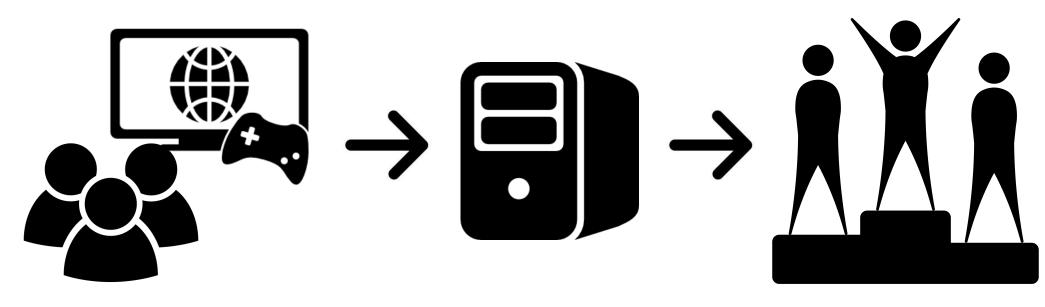
Player Behavior and Optimal Team Compositions in Online Games

Hao Yi Ong, Sunil Deolalikar, and Mark Peng CS 229: Machine Learning Class Project

Introduction

• In online role-playing games, players work in teams to accomplish a common objective (e.g., defeating an opposing team)



• In a game, given the teams' player compositions and their player statistics, we want to predict the players' play style and forecast the game outcome

Player behavior

- In-game play style; e.g., prefers
 Types of players on a team, each more offense-oriented strategies
- Also encompasses skill level
- Predict from player statistics

Team composition

- classified by their play styles
- Predict from game server database's match histories

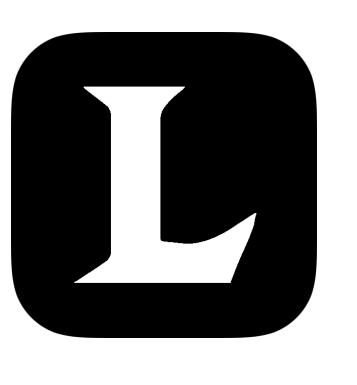
Problem Description

- Given
- Match histories containing participant IDs and match statistics
- Player statistics containing player histories and overall game statistics
- Output
- Play style classifier that groups players by their in-game tendencies given their game histories
- Outcome predictor that guesses which team will win given the various team compositions
- In order to
- Gain insight on player behaviors and game strategies
- Maximize accuracy on predicting game outcomes

Target Game

League of Legends

- Multiplayer battle arena game with 27 million plays per day
- Free online API to retrieve deidentified game data (120,000 training and 12,000 test samples)
- Official guide provides clustering information for players based on in-game character choices (e.g., character with good defense)



Baseline Outcome Predictor

- Features are team compositions for each team in a game based on official game guide's clustering information (each character is mapped to a play style)
- Logistic regression with 10% hold-out cross validation
- Poor accuracy of 55.1% on training samples, 54.4% on test samples

Behavioral Clustering

- Features are normalized player statistics (damage dealt, money earned,...)
- Clustering algorithms
- **k-means** with 10-fold cross validation over parameter k gave 12 clusters
- **DP-means** is an expectation-maximization algorithm derived using a Dirichlet process mixture model (Kulis and Jordan, 2012) Intuitively, a new cluster is formed whenever a point is sufficiently far away from all existing centroids, as determined by some threshold distance λ We ran it with 10% hold-out cross validation with $\lambda = 3.3$, giving 8 clusters
- Implementation in MATLAB, ran on 2.7 GHz Intel Core i7, 8 GB RAM

given training set of size N, threshold distance λ repeat until clusters converge

For
$$n=1,\ldots,N$$

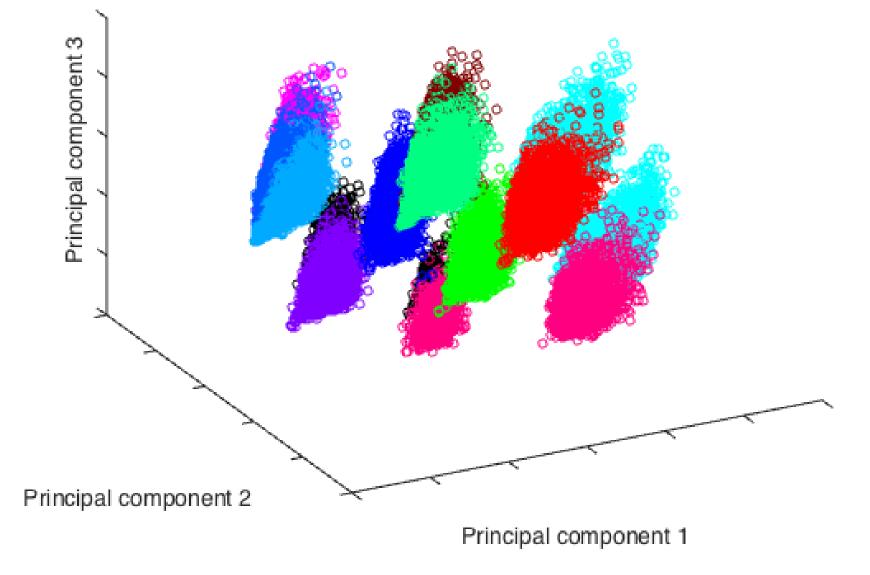
- 1. Assign sample n to the closest cluster if the contribution to objective from the squared distance is at most λ^2
- 2. Otherwise, form a new cluster with just sample n

Summary: Play style clustering algorithm results (10 trials average)

	cross validation method	no. of clusters	cpu time (s)
k-means	$k ext{-fold}\;(k=10)$	12	154.1
DP-means ($\lambda = 3.3$)	10% hold-out	8	65.4

Cluster Visualization

• Principal component analysis We used 3 principal components to visualize our full dataset in 3D; observe that the data is clearly clustered



Game Outcome Prediction

- **Features** are team compositions for each team in a game based on behavioral groupings generated from k-means and DP-means clustering
- Classification algorithms
- Logistic regression Lorem ipsum
- Gaussian discriminant analysis Lorem ipsum
- Support vector machine Lorem ipsum

Summary: Outcome prediction algorithm results (10 trials average)

	k-means (%)		DP-means (%)		cpu time (s)	
	train acc.	test acc.	train acc.	test acc.	k-means	DP-means
LR	72.25	68.75	69.67	67.11	7.4	7.1
GDA	74.79	70.14	70.88	68.39	7.7	7.1
SVM	74.75	70.39	71.71	69.21	91.2	41.6

Conclusion and Extensions

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