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Hierarchy2vec: Representation Learning in Hierarchical Collaboration Networks for Team Performance Prediction

Sulyun Lee[1] and Kang Zhao[2]

[1] Interdisciplinary Graduate Program in Informatics, University of Iowa

[2] Department of Business Analytics, University of Iowa

What is collaboration?

- Important component of teamwork
- Can boost work productivity and improve team performance by putting together individuals’ disciplines, expertise, and background
- Example
  - Academic collaboration
  - Business collaboration
  - Sports collaboration

Collaboration from network perspective

- View collaborations from the network perspective

- Understanding collaboration network patterns associated with team performance helps decision-making
  - Ex) Sports team lineup decision, hire for a project team

- Existing studies that predict team performance on collaboration networks
  - Use average structural centrality of team members as features
  - Use dynamics of historical team performance as features

- Limitations of existing works
  - Manual feature engineering is required to represent the whole team
  - Do not consider the hierarchical structures in teams

Proposed method: Hierarchy2vec

- Goal: Predict team performance based on team collaborations
- Contributions:
  1. Capture the hierarchical relationships among team members
  2. Preserve team members' characteristics and collaboration structures in a team
  3. Adopt network embedding approaches for learning representations of team members and teams
  4. Predict future team performance

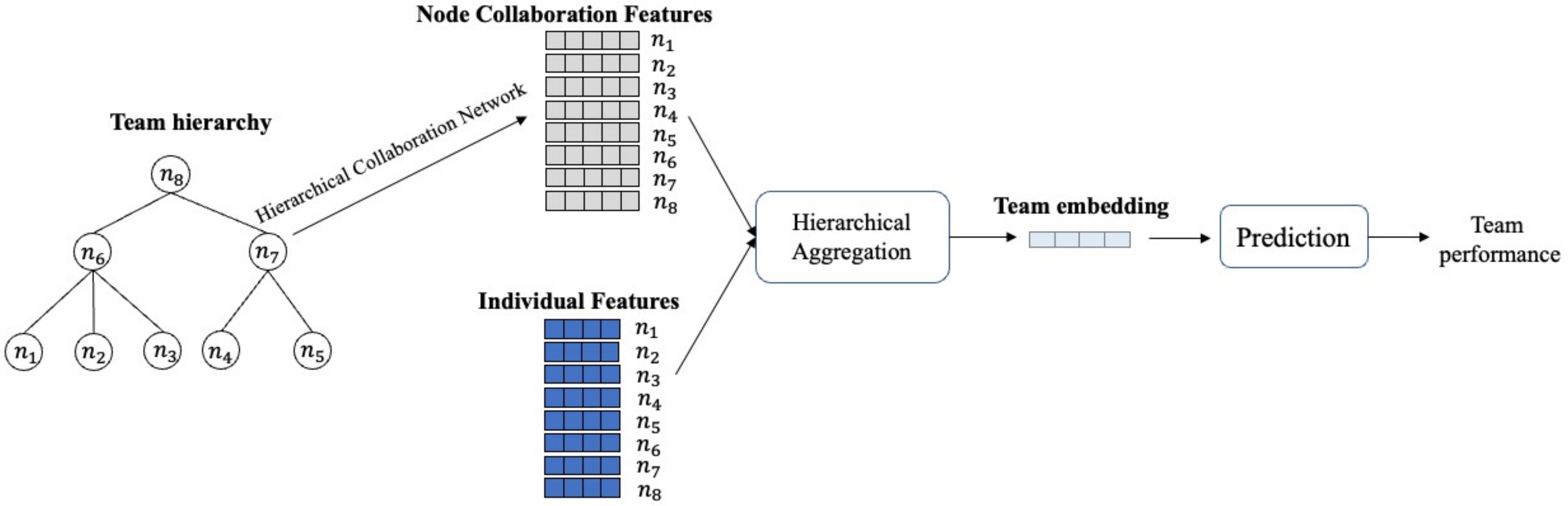
Methods

Hierarchy2vec Architecture overview

(1) Given a team hierarchy, generate node features using hierarchical collaboration network

(2) Aggregate node features in a hierarchical way using an end-to-end architecture to learn team representations

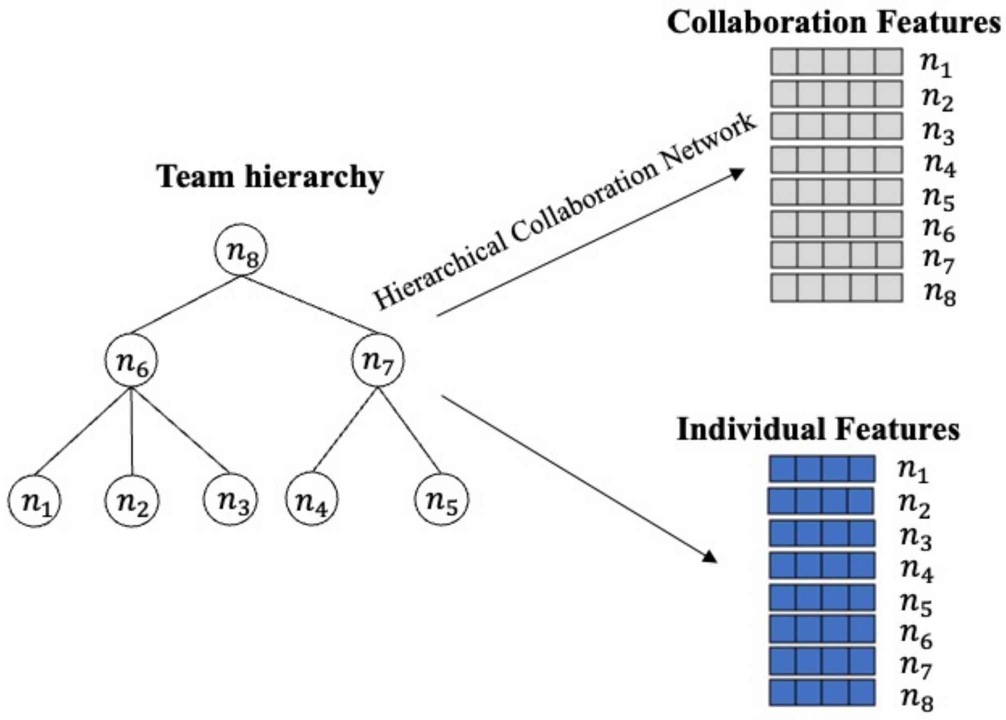
(3) Predict team performance



Methods

Generating node features

- Construct team hierarchy with individual team members in the same team
- Generate features for every team member
- Features include:
  (1) Individual features
  (2) Collaboration features



Methods

Generating node features

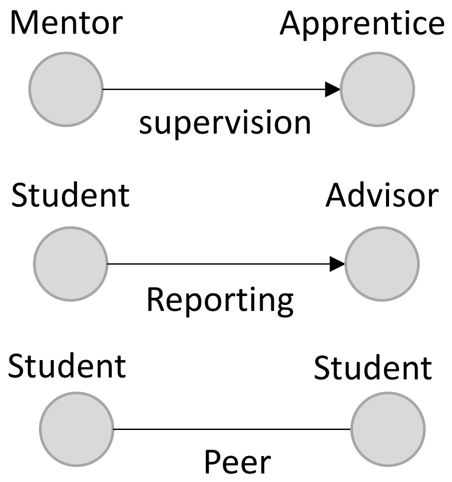
(1) Individual features: represent individual characteristics

