HỌC VIỆN CÔNG NGHỆ BƯU CHÍNH VIỄN THÔNG

KHOA CÔNG NGHỆ THÔNG TIN 1

Introduction to Data Science

Final project: Lol Draft recommendation

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Hà Nội – 2025

I. Introduction about dataset

This dataset contains detailed match and player data from League of Legends, one of the most popular multiplayer online battle arena (MOBA) games in the world. It includes 148,000+ matches and contains 300,000+ summoner statistics, capturing a wide range of in-game statistics, such as champion selection, player performance metrics, match outcomes, and more.

The dataset is structured to support a variety of analyses, including:

- Predicting match outcomes based on team compositions and player stats
- Evaluating player performance and progression over time
- Exploring trends in champion popularity and win rates
- Building machine learning models for esports analytics

Data Schema and Dictionary

Data was collected many games from Riot Games API from Patch 25.19

The dataset consists of 7 csv files:

- **MatchStatsTbl** - Match Stats given a summonerID and MatchID.Contains K/D/A, Items, Runes,Ward Score, Summoner Spells, Baron Kills, Dragon Kills, Lane, DmgTaken/Dealt, Total Gold, cs, Mastery Points and Win/Loss
- **TeamMatchStatsTbl** - Containes Red/Blue Champions,Red/Blue BaronKills,Blue/Red Turret Kills, Red/Blue Kills, RiftHearaldKills and Win/loss
- **MatchTbl**- Contains MatchID,Rank,Match Duration and MatchType.
- **RankTbl** - Contains RankID and RankName
- **ChampionTbl**- Contains ChampionID and ChampionName
- **ItemTbl** - Contains ItemID and ItemName
- **SummonerTbl** - Contains SummonerID and SummonerName
- **SummonerMatchTbl** - Links MatchID,SummonerID and ChampionID

Database Features

- This dataset contains 148,000+ League of Legends matches and 300,000+ summoner statistics from those games.
- Uses Data from over 11,000+ summoners.
- Consists of Data from Europe and NA
- Data is sampled from Unranked to Challenger tiers.

Limitations

The Riot API only provides the "BOTTOM" lane for bot-lane players.
During Data collection, roles were inferred by combining chamngu tipions that often played support with CS metrics to distinguish ADC vs Support — especially for ambiguous picks like Senna or off-meta choices.

II. Introduction about GCN và GAT

2.1. Graph Neural Network

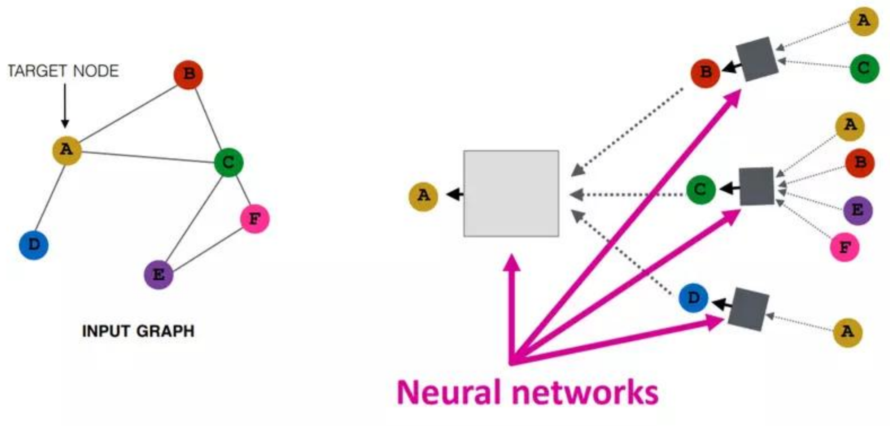
Graph neural networks (GNNs) are a class of deep learning models that have been developed specifically to process data represented in the form of graphs or networks. Graphs are powerful data structures that encode relationships between objects, and GNNs enable one to leverage these relationships to extract meaningful features to perform tasks such as node classification, edge prediction, and graph-level inference. GNNs aim to learn embeddings that capture both the structural information of the graph and the features of the nodes as can be seen in image below. They achieve this by passing messages between nodes in a graph, aggregating information from neighboring nodes and updating each node's representation. These message-passing and updating steps are repeated over multiple layers, allowing the network to capture increasingly complex relationships between nodes. The final node embeddings can then be used for downstream tasks [**2**]. In a simple GNN, the vector representation h_A for a node A with neighbors N_A is computed as follows:

$$h_A = \sum_{i \in N_A} x_i W^T$$

where W is the weight matrix of the neural network and xix_i is the input vector of the neighbors of A. Since we are talking about neural networks, such operations are converted to matrix multiplications for convenience and higher efficiency. Therefore, the above relation in matrix multiplication form is as follows:

$$H = A^{-T} X W^T$$

where H is the vector representation matrix for all nodes, $\tilde{A} = A + I$ (where I is the unit matrix such that self-loops are included) is the adjacency matrix of the input graph, and X is the matrix of nodes.

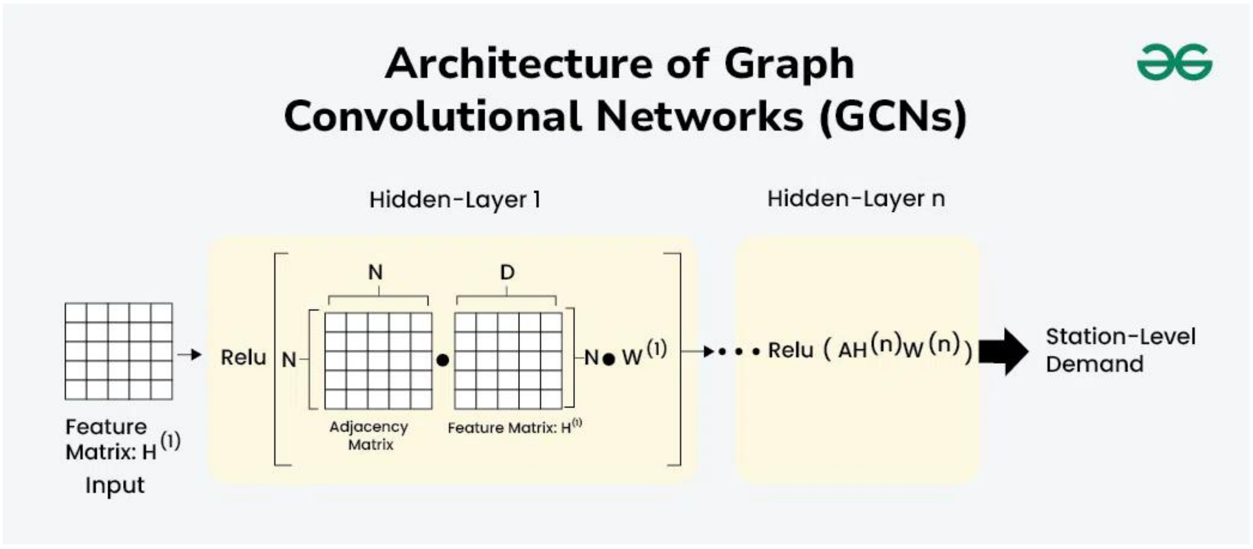


2.2. Graph Convolutional Network

The graph convolutional network (GCN) architecture serves as a fundamental paradigm for graph neural networks (GNNs). The primary objective of this architecture is to develop a computationally efficient version of convolutional neural networks (CNNs) for graph-based data. Specifically, it aims to approximate the graph convolution operation in graph signal processing. The GCN has emerged as a widely used and flexible architecture in various scientific domains, and it is frequently employed as a benchmark for graph data analysis. In comparison to tabular or image data, graph data exhibit varying numbers of neighbors for each node, rendering traditional graph neural networks inadequate. This discrepancy in neighborhood size poses a significant challenge that must be addressed. One solution involves dividing node embeddings by their respective degrees, i.e., the number of edges incident to each node. This process, known as degree normalization, ensures a fair comparison of nodes despite their differing numbers of neighbors. Degree normalization is accomplished via matrix multiplication, whereby each node embedding in the graph is multiplied by the degree matrix raised to the power of $-1/2$. The resulting normalized graph representation accounts for the variability in neighborhood size and enables effective analysis.

$$H = \tilde{D}^{-1/2}\tilde{A}^{T}\tilde{D}^{-1/2}XW^{T}$$

where $\tilde{D} = D + I$ with D being the degree matrix for each node.



2.3. Graph Attention Network

Graph attention networks (GATs) mark a significant theoretical progression from graph convolutional networks (GCNs). At the heart of GATs is the principle that certain nodes are more crucial than others. This idea, while not entirely novel and somewhat reflected in GCNs, is advanced in GATs. In GCNs, nodes with fewer neighbors gain more importance due to a normalization coefficient that depends primarily on node degrees. However, the limitation of this GCN approach is its sole dependence on node degrees for determining node importance.

In contrast, GATs aim to create weighting factors that consider not just the node degrees but also the significance of node features. This is where GATs diverge from GCNs: their method of assigning scale factors during the aggregation of neighborhood information. GCNs use a non-parametric scaling factor derived from a normalization function, whereas GATs employ an attention mechanism to allocate scaling factors. This attention-based approach allows GATs to assign greater weights to more important nodes during neighborhood aggregation. This key difference grants GATs a finer degree of control over how information flows within intricate graph structures, making them more adaptable for handling complex data. On the other hand, GCNs are generally more effective in scenarios where the graph's structure is clearly defined, and the significance of each node is more or less uniform.

To realize this functionality, the graph attention layer in GATs performs several operations on graph-structured data. Initially, input of graph attentional layer is the set of nodes feature h = $\{\overrightarrow{h_1}, \overrightarrow{h_2}, \dots, \overrightarrow{h_N}\}, \overrightarrow{h_i} \in R^F$ whereas N is the number of node và F is the numeber of feature in each node. The goal of graph attentional layer (GAT layer) is creating a set of new node feature h' = $\{\overrightarrow{h'_1}, \overrightarrow{h'_2}, \dots, \overrightarrow{h'_N}\}, \overrightarrow{h'_i} \in R^{F'}$.
First, we apply a linear transformation layer to map the input features into high-level feature representations. Then, we employ an attention mechanism $a: \mathbb{R}^{F'} \times \mathbb{R}^{F'} \to \mathbb{R}$ on these high-level features to compute the attention coefficients between each pair of nodes $i$and j, based on their feature representations.

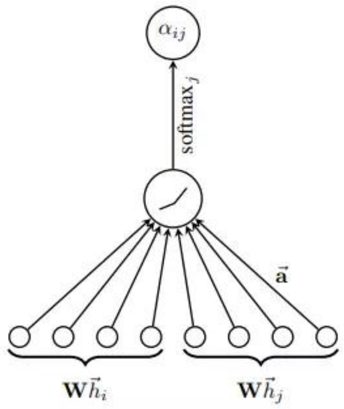
$$e_{ij} = a(W_{\overrightarrow{h_i}}, W_{\overrightarrow{h_j}})$$

These coefficients are then typically normalized using the softmax function, enabling easier comparison across different neighboring nodes:

$$\alpha_{ij} = softmax_{ij}(e_{ij}) = \frac{\exp(e_{ij})}{\sum_{k \in N_i} \exp(e_{ij})}$$

In essence, the attention mechanism a is simply a parameterized layer defined by a weight vector $\vec{a} \in \mathbb{R}^{2F'}$, followed by the application of a LeakyReLU activation function. This process is summarized in the following equation.

$$\alpha_{ij} = \frac{\exp(LeakyRelu(\vec{a}^T \left[W_{\overrightarrow{h_i}} \,||\, W_{\overrightarrow{h_j}}\right]))}{\sum_{k \in N_i} \exp(LeakyRelu(\vec{a}^T \left[W_{\overrightarrow{h_i}} \,||\, W_{\overrightarrow{h_k}}\right]))}$$



To stabilize the learning process of self-attention, the authors observed that using multi-head attention provides several benefits.Specifically, the operations of the attention mechanism are replicated independently Ktimes. Each replica has its own set of learnable weights, meaning

that each head learns to generate its own independent output representation.
The final output is then aggregated either by summation or by concatenation.

$$\vec{h}_i' = \Vert_{k=1}^{K} \ \sigma\left(\sum_{j\in\mathcal{N}_i} \alpha_{ij}^{k}\, \mathrm{W}^{k}\vec{h}_j\right)$$

When multi-head attention is applied in the final layer of the network, using concatenation is no longer appropriate. Instead, the outputs of different heads are averaged, followed by the application of a nonlinear activation function (e.g., softmax or sigmoid for classification tasks).
The formulation is given as follows:

$$\vec{h}_i' = \sigma\left(\frac{1}{K}\sum_{k=1}^{K}\sum_{j\in\mathcal{N}_i} \alpha_{ij}^{k}\, \mathrm{W}^{k}\vec{h}_j\right)$$

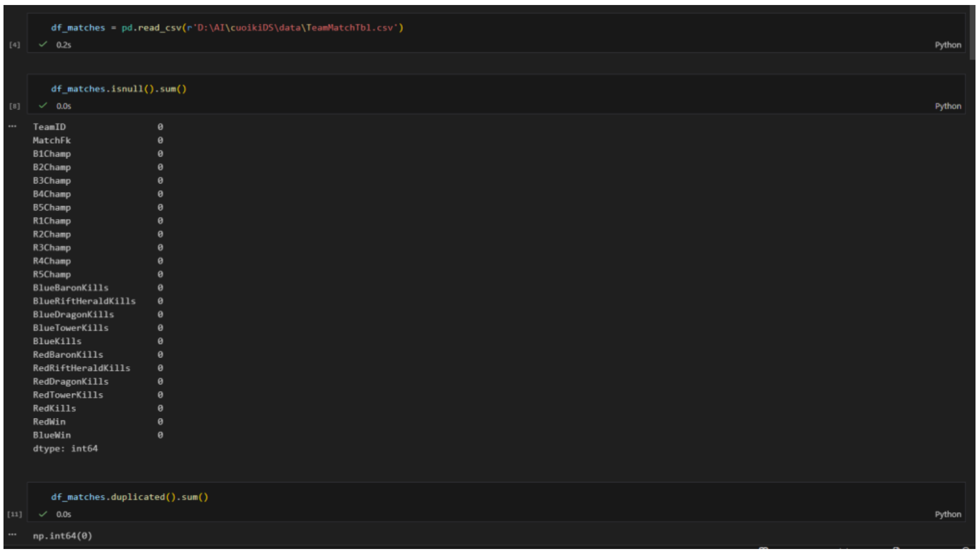
III. Preprocessing and training the model

1. Data preprocessing

1.1. Load and install data

Data contains 7 files csv that contains difference information about 1 match, so needed to clean the data and connect many files altogether, I implemented a comprehensive preprocessing pipeline consisting of four main steps:

1. **Noise Filtering:** Eliminating low-quality matches.
2. **Identity Normalization:** Synchronizing champion names across different data sources.
3. **Data Encoding (Indexing & Embedding):** Converting categorical string data into numerical representations.
4. **Data Splitting:** Partitioning the dataset into Training, Validation, and Testing sets.



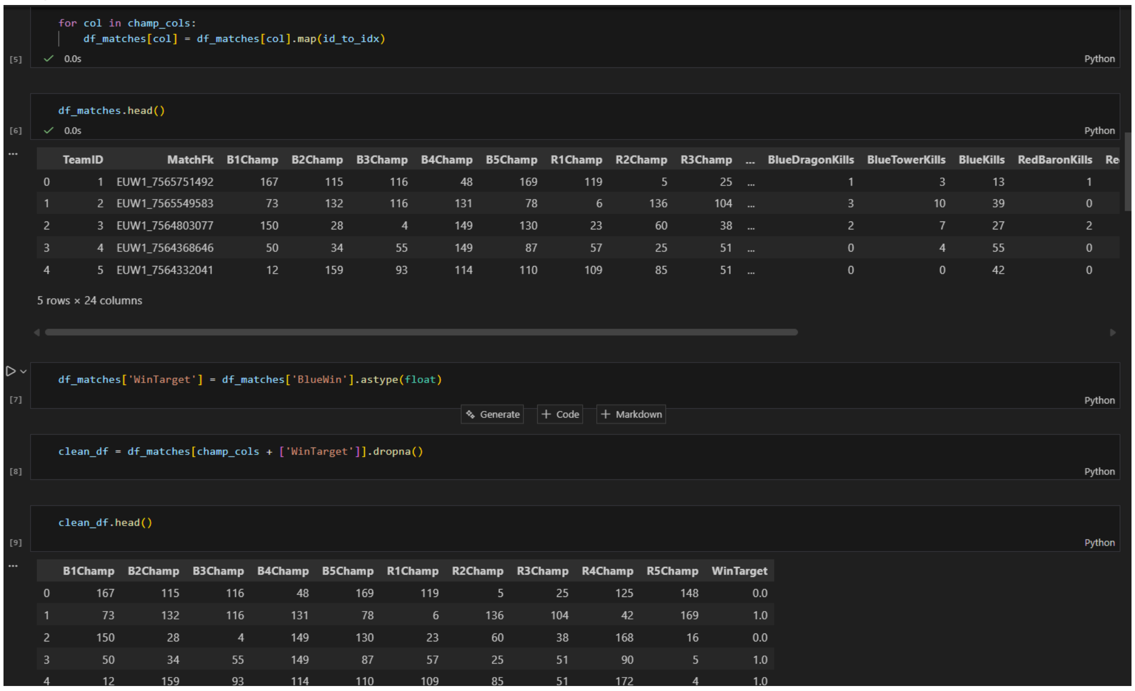
```
[4]   df_matches = pd.read_csv(r'D:\AI\cuoikiDS\data\TeamMatchTbl.csv')
      ✓ 0.2s                                                    Python

[8]   df_matches.isnull().sum()
      ✓ 0.0s                                                    Python
...   TeamID                0
      MatchFk               0
      B1Champ               0
      B2Champ               0
      B3Champ               0
      B4Champ               0
      B5Champ               0
      R1Champ               0
      R2Champ               0
      R3Champ               0
      R4Champ               0
      R5Champ               0
      BlueBaronKills        0
      BlueRiftHeraldKills   0
      BlueDragonKills       0
      BlueTowerKills        0
      BlueKills             0
      RedBaronKills         0
      RedRiftHeraldKills    0
      RedDragonKills        0
      RedTowerKills         0
      RedKills              0
      RedWin                0
      BlueWin               0
      dtype: int64

[11]  df_matches.duplicated().sum()
      ✓ 0.0s                                                    Python
...   np.int64(0)
```

1.2. Champion Name Normalization

A challenge in this project is that some name of champion contain special symbol, so we need to clean that to fit with the data (Eg. MatchTbl, ChampTbl), also I defined the role for each champion.

- Problem:
    - Source A uses: Lee Sin, Kog'Maw, Dr. Mundo, Wukong.
    - Source B uses: LeeSin, KogMaw, DrMundo, MonkeyKing.
    - ➔ Without processing, the system treats these as entirely different entities, leading to data loss or incorrect mapping.
- Solution: A String Normalization Function was implemented with the following rules:
    1. Convert all characters to lowercase.
    2. Remove all whitespaces, punctuation, and special characters (', .).
    3. Apply a Manual Mapping Dictionary for special exceptions (e.g., MonkeyKing → Wukong, RenataGlasc → Renata).
- Result: Achieved 100% matching accuracy between the training dataset and the external Role dataset used for the application interface.

