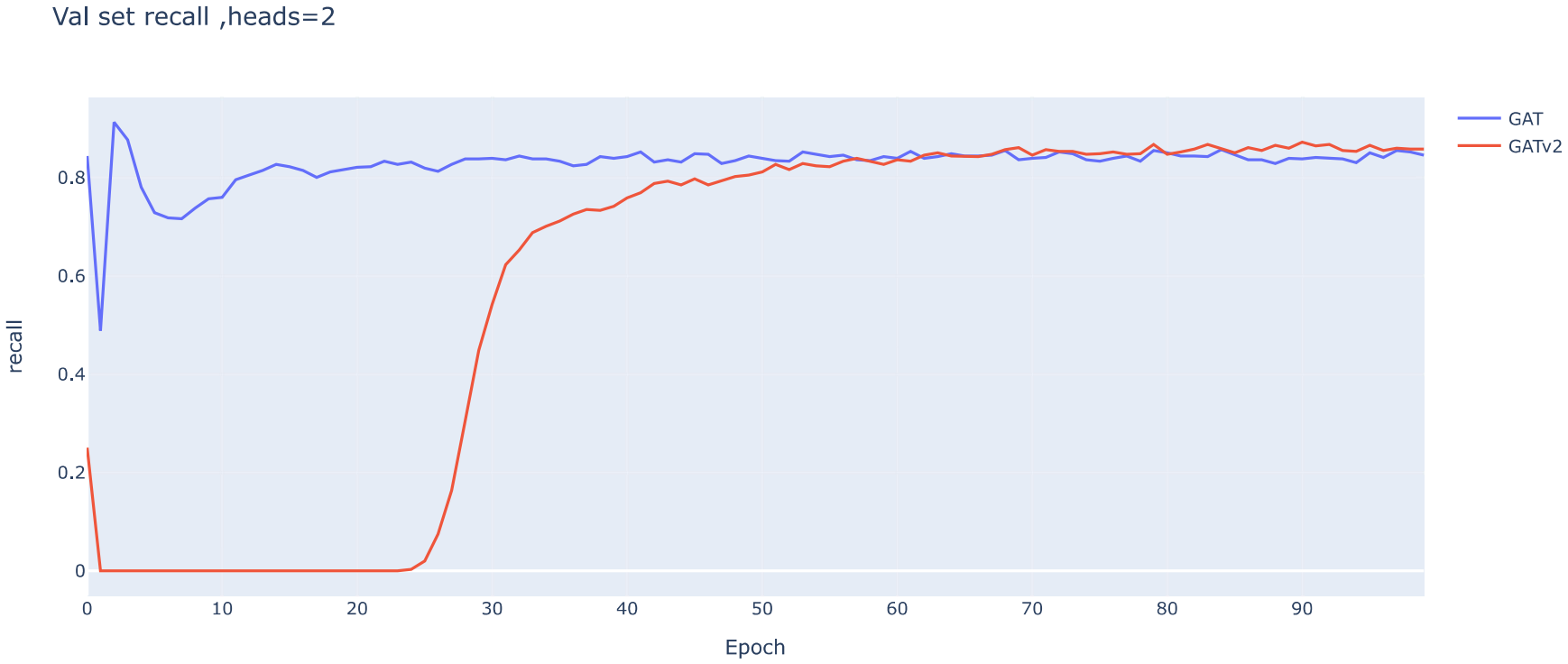
In [13]:
```
# Visualisasi komparasi hasil model GAT vs GATv2
plot_training_comp([mmGATprebuilt,mmGATv2prebuilt], ["GAT" ,"GATv2" ],"f1micro",title="Val set f1micro, heads=2")
plot_training_comp([mmGATprebuilt,mmGATv2prebuilt], ["GAT" ,"GATv2" ],"accuracy",title="Val set accuracy ,heads=2")
plot_training_comp([mmGATprebuilt,mmGATv2prebuilt], ["GAT" ,"GATv2" ],"f1macro",title="Val set f1macro ,heads=2")
plot_training_comp([mmGATprebuilt,mmGATv2prebuilt], ["GAT" ,"GATv2" ],"aucroc",title="Val set aucroc ,heads=2")
plot_training_comp([mmGATprebuilt,mmGATv2prebuilt], ["GAT" ,"GATv2" ],"recall",title="Val set recall ,heads=2")
plot_training_comp([mmGATprebuilt,mmGATv2prebuilt], ["GAT" ,"GATv2" ],"precision",title="Val set precision ,heads=2")
```