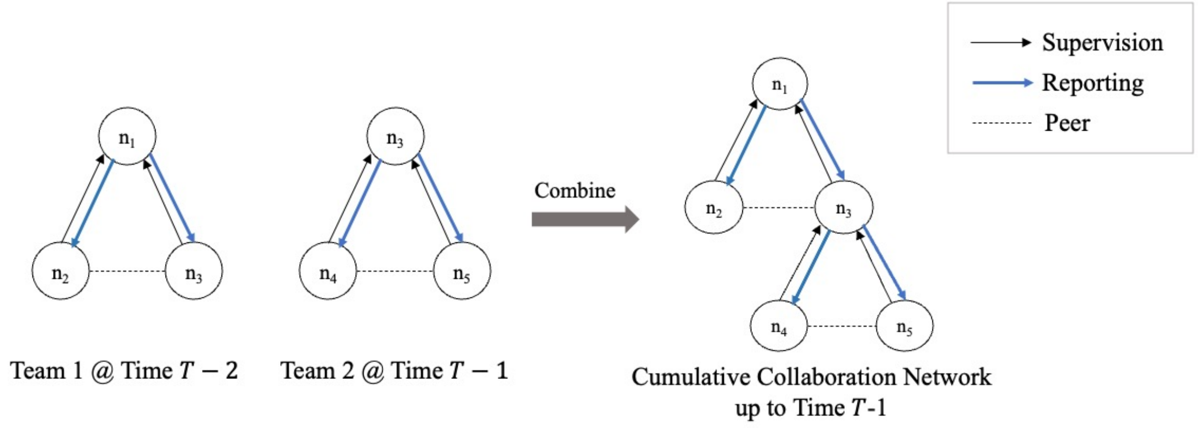
- Individual expertise, skills, or previous performance of team members

(2) Collaboration features: represent previous collaboration experience

- Construct hierarchical collaboration network using team members' prior collaborations
- Nodes: team members (e.g., scholars, sports players)
- Edges: three types based on hierarchical structure
    - Supervision ties (directed) -- "Supervising" relationships
    - Reporting ties (directed) -- "reporting to" or "working for" relationships
    - Peer ties (undirected) -- colleagues working for the same supervisor

- Combine all collaborations for cumulative collaboration network



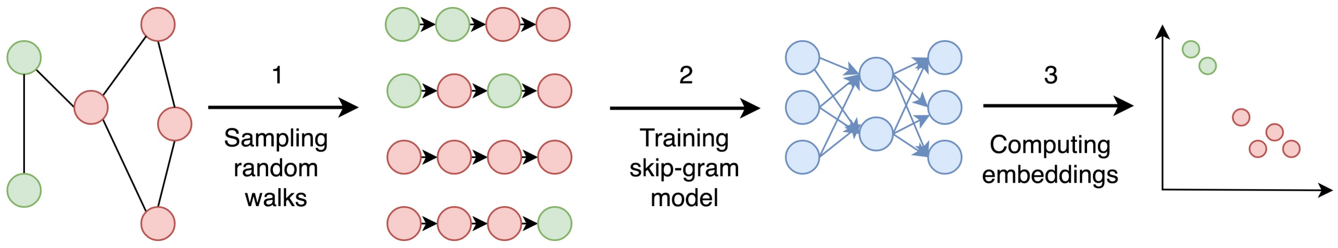


Methods

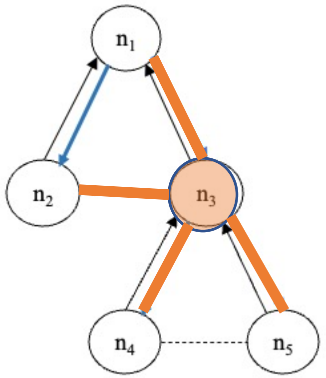
Generating node features

(2) Collaboration features

- Learn node embeddings on the cumulative hierarchical collaboration network
- Extend DeepWalk (Perozzi et al., 2014) model to learn node similarities with hierarchy in mind.
- Vanilla DeepWalk: unbiased random walk



- Our model: hierarchically biased random walk
  - Give different probabilities (unnormalized probabilities p, q, and $1\text{-}p\text{-}q$) for supervision, reporting and peer ties



Probability p for supervision edges

Probability q for reporting edges

Probability $1\text{-}p\text{-}q$ for peer edges

Perozzi, B., Al-Rfou, R., & Skiena, S. (2014, August). Deepwalk: Online learning of social representations. In *Proceedings of the 20th ACM SIGKDD international conference on Knowledge discovery and data mining* (pp. 701-710).

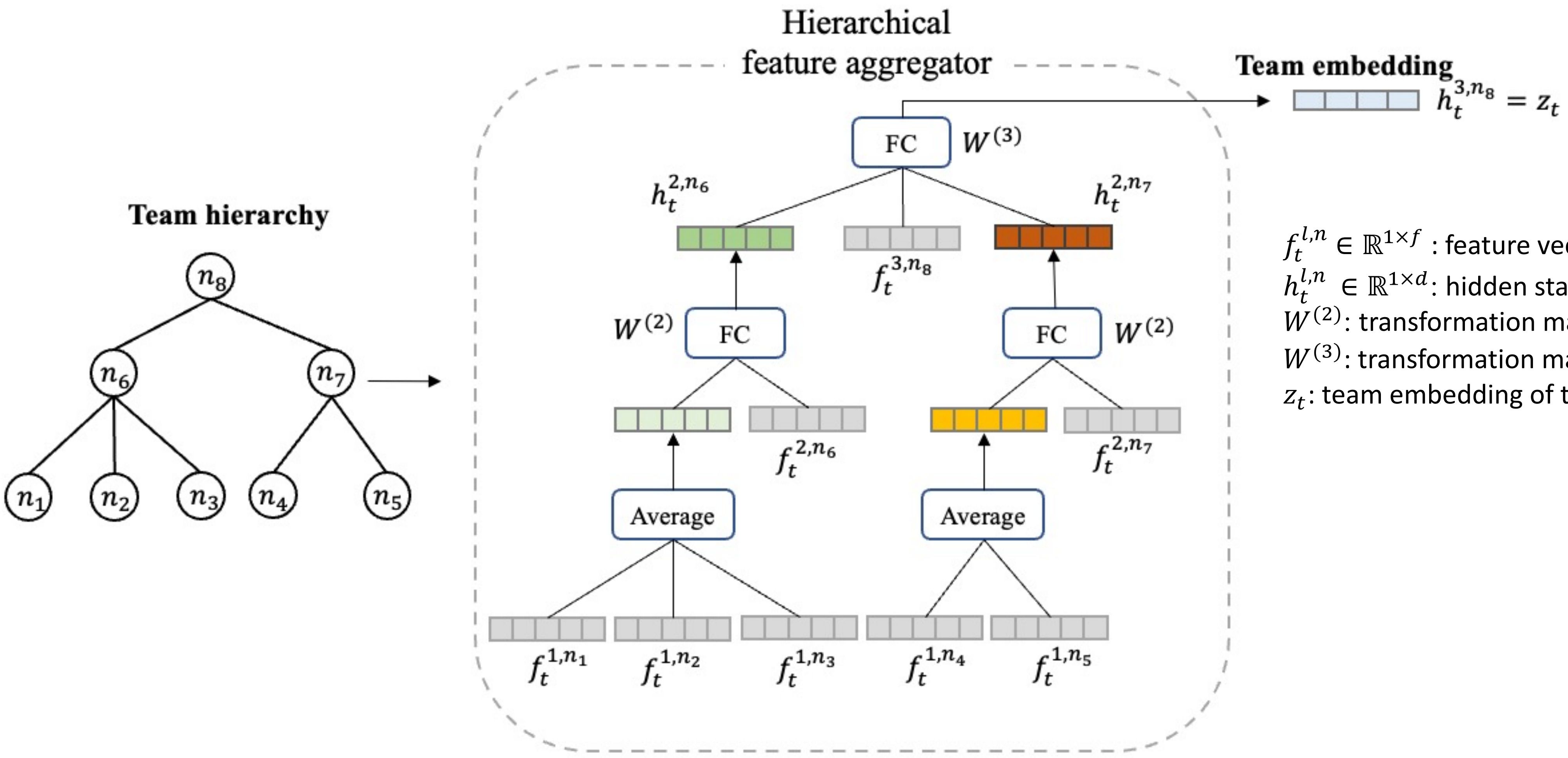
Methods

Hierarchical node feature aggregation

- Aggregate node features of all team members to generate team-level representations
- Give more importance to team members at the upper hierarchy
- Aggregation starts from the lowest level of team’s hierarchy up to the top level (i.e., bottom-up fashion)
- The final features aggregated at the top-level become the embedding of teams @ time T.

Methods

Hierarchical node feature aggregation



$f_t^{l,n} \in \mathbb{R}^{1\times f}$: feature vector of node n in level l

$h_t^{l,n} \in \mathbb{R}^{1\times d}$: hidden state of node n in level l

$W^{(2)}$: transformation matrix

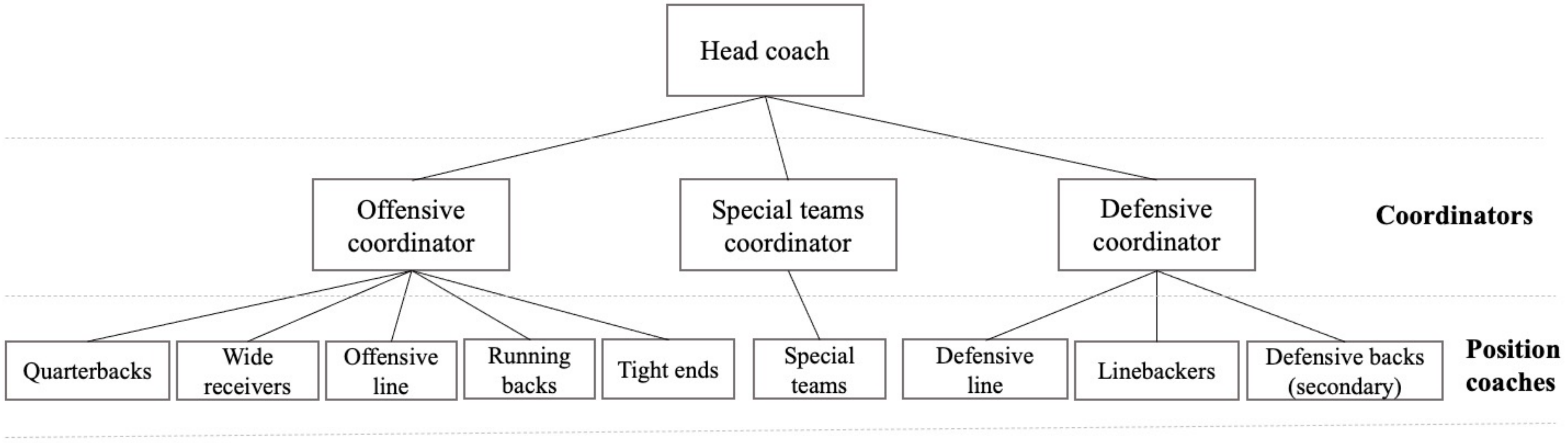
$W^{(3)}$: transformation matrix

z_t: team embedding of team t

Experiments

Data

- Dataset of coaches and teams in the National Football League (NFL)
- Seasons between 2002 and 2019
- Only considered qualified coaching roles within each team (head coach, coordinators, position coaches)
  - Assistant, Associate, Intern, Quality control positions are not considered.
- Team hierarchy: three levels of hierarchy in NFL coach collaboration
  - First level (bottom): position coaches – responsible for players at one specific position
  - Second level: coordinators (defensive / offensive / special teams) – responsible for one area of team's play
  - Third level (top): head coach – greatest authority and responsibility



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Experiments

Experiment design

- Experimented on predicting failures.
  - Failure of a team: team failed to win 50% of its regular season games or head coach was fired in the middle of the season.
  - We generated node features using data up to year y-1 to predict team failures in year y.
- Train: 14 seasons (2002-2015) / Validation: 2 seasons (2016-2017) / Test: 2 seasons (2018-2019)

Table 1: NFL collaboration network statistics

	Training	**Validation**	**Test**
Number of coaching teams	448	64	64
Number of coaching teams with failures	196	27	33
Number of nodes	5,493	806	804
Number of edges	6,817	1,065	1,154

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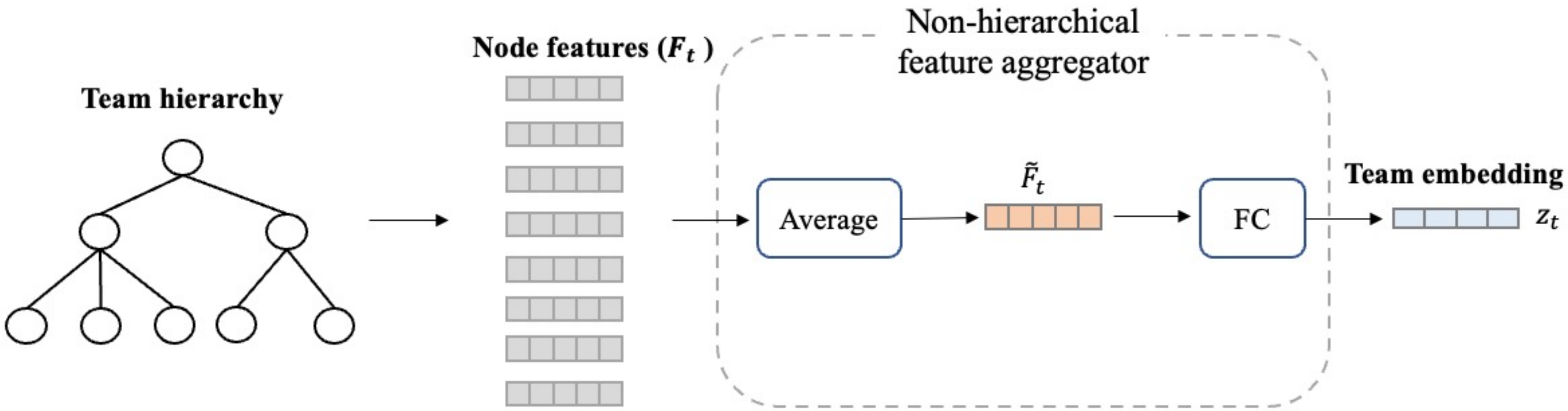
Experiments

Experiment design

- Individual features: prior achievements as NFL coach
    - Total years of NFL coaching career
    - Best winning percentage during the previous 5 seasons
    - Avg. winning percentage during the previous 5 seasons
- Collaboration features: node embeddings learned from previous hierarchical collaboration network
- Baseline models
    - Collaboration features using DeepWalk (unbiased random walk)
    - Aggregation of coach features in non-hierarchical way
        - Average all node features and a FC layer transforms into a team embedding size.



Results

- Performed 10 repeated model trainings.
- Evaluation metric: Averaged AUCs over 10 test predictions.
- Feature set 1: Individual features
- Feature set 2: Individual features + Collaboration features (DeepWalk)
  - Used unbiased random walk for traversing nodes
- Feature set 3: Individual features + Collaboration features (Hierarchical Walk)
  - Probability ratio of traversing supervision, peer, and reporting ties = 1:3:5

Table 2: Model comparisons

	Non-hierarchical aggregation	Hierarchical aggregation
Feature set 1	0.572	0.631
Feature set 2 (DeepWalk)	0.585	0.597
Feature set 3 (Hierarchical walk)	0.600	**0.653**

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Conclusion

- This work proposed hierarchy2vec that learns graph representations designed for teams’ hierarchical structures.
- Leveraged hierarchically biased walk
- Aggregated node features in a hierarchical way using end-to-end team embedding model
- Future work
  - Robustness check for different model parameters and experiment settings
  - Consider the recency and strength of collaboration ties while learning collaboration features
  - Experiment on different data with hierarchical structures for generalizability

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