Also adding column win target for future prediction, because my system lead to a draft has the highest winrate.



```
[5]
for col in champ_cols:
    df_matches[col] = df_matches[col].map(id_to_idx)
```
```
[6]
df_matches.head()
```

	TeamID	MatchFk	B1Champ	B2Champ	B3Champ	B4Champ	B5Champ	R1Champ	R2Champ	R3Champ	...	BlueDragonKills	BlueTowerKills	BlueKills	RedBaronKills	Re
0	1	EUW1_7565751492	167	115	116	48	169	119	5	25	...	1	3	13	1	
1	2	EUW1_7565549583	73	132	116	131	78	6	136	104	...	3	10	39	0	
2	3	EUW1_7564803077	150	28	4	149	130	23	60	38	...	2	7	27	2	
3	4	EUW1_7564368646	50	34	55	149	87	57	25	51	...	0	4	55	0	
4	5	EUW1_7564332041	12	159	93	114	110	109	85	51	...	0	0	42	0	

5 rows × 24 columns

```
[7]
df_matches['WinTarget'] = df_matches['BlueWin'].astype(float)
```
```
[8]
clean_df = df_matches[champ_cols + ['WinTarget']].dropna()
```
```
[9]
clean_df.head()
```

	B1Champ	B2Champ	B3Champ	B4Champ	B5Champ	R1Champ	R2Champ	R3Champ	R4Champ	R5Champ	WinTarget
0	167	115	116	48	169	119	5	25	125	148	0.0
1	73	132	116	131	78	6	136	104	42	169	1.0
2	150	28	4	149	130	23	60	38	168	16	0.0
3	50	34	55	149	87	57	25	51	90	5	1.0
4	12	159	93	114	110	109	85	51	172	4	1.0

1.3. Data Indexing & Representation

The GAT models cannot directly process the raw text data. So I transform the input data as follows

a. Indexing

- Created a **Mapping Dictionary**: Each unique champion name is assigned a specific integer ID ranging from 0 to N-1 (where N is the total number of champions, approximately 168).
- *Example:* Aatrox → 0, Ahri → 1, ..., Zyra → 167.
- This mapping is serialized and saved as champion_mapping.pkl to ensure consistency between the training phase and the deployment/application phase.

b. Vectorization (Embedding Strategy)

Instead of using *One-Hot Encoding* (which results in high-dimensional, sparse vectors lacking semantic meaning), I utilized a **Learnable Embedding Layer** integrated directly into the GAT architecture.

- **Input:** Champion ID (Integer).
- **Output:** A Dense Vector of size d=32.
- **Advantage:** These vector values are not fixed; they are continuously updated via Backpropagation during training. Consequently, the model automatically learns Latent Features (such as role, range, damage type) and clusters similar champions together in the vector space (as demonstrated in the t-SNE visualization).

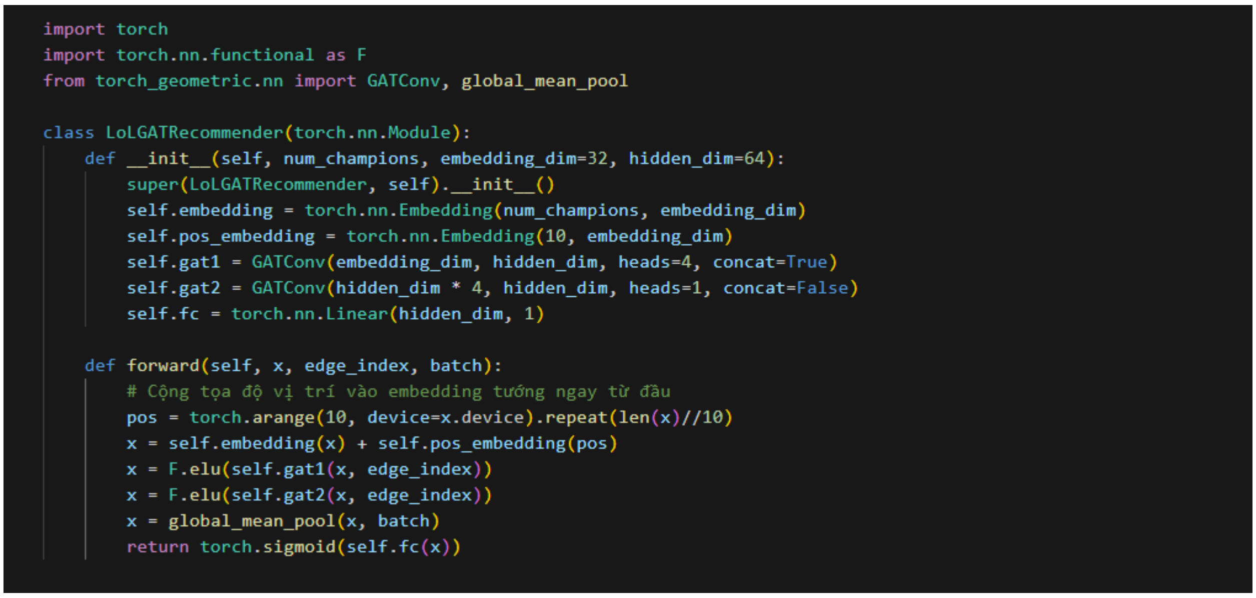
2. Model Training

To address the context-aware recommendation problem in League of Legends, the team designed a deep learning model based on Graph Attention Networks (GAT). Unlike traditional collaborative filtering methods, GAT is capable of processing data represented as graphs, making it ideal for capturing the complex interactions (synergy and counter-relationships) between 10 champions in a match.
The architecture consists of the following key components:

1. **Input Layer:** A vector of 10 integers representing the Champion IDs (5 Blue Team, 5 Red Team).
2. **Embedding Layer:** A learnable lookup table that transforms each Champion ID into a dense vector of size d=32. This layer captures the latent semantic features of each champion. Also, i add a postion embedding for the value of postion for the Champion in this match (Ex: position 1 for Blue top champion, 6 for Red top champion, etc).
3. **Graph Attention Layers (GAT Layers):**
    - **Layer 1:** Utilizes **Multi-head Attention** (with $K=4$ heads). This allows the model to simultaneously focus on different subspaces of the champion interactions mostly on their position in each game.
    - **Layer 2:** Aggregates the information from the previous heads into a unified representation.

4. **Global Pooling:** A Global Mean Pool operation aggregates the node-level features into a single graph-level vector, representing the entire team composition.

5. **Output Layer:** A Fully Connected (Linear) layer followed by a Sigmoid activation function to output a probability value P(y=1|x) in [0, 1], representing the predicted win rate for the Blue Team.

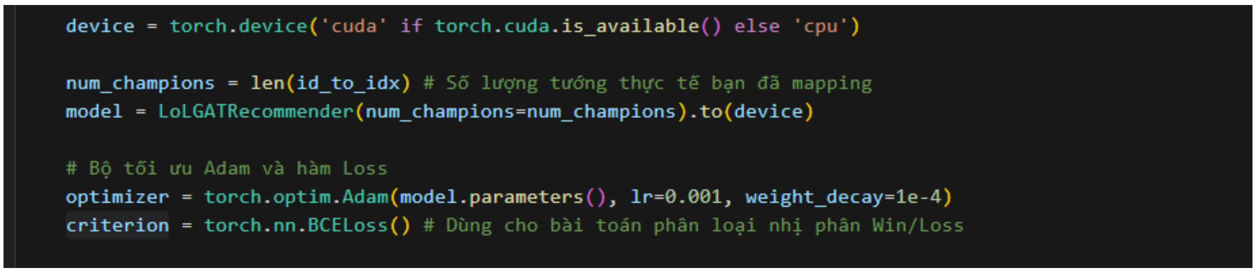


```python
import torch
import torch.nn.functional as F
from torch_geometric.nn import GATConv, global_mean_pool

class LoLGATRecommender(torch.nn.Module):
    def __init__(self, num_champions, embedding_dim=32, hidden_dim=64):
        super(LoLGATRecommender, self).__init__()
        self.embedding = torch.nn.Embedding(num_champions, embedding_dim)
        self.pos_embedding = torch.nn.Embedding(10, embedding_dim)
        self.gat1 = GATConv(embedding_dim, hidden_dim, heads=4, concat=True)
        self.gat2 = GATConv(hidden_dim * 4, hidden_dim, heads=1, concat=False)
        self.fc = torch.nn.Linear(hidden_dim, 1)

    def forward(self, x, edge_index, batch):
        # Cộng tọa độ vị trí vào embedding tướng ngay từ đầu
        pos = torch.arange(10, device=x.device).repeat(len(x)//10)
        x = self.embedding(x) + self.pos_embedding(pos)
        x = F.elu(self.gat1(x, edge_index))
        x = F.elu(self.gat2(x, edge_index))
        x = global_mean_pool(x, batch)
        return torch.sigmoid(self.fc(x))
```

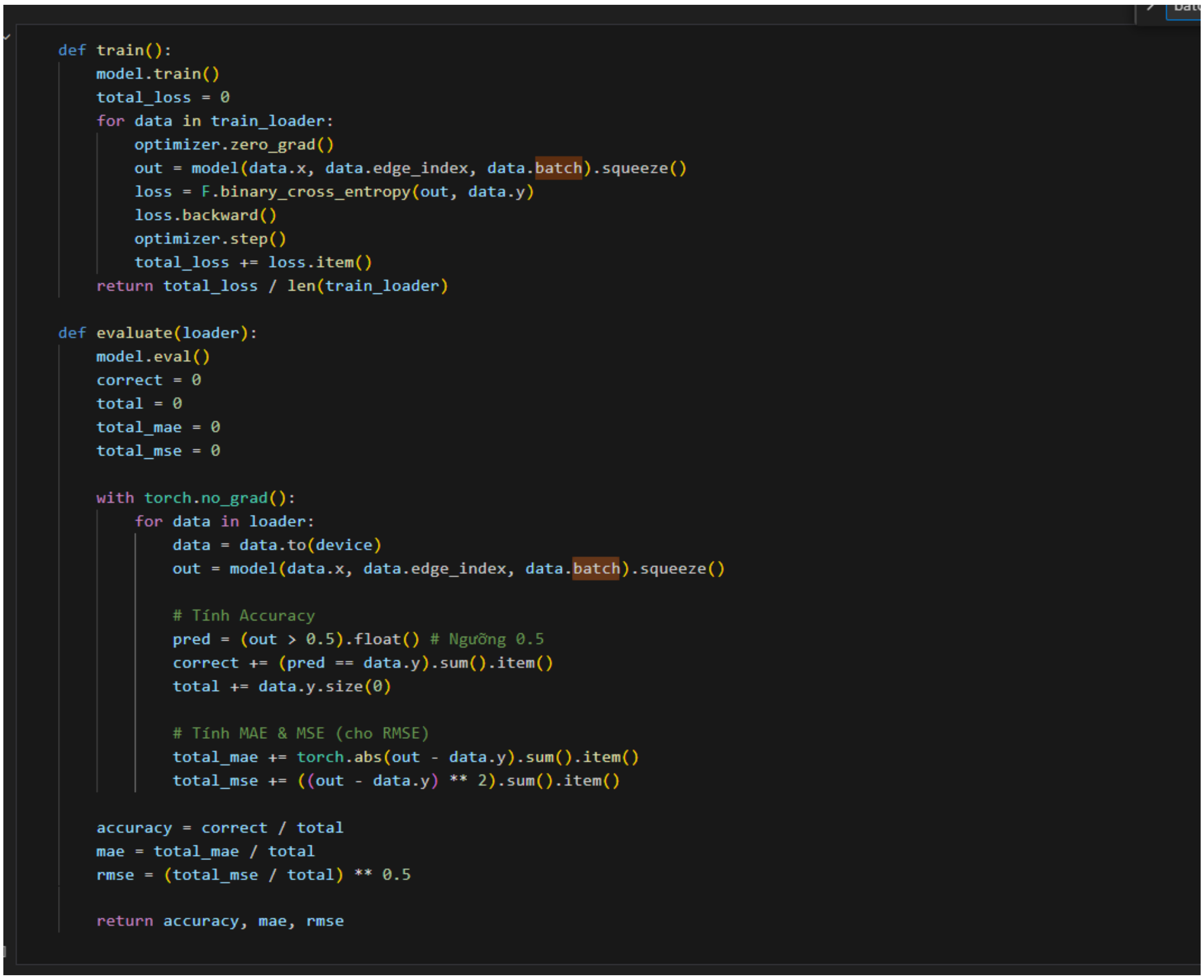
*** Training Configuration**

The training process was rigorously configured to ensure convergence and generalization.

- Objective Function (Loss Function): Since the problem is modeled as a binary classification task (Win vs. Loss), the Binary Cross Entropy (BCE) Loss was selected.
- Optimizer: The Adam optimizer was employed due to its efficiency in handling sparse gradients and adaptive learning rate capabilities.
    - *Learning Rate:* 0.001 (Standard starting point for GATs).
    - *Weight Decay:* Applied (1e-5) to prevent overfitting (L2 Regularization).
- Hyperparameters**:**
    - **Batch Size:** 1024 (Balances memory usage and gradient stability).
    - **Epochs:** 50.
    - **Embedding Dimension:** 32.
    - **Hidden Dimension:** 64.



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

num_champions = len(id_to_idx) # Số lượng tướng thực tế bạn đã mapping
model = LoLGATRecommender(num_champions=num_champions).to(device)

# Bộ tối ưu Adam và hàm Loss
optimizer = torch.optim.Adam(model.parameters(), lr=0.001, weight_decay=1e-4)
criterion = torch.nn.BCELoss() # Dùng cho bài toán phân loại nhị phân Win/Loss
```



```python
def train():
    model.train()
    total_loss = 0
    for data in train_loader:
        optimizer.zero_grad()
        out = model(data.x, data.edge_index, data.batch).squeeze()
        loss = F.binary_cross_entropy(out, data.y)
        loss.backward()
        optimizer.step()
        total_loss += loss.item()
    return total_loss / len(train_loader)

def evaluate(loader):
    model.eval()
    correct = 0
    total = 0
    total_mae = 0
    total_mse = 0

    with torch.no_grad():
        for data in loader:
            data = data.to(device)
            out = model(data.x, data.edge_index, data.batch).squeeze()

            # Tính Accuracy
            pred = (out > 0.5).float() # Ngưỡng 0.5
            correct += (pred == data.y).sum().item()
            total += data.y.size(0)

