# D2Rec:
# A Dota2 Item Recommender System

Yukun Zeng | Guanlun Zhao | Victor Lin | Wei Shi

COMPUTER SCIENCE & ENGINEERING
TEXAS A&M UNIVERSITY

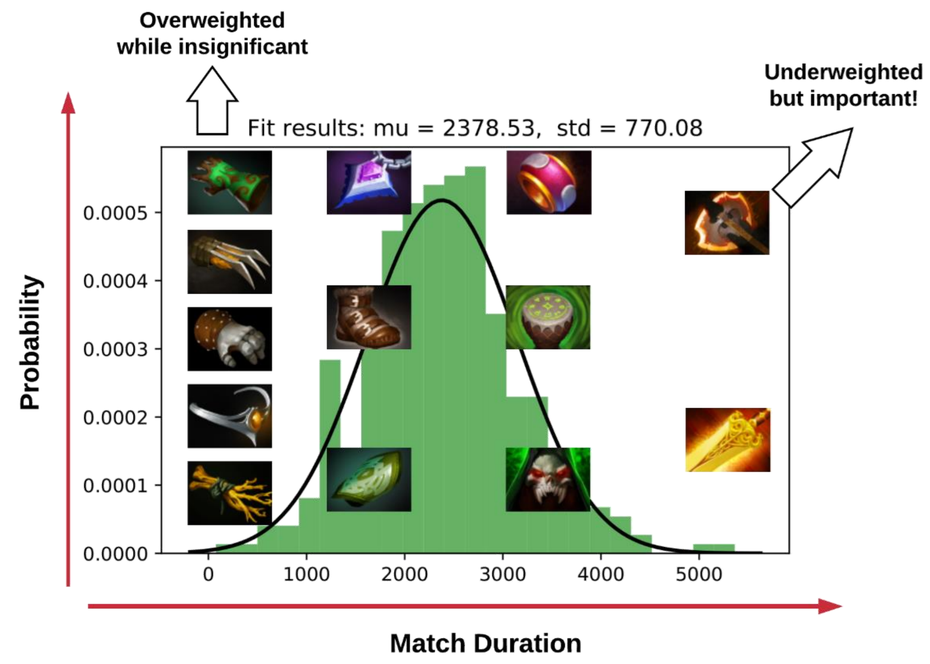
## Introduction

Dota2 is a popular MOBA (multiplayer online battle arena) game on PC. Dota2 is played between 2 teams of five players, with each team occupying and defending their own separate bases on the map. During each match, players update abilities and choose proper items to successfully battle the opposing team. As the match goes on, they need to update or purchase more powerful items to boost their capabilities.
In a big picture, a game match consists of the followings:

- 115 Heroes
- 150 Items (12 consumables, 86 craft-ables)

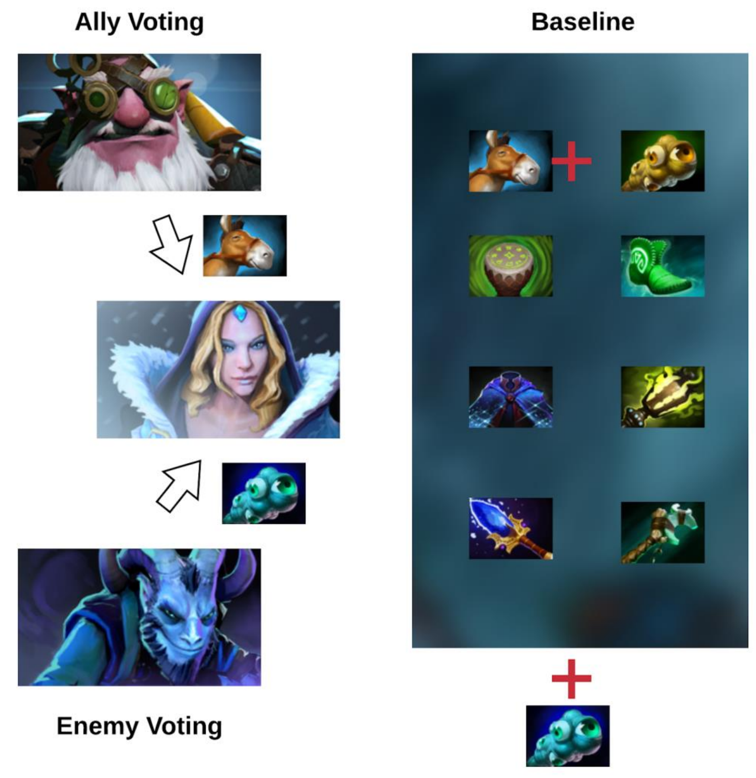
Our goal is to train several models to recommend most useful items as well as their buying order. By evaluating with testing set, we achieve the following similarities:

- Baseline: 0.69
- Wei: 0.75
- TDIPV with Classification: 0.76




▲ Item purchase distribution over different match stages: Basic items account for large percentage throughout time

▼ TDIPV's impact on Baseline model
- Ally/Enemy vote what they like/hate
  => baseline ranking changes based on team draft




## Core Algorithm

Basic Hero Item Preference

*baseline=[hero ✕ item]*

Captures basic statistical hero-item preference

- Assumptions
  - Item popularity indicates possible item fitness
  - Winning matches strengthen the fitness of an item
- Calculation: $baseline_{h,i}: p(h,i) = \alpha w + \beta l$
  - $\alpha,\beta$: Winning Score, Losing Score
  - $w,l$: Winning Match Count, Losing Match Count where hero h selects item $i$
  - Parameter setting: $\alpha > \beta$

Team Draft based Item Preference Variation (TDIPV)

Captures other heroes' influence on item choice

- Theorems
  - Enemy's enemy is my friend: items that statistically reduce enemy hero's winning rate
  - Friend's friend is my friend: items that statistically improve ally hero's winning rate
- Calculation
  - Ally Item Voting matrix
    $$\mathrm{AIV}_{h,i} = P(h\ victory|i\ in\ ally) - 0.5$$
  - Enemy Item Voting matrix
    $$\mathrm{EIV}_{h,i} = P(h\ lose|i\ in\ enemy) - 0.5$$
  - Matchwise Baseline Item Preference
    $$\mathrm{MBIP} = \mathrm{baseline}_h + \sum_{a \in Alley} AIