NeuralAC: Learning Cooperation and Competition Effects for Match Outcome Prediction

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Outline

- Background
- Problem Definition
- Related Work
- NeuralAC Model
- Experiments
- Conclusion and Future Work

Background

- Match outcome prediction in group comparison setting
  - Two teams involved
  - Goal: predict the match outcome before the start of the match
- Fundamental task
  - Rating individual ability
  - Creating fair matches for players
  - Increasing the teams' probability of winning

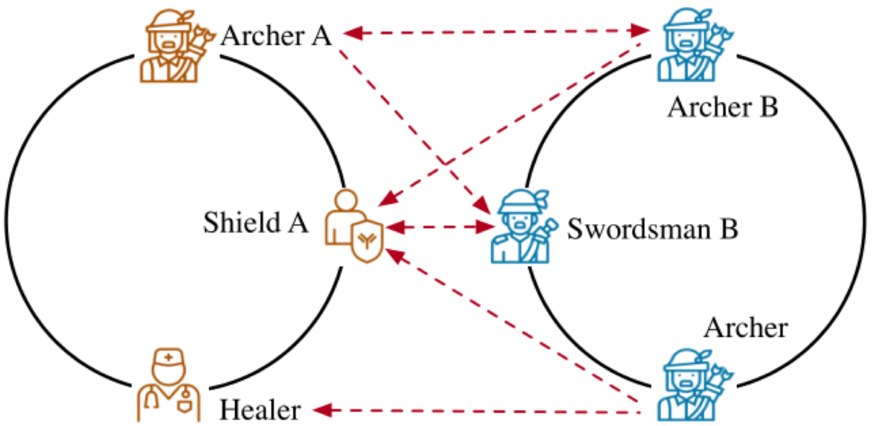
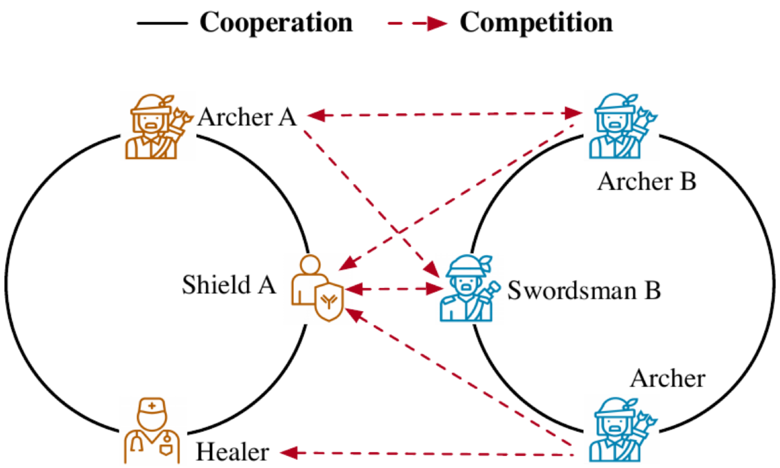


Figure 1: An example of group comparisons.

Background

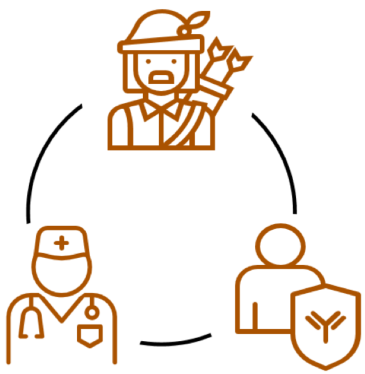
- Usually multiple interactions involved, including intra-team interactions and inter-team interactions.
- Intra-team interactions (cooperation effects):
  - The shield soldier A protects teammates
  - The healer A cures teammates
- Inter-team interactions (competition effects):
  - archer A shoot swordsman B
  - shield soldiers A resist swordsman B's attack



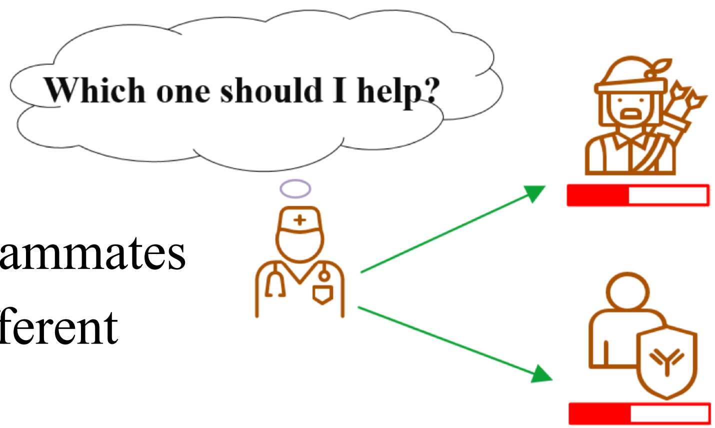
- Fail to modeling Cooperation and Competition Effects may lead to suboptimal prediction performance.

Challenge

- How to model cooperation effects?
  - The shield soldier protects teammates
  - The healer cures teammates

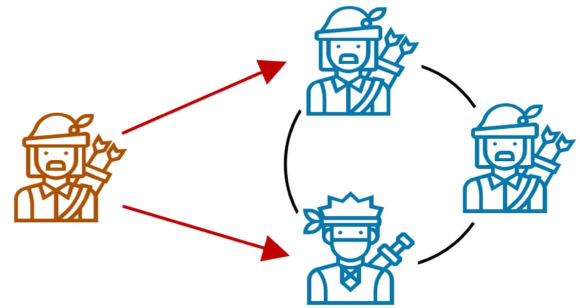


- How to model intra-team attention?
  - Key persons play a more important role
  - Key persons receive more attention from teammates
  - Interacting with different characters has different importance

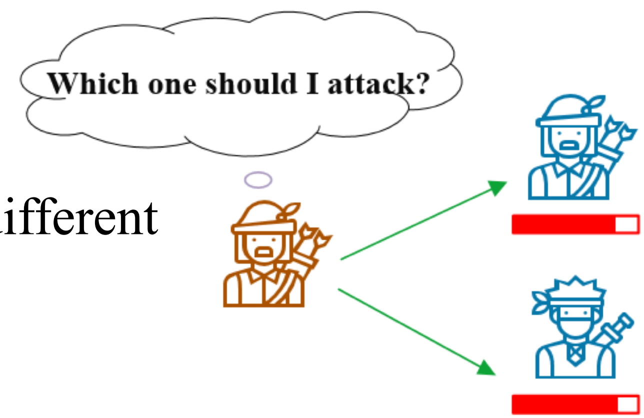


Challenge

- How to model competition effects?
  - Archer on the left shoot archer in blue
  - Archer on the left shoot swordsman in blue

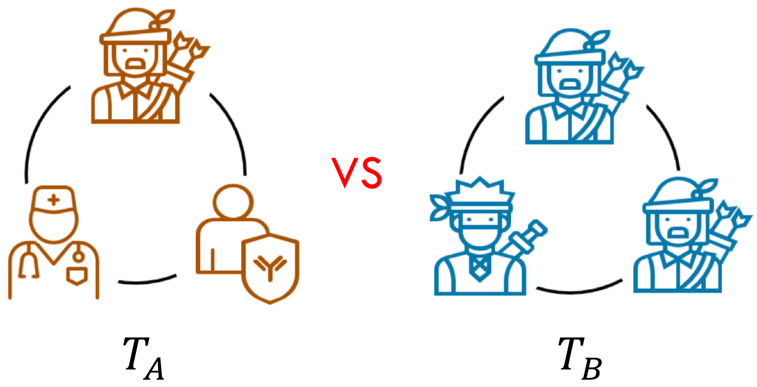


- How to model inter-team attention?
  - Key persons receive more attention from opponents
  - Interacting with different opponents has different importance



Problem Definition

- Preliminary：
  - Suppose there are n individuals {1,2,...,n}.
  - Each match involves two teams T_A and T_B, and each team is a subset of {1,2,...,n}.
- Given：
  - Two teams T_A and T_B
- Goal:
  - Predict the probability of T_A beats T_B



Related Work

- Traditional method
  - TrueSkill **[Herbrich et al. 2007]**
  - Generalized Bradly-Terry **[Huang et al. 2008]**

$$P(A \; beats \; B) = \frac{\exp(S_A)}{\exp(S_A) + \exp(S_B)} \qquad S_A = \boxed{\sum_{i \in T_A} w_i}$$

individual effects

  - HOI **[Li et al. 2018]**

$$S_A = \sum_{i \in T_A} w_i + \boxed{\sum_{i \in T_A} \sum_{j \in T_A, i \neq j} \mathbf{v}_i^T \mathbf{v}_j}$$

cooperation effects

- Neural network based method

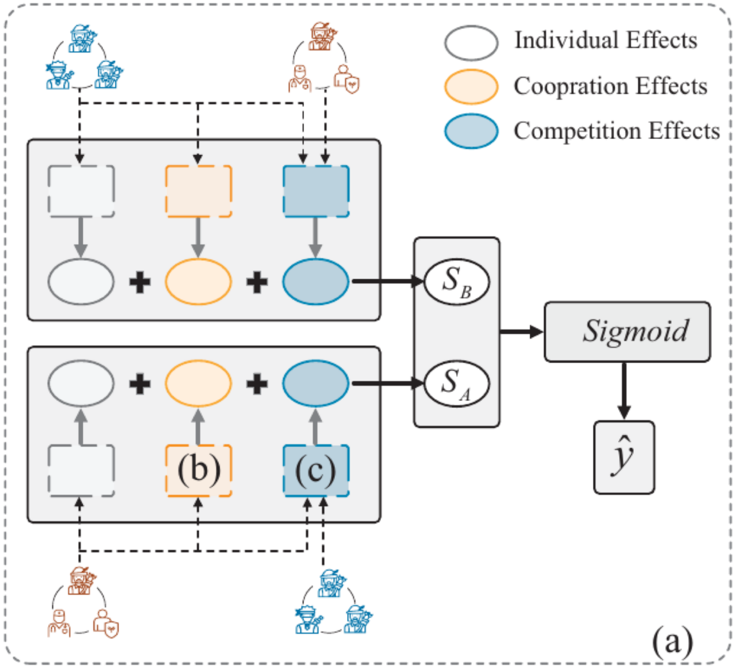
  Aggregate players' representations to obtain the team representation, then predict the outcome based on the team representation.
  - BalanceNet **[Delalleau et al. 2012]**
  - Optmatch **[Gong et al. 2020]**

Lack of Interpretability

Model Overview

- We assume that each team has an underlying score ***S***, which represents the overall ability of the team.
- The probability of T_A defeating T_B:

$$P(A\ beats\ B) = \frac{\exp(S_A)}{\exp(S_A) + \exp(S_B)} = \frac{1}{1 + \exp(-(S_A - S_B))}$$



- Overall ability of the team T_A:

$$S_A = \boxed{\sum_{i \in T_A} w_i} + \boxed{F_{\text{coop}}(T_A)} + \boxed{F_{\text{comp}}(T_A, T_B)}$$

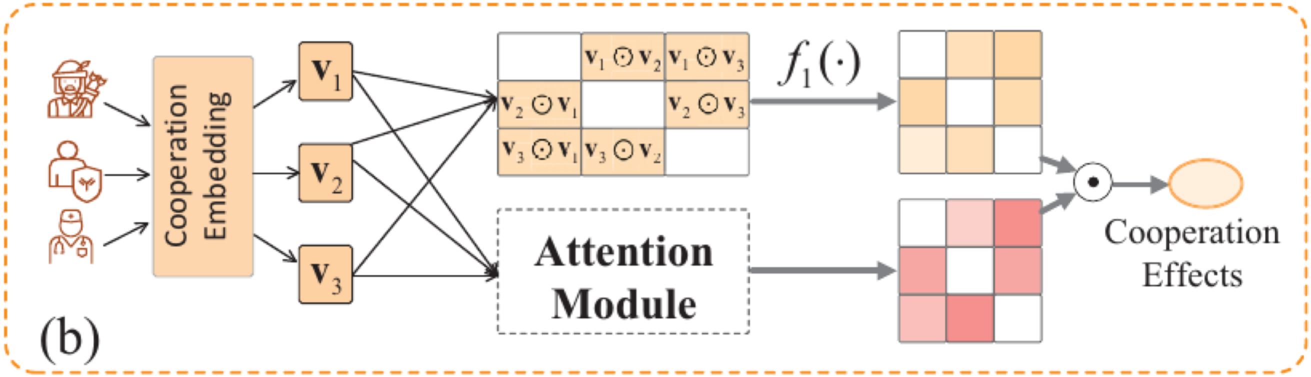
individual effects cooperation effects competition effects

NeuralAC Model

- Motivation:
  - The cooperation characteristics of two teammates
- Modeling Cooperation Effects
  - Input two teammates' cooperation vectors
  - DNNs f_2 as the interaction function
  - Output a cooperation score between i and j

$$F_{coop} = \sum_{i \in T_A} \sum_{j \in T_A, j \neq i} \boxed{a_{ij}^{\text{coop}}} \boxed{f_1} (\boxed{\mathbf{v}_i} \odot \boxed{\mathbf{v}_j})$$

Attention score



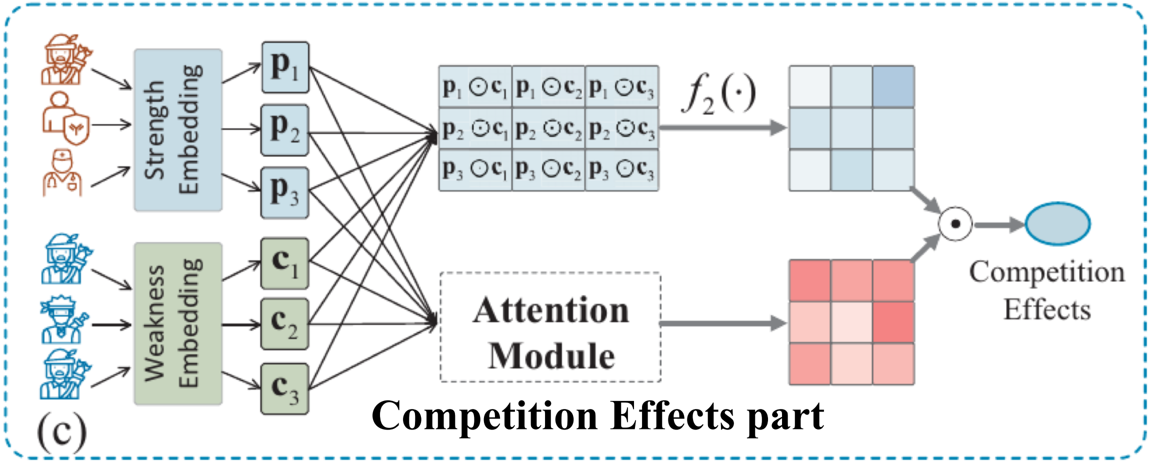
Cooperation Effects part

NeuralAC Model

- Motivation:
  - The offensive's strengths and the defensive's weaknesses
- Modeling Competition Effects:
  - Input one's strength vector and opponent's weakness vector
  - DNNs f_2 as the interaction function.
  - Output a competition score when i against j

$$F_{comp}(T_A, T_B) = \sum_{i \in T_A} \sum_{j \in T_B} \boxed{a_{ij}^{comp}} \boxed{f_2} (\boxed{\mathbf{p}_i} \odot \boxed{\mathbf{c}_j})$$

Attention score



Attention module

- Motivation:
  - The key person has a greater influence on the match outcome
  - Not all interactions should share the same weight as they contribute differently to the final game outcome.
- Cooperation attention module:
  - Input two teammates' cooperation vectors
  - Output a cooperation attention score

$$r_{ij}^{\text{coop}} = \boxed{\mathbf{v}_i^T}\mathbf{W}_{\text{coop}}\boxed{\mathbf{v}_j},$$

attention is asymmetry

$$a_{ij}^{\text{coop}} = \frac{\exp(r_{ij}^{\text{coop}})}{\sum_{j \in T_A, j \neq i} \exp(r_{ij}^{\text{coop}})}$$

- Competition attention module:
  - Input one's strength vector and his opponent's weakness vector
  - Output a cooperation attention score

$$r_{ij}^{\text{comp}} = \boxed{\mathbf{p}_i^T}\mathbf{W}_{\text{comp}}\boxed{\mathbf{c}_j},$$

$$a_{ij}^{\text{comp}} = \frac{\exp(r_{ij}^{\text{comp}})}{\sum_{j \in T_B} \exp(r_{ij}^{\text{comp}})}$$

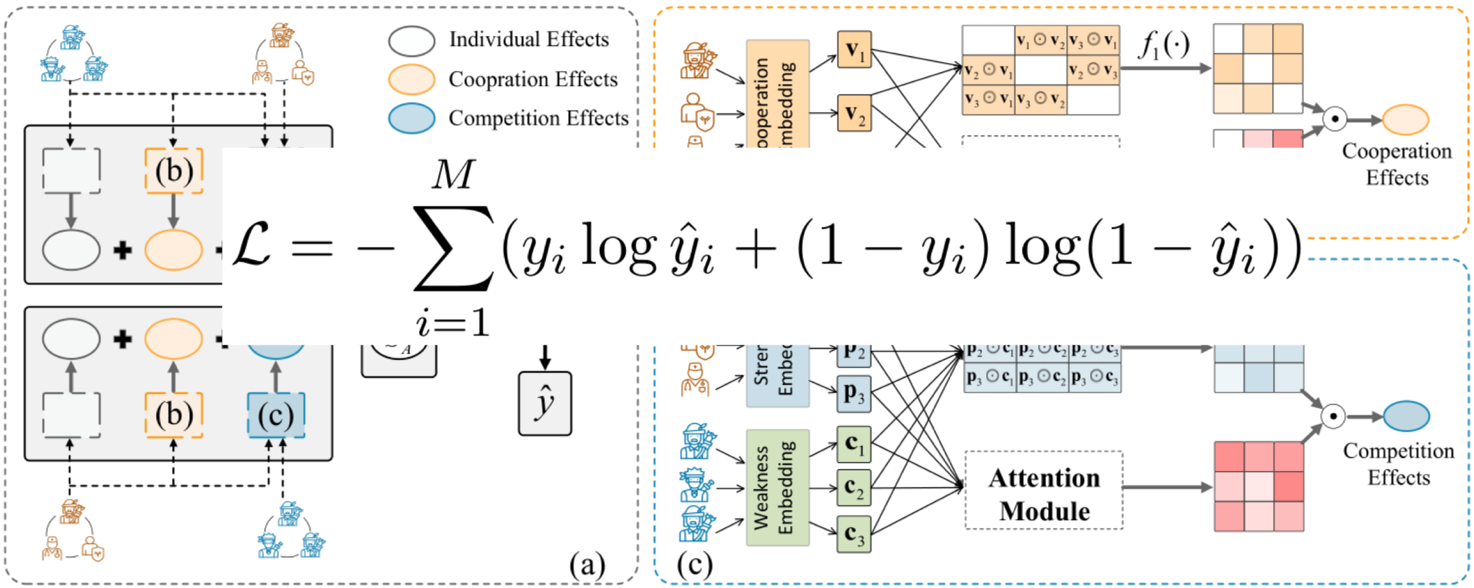
NeuralAC Model

- To summarize:

$$S_A = \sum_{i \in T_A} w_i + \sum_{i \in T_A} \sum_{j \in T_A, j \neq i} a_{ij}^{\text{coop}} f_1(\mathbf{v}_i \odot \mathbf{v}_j)$$

$$+ \sum_{i \in T_A} \sum_{j \in T_B} a_{ij}^{\text{comp}} f_2(\mathbf{p}_i \odot \mathbf{c}_j),$$

- '



$$\mathcal{L} = -\sum_{i=1}^{M} (y_i \log \hat{y}_i + (1 - y_i) \log(1 - \hat{y}_i))$$

Generality of NeuralAC

- NeuralAC is general and can cover some traditional models.
- Generalized Bradly-Terry:
  - Considering individual effects

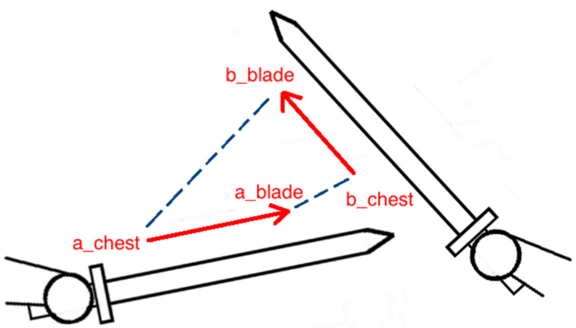
$$S_A = \sum_{i \in T_A} w_i$$

- HOI:
  - Considering individual effects and cooperation effects
  - The cooperation effect is modeled by inner product of two latent vectors

$$S_A = \sum_{i \in T_A} w_i + \sum_{i \in T_A} \sum_{j \in T_A, i \neq j} \mathbf{v}_i^T \mathbf{v}_j$$

Generality of NeuralAC

- Blade-Chest-Inner **[Chen et al. 2016]** :
  - Considering competition effects, and designed for one vs one case.
  - If player a's blade (strength vector $\mathbf{p}$) is closer to player b's chest (weakness vector $\mathbf{c}$) than vice versa, then player a has more edges when against player b.



$$S_a = \underbrace{\boxed{w_a}}_{\text{individual effect}} + \underbrace{\boxed{\mathbf{p}_a^T \mathbf{c}_b}}_{\text{competition effect}}$$

- If set team size of both sides to 1, NeuralAC can be reduced to:

$$S_A = \sum_{i \in \{a\}} w_i + 0 + \sum_{i \in \{a\}} \sum_{j \in \{b\}} \mathbf{p}_i^T \mathbf{c}_j$$

Experiments Setup

- Datasets
  - Each hero is treated as an individual
  - We filter out matches that played less than 15 minutes

Dataset	Matches	#Heroes	Mode
Dota2015	800,000	110	5v5
Dota2018	580,270	116	5v5
LoL	754,700	148	5v5
TFT	800,000	188	N1vN2

DOTA2

TFT

Experiments Setup

- Baselines
  - Logistic Regression (LR): A linear classifier with L2 regularization
  - Generalized Bradly-Terry (BT): Another linear model.
  - TrueSkill: An algorithm based on probability graph.
  - LightGBM (LGB): a state of the art machine learning algorithm.
  - HOI: A FM based model that takes pair-wise interaction of teammates into account.
  - OptMatch: A method that based on multi-head self-attention.

- Model Variants
  - no-coop: A variant of NeuralAC that does not consider the cooperation effect.
  - no-comp: A variant of NeuralAC that does not consider the competition effect.
  - no-att: A variant of NeuralAC that all attention modules are removed

Experimental Results

Individual effects

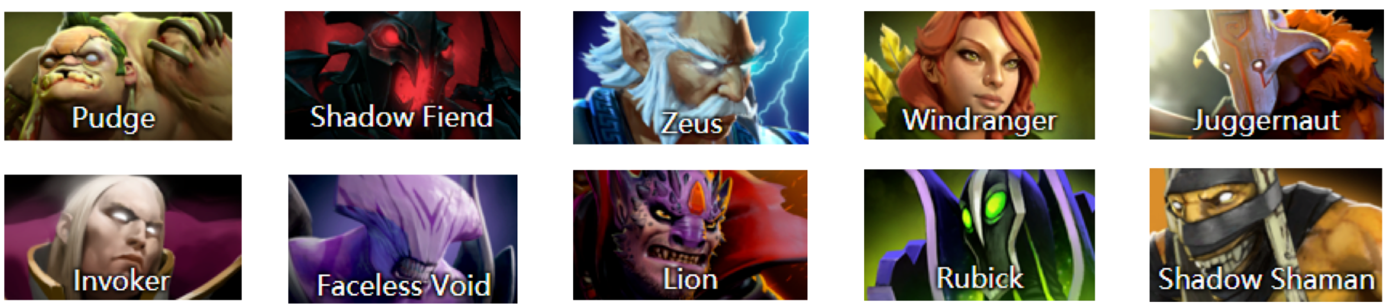
intra-team interaction

Model	Dota2015		Dota2018		LoL		TFT	
	AUC	Acc	AUC	Acc	AUC	Acc	AUC	Acc
BT	0.6330	0.5955	0.6116	0.5784	0.6347	0.5969	0.7634	0.6935
LR	0.6330	0.5956	0.6116	0.5784	0.6347	0.5969	0.7634	0.6935
TrueSkill	0.6110	0.5789	0.5805	0.5577	0.6129	0.5811	0.7506	0.6832
LGB	0.6445	0.6035	0.6224	0.5929	0.6411	0.6028	0.8015*	0.7234*
HOI	0.6373	0.5989	0.6144	0.5821	0.6337	0.5965	0.7728	0.6989
OptMatch	0.6325	0.5961	0.6173	0.5851	0.6523	0.6101	-	-
NeuralAC	**0.6615**	**0.6156**	**0.6411**	**0.6012**	**0.6663**	**0.6209**	**0.8082**	**0.7279**
no-coop	0.6525	0.6086	0.6333	0.5951	0.6531	0.6110	0.7992	0.7215
no-comp	0.6444	0.6051	0.6203	0.5841	0.6546*	0.6115*	0.7740	0.7000
no-att	0.6606*	0.6150*	0.6396*	0.5991*	0.6480	0.6070	0.7780	0.7037

- NeuralAC outperforms all the other baselines on all datasets.
- Compared with other variants, NeuralAC performs better, which proves the importance of incorporating comprehensive interactions, and attention mechanisms.
- no-comp performs better than HOI, which indicates that the inner product may fail to model complex interactions.

Model Interpretation

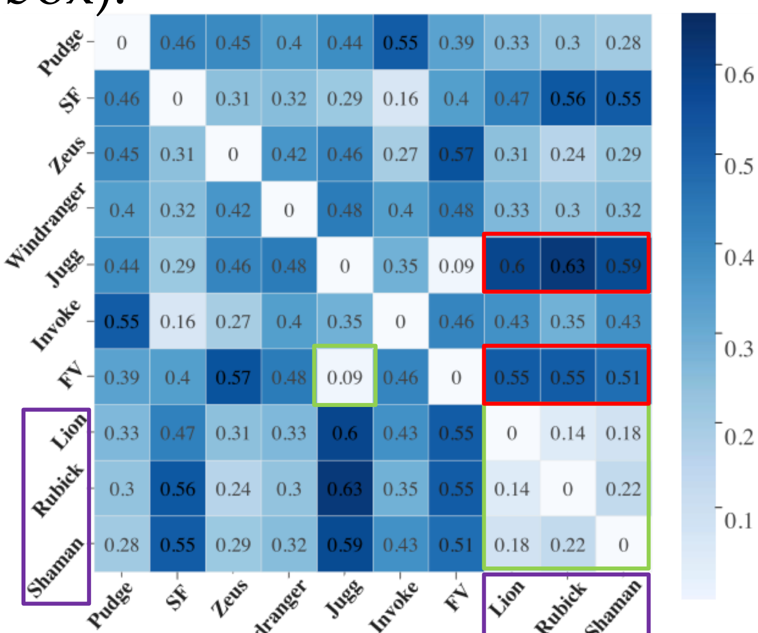
- We choose the most 10 popular heroes in Dota2018, then calculate their pair-wise cooperation scores, competition scores, and attention values separately.
- The most 10 popular heroes:



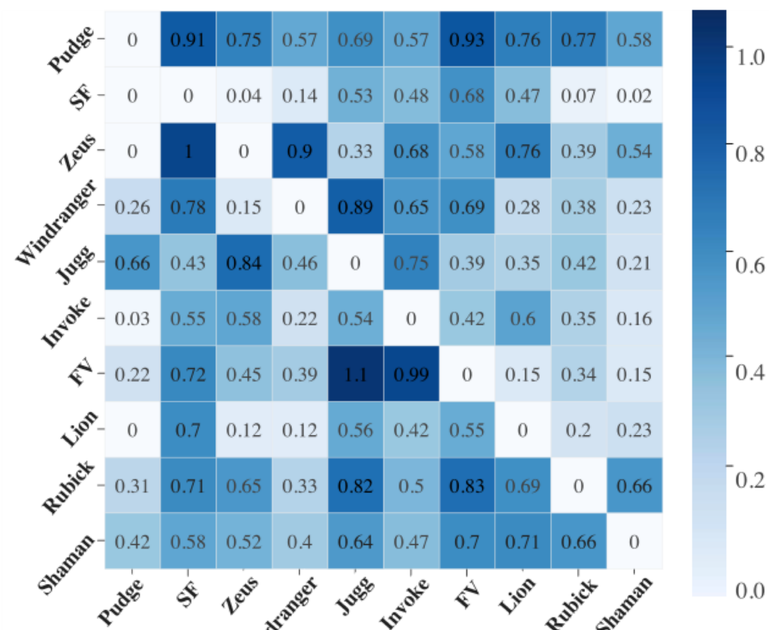
- Jugg and FV are melee Damage Per Second (DPS) heroes.
  Lion, Rubick, and Shaman are ranged wizards with stun spells.

Model Interpretation

- If two individuals *i* and *j* perform better when they play together, they are more likely to get a higher cooperation score.
- Jugg or FV get a high score when they play with Lion, Rubick, or Shaman (red box).
- The Cooperation score between Jugg and FV is extremely low (green box).



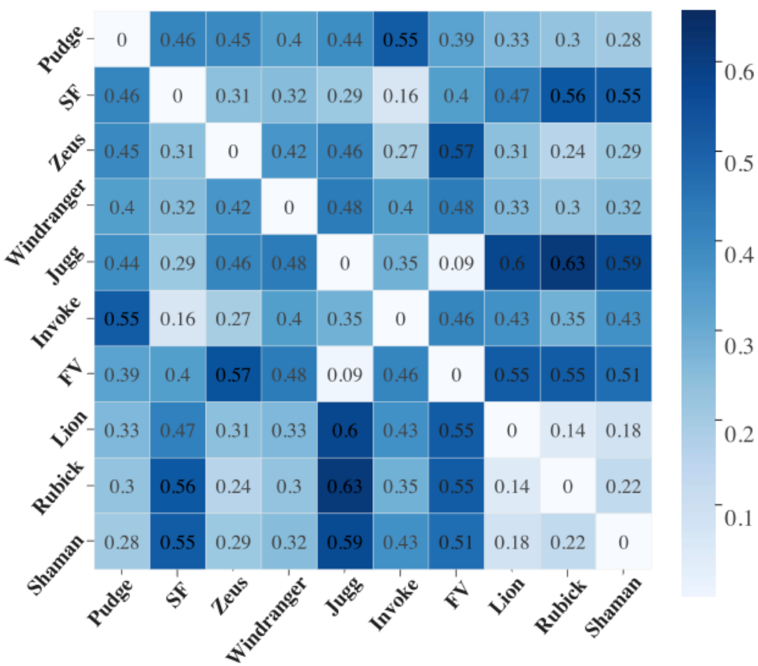
Cooperation scores



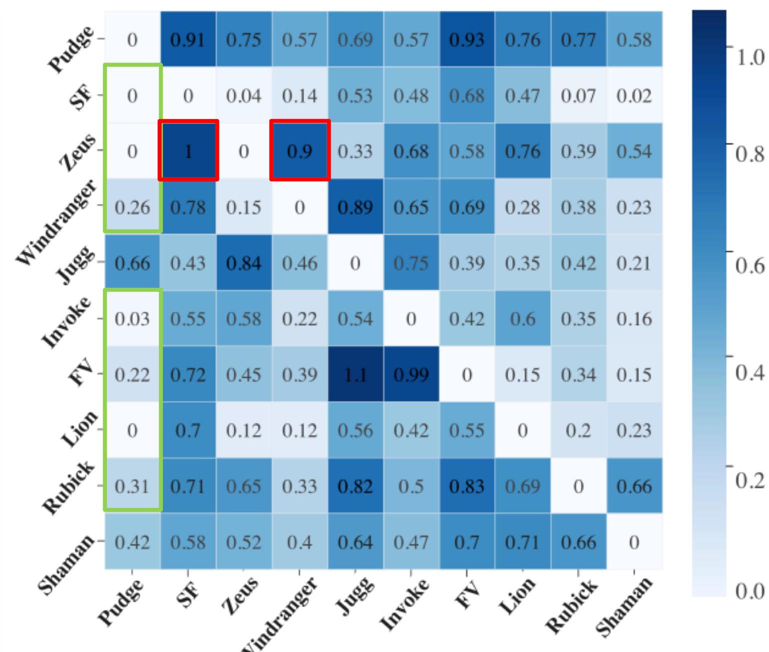
Competition scores

Model Interpretation

- Similarly, if i suppress j more when j is i's opponent, i is more likely to get a higher competition score over j.
- Pudge almost immune from SF, Zeus, Invoker, Lion (green box).
- Zeus gets high competition scores when he against SF and Windranger (red box).



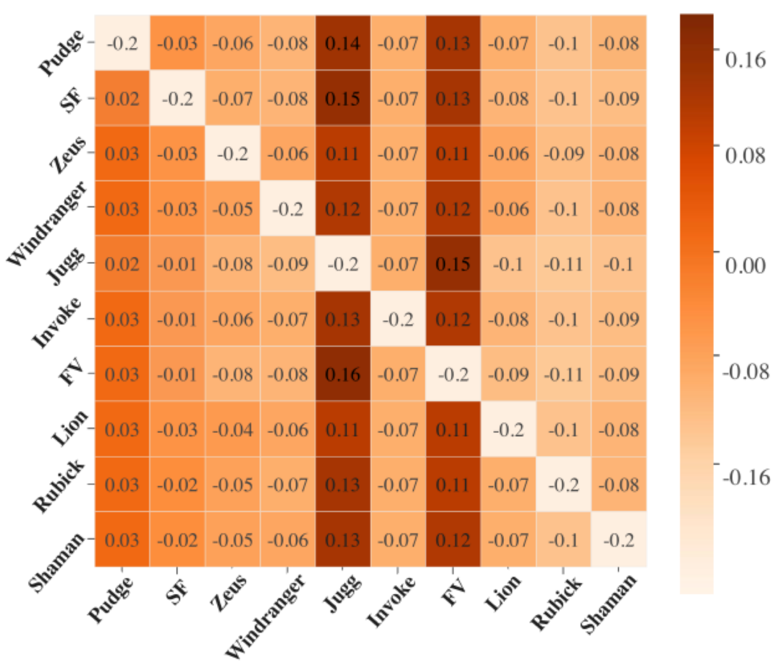
Cooperation scores



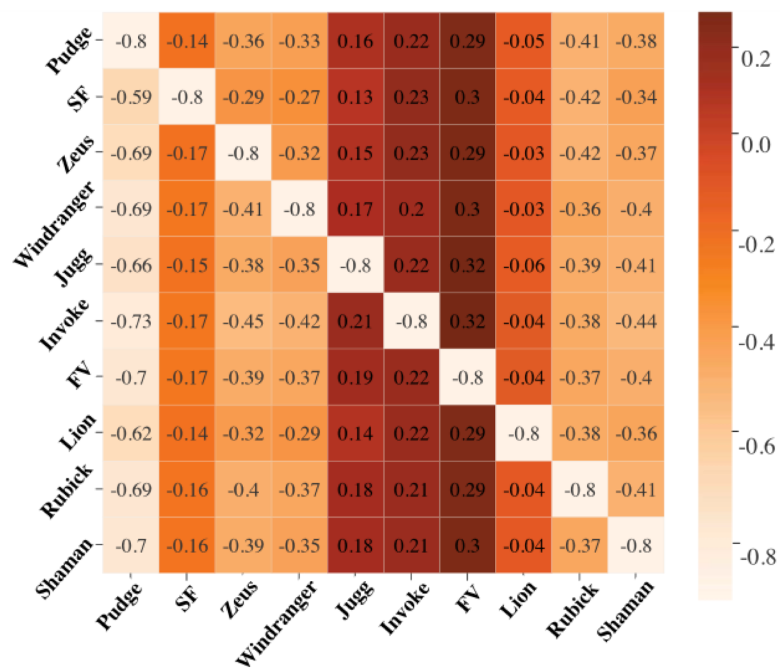
Competition scores

Model Interpretation

- Recall that the important ones receive more attention from teammates and opponents.
- Jugg and FV get relatively high attention values in two figures.
- Invoker get low attention from teammates, but high attention from opponents.



Cooperation attention values



Competition attention values

Impact of embedding size

- Our model consistently performs the best under all parameter settings.
- HOI performs slightly worse when embedding size increases.
- OptMatch performs unstable.

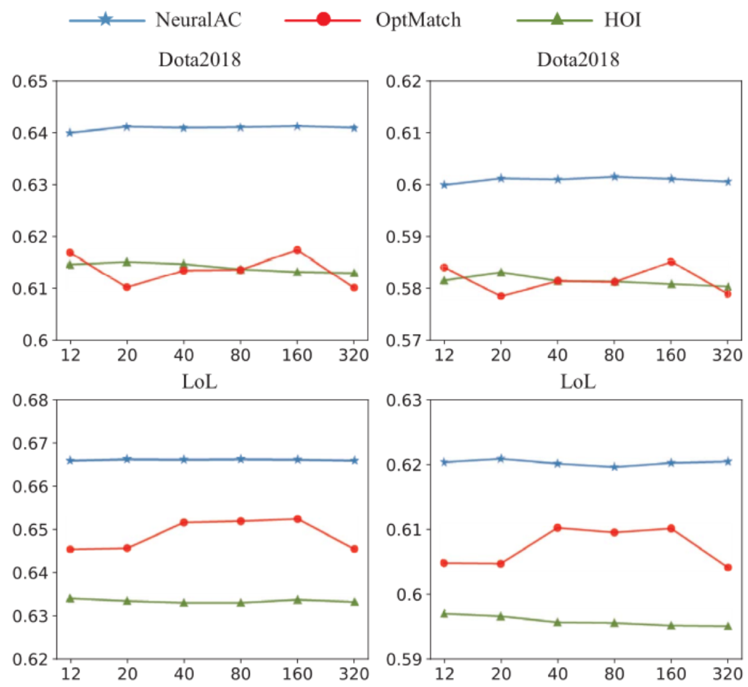


Figure 4: Test Acc and AUC w.r.t. embedding size k.

Conclusion & Future work

- Conclusion
  - We proposed a novel model: **N**eural **A**ttentional **C**ooperation-competition (NeuralAC), which models both attentional cooperation effects and attentional competition effects with deep neural networks.
  - Several previous methods can be seen as special cases of NeuralAC.
  - Extensive experiments showed the effectiveness of NeuralAC.
  - NeuralAC can provide meaningful and reasonable relationships between individuals. The intermediate results can be further used in team formations, online game hero recommendation, MOBA game balance detection.
- Future work
  - Explore higher order interactions
  - Consider human factor
  - Consider real world scenarios

Thank you for listening!

Codes: https://github.com/alphanumericmax/NAC