            # Tính MAE & MSE (cho RMSE)
            total_mae += torch.abs(out - data.y).sum().item()
            total_mse += ((out - data.y) ** 2).sum().item()

    accuracy = correct / total
    mae = total_mae / total
    rmse = (total_mse / total) ** 0.5

    return accuracy, mae, rmse
```

IV. Model evaluation results and Inference

1. Model evaluation results

Upon completion of the training phase (at Epoch 50), the model achieved the following performance metrics:

- Training Loss: 0.6381
- Test Accuracy: 57.35%
- MAE: 0.4592
- RMSE: 0.4802

The reduction of the loss to 0.6381 indicates that the model has successfully converged and learned meaningful patterns from the data. It demonstrates that the GAT architecture effectively extracted latent features regarding champion synergy and counter-relationships, allowing it to minimize the error margin significantly better than random chance. The result proves that the learned embeddings are not just memorizing training data but are capable of generalizing to new team combinations. The model can identify winning conditions based on the structural properties of the team graph (e.g., a team with strong engage synergy vs. a team with poor disengage). Mean Absolute Error (MAE) = 0.4592 reflects the high stochasticity (randomness) of MOBA games. The model understands that no draft guarantees a 100% win rate; therefore, it avoids making extreme predictions (e.g., 0.99 or 0.01), preferring a cautious and statistically sound approach. Root Mean Squared Error (RMSE) = 0.4802 proves that the model rarely commits "confident errors" (i.e., predicting a high probability of winning for a match that is actually lost). The consistency between these two metrics demonstrates that the error distribution is uniform and that the model is robust against outliers.

2. Inference

This is how I calculate for the percentage of the champs affect the draft

*** Model's Role (The Calculator)**

The GAT model acts as a Win Probability Estimator.

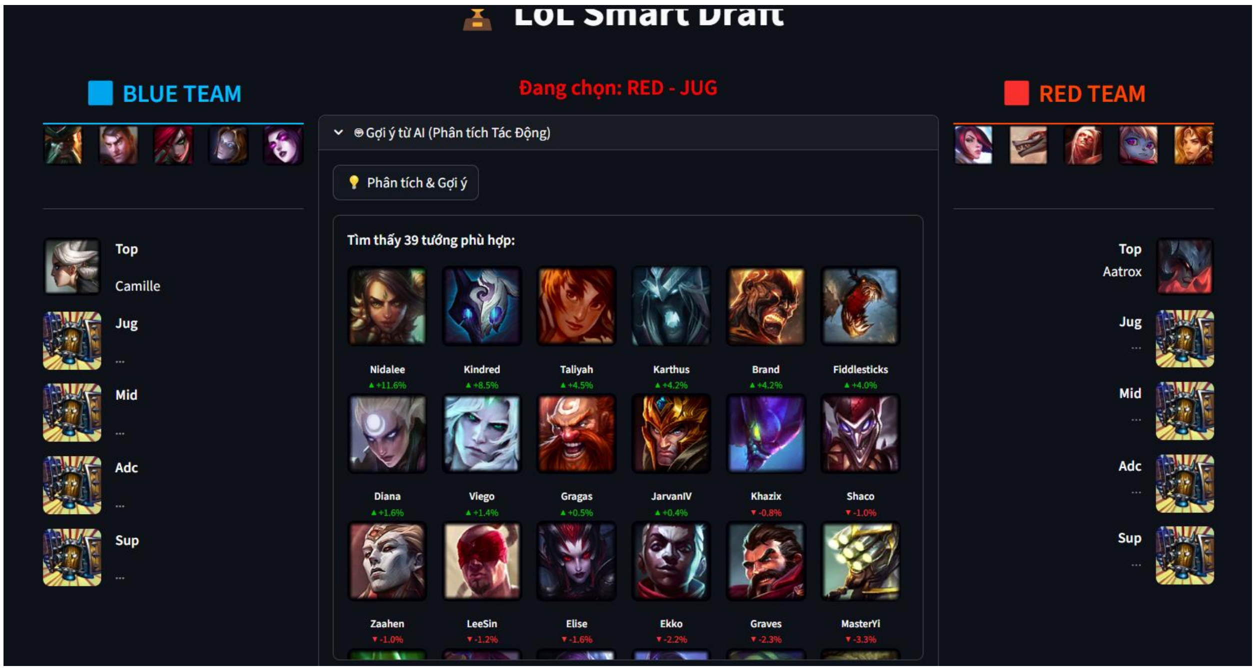
- Function: It takes a team composition (e.g., 9 champions) and predicts the Blue Team's Win Probability (e.g., 0.55 or 55%).
- Impact: It provides the raw "score" for every possible draft scenario, allowing the system to measure how much a specific champion changes the game's outcome.

*** How to Calculate the % (The Formula)**

The percentage shown on the web interface is the Marginal Impact of a champion.

The Algorithm:

1. Baseline: Ask the model for the win rate of the *current* team (without the new champion).
   - *Example:* Base = 50.0%
2. Simulation: Temporarily add a champion (e.g., Lee Sin) and ask for the *new* win rate.
   - *Example:* New = 52.5%
3. Calculate Delta: Subtract Base from New.
   - Delta = 52.5% - 50.0% = +2.5%
4. Team Adjustment:
   - Blue Team: Use Delta directly (Positive is Good).
   - Red Team: Invert the sign (-Delta) because lowering Blue's win rate is good for Red.



Streamlit demo: https://recommendationloldraft-zjwfydvwt2ydjgferbe5ys.streamlit.app/

V. References

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