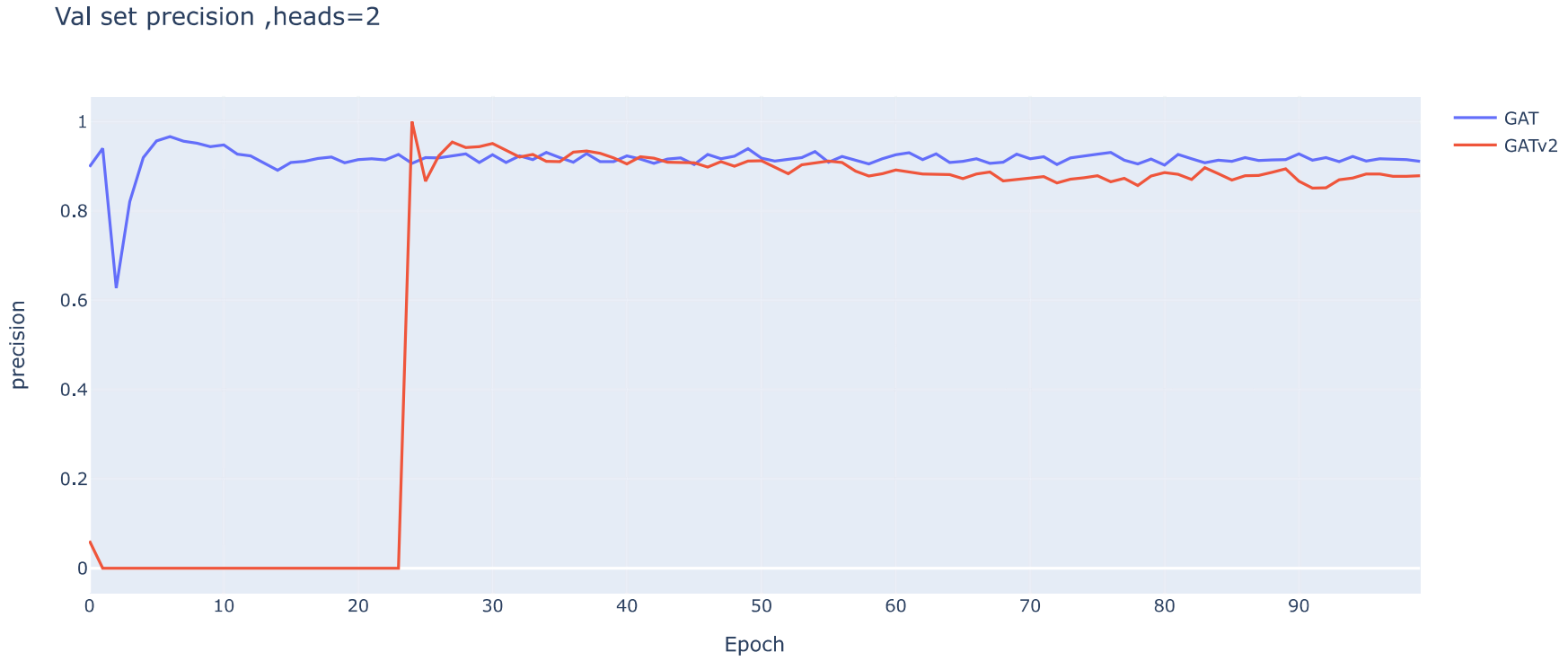



Val set accuracy ,heads=2
accuracy
Epoch
GAT
GATv2
1
0.95
0.9
0.85
0.8
0.75
0.7
0.65
0.6
0
10
20
30
40
50
60
70
80
90


Val set f1macro ,heads=2
f1macro
Epoch
GAT
GATv2
0.4
0.5
0.6
0.7
0.8
0.9
0
10
20
30
40
50
60
70
80
90


Val set aucroc ,heads=2
aucroc
Epoch
GAT
GATv2
1
0.9
0.8
0.7
0.6
0.5
0
10
20
30
40
50
60
70
80
90


Val set recall ,heads=2
recall
Epoch
GAT
GATv2
0
0.2
0.4
0.6
0.8
0
10
20
30
40
50
60
70
80
90

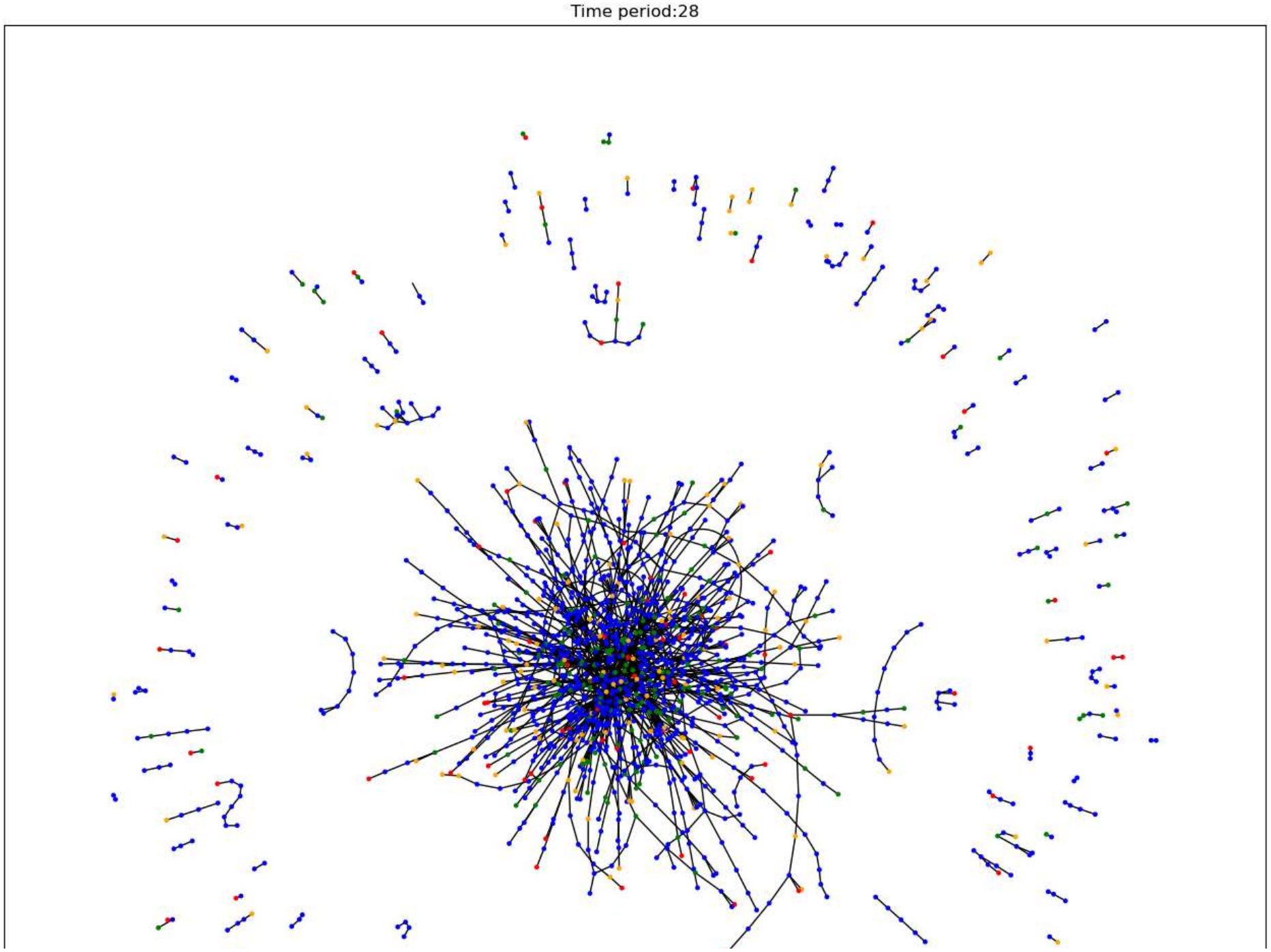


In [52]:
```
#Visualisasi Graph
import networkx as nx
import matplotlib.pyplot as plt

# Misalkan kita ambil model GATv2
m1 = GATv2(data_train.num_node_features, args['hidden_dim'], 1, args).to(device).double()
m1.load_state_dict(torch.load("./GATv2prebuilt.pth"))
gnn_t2 = GnnTrainer(m1)
output = gnn_t2.predict(data=data_train, unclassified_only=False)
output
```

Out[52]:
```
{'pred_scores': array([2.62891543e-03, 3.46962787e-07, 0.00000000e+00, ...,
        4.96969057e-64, 2.54770454e-02, 2.06414141e-05]),
 'pred_labels': array([False, False, False, ..., False, False, False])}
```

In [54]:
```
# Mengambil satu periode waktu
time_period = 28
sub_node_list = df_merge.index[df_merge.loc[:, 1] == time_period].tolist()
```

```
# Mengambil daftar edges untuk periode watu yang sudah dipilih
edge_tuples = []
for row in data_train.edge_index.view(-1, 2).numpy():
  if (row[0] in sub_node_list) | (row[1] in sub_node_list):
    edge_tuples.append(tuple(row))
len(edge_tuples)

# Mengambil hasil prediksi untuk periode waktu yang sudah dipilih
# Sudah teridentifikasi: merah = fraud, hijau = non fraud
# Hasil prediksi model: orange = diprediksi fraud, biru = diprediksi non fraud
node_color = []
for node_id in sub_node_list:
  if node_id in classified_fraud_idx: #
     label = "red" # fraud
  elif node_id in classified_nonfraud_idx:
     label = "green" # not fraud
  else:
    if output['pred_labels'][node_id]:
      label = "orange" # Predicted fraud
    else:
      label = "blue" # Not fraud predicted

  node_color.append(label)

# Membuat graph dengan networkX
G = nx.Graph()
G.add_edges_from(edge_tuples)

# Plot graph
plt.figure(3,figsize=(16,16))
plt.title("Time period:"+str(time_period))
nx.draw_networkx(G, nodelist=sub_node_list, node_color=node_color, node_size=6, with_labels=False)
```


Time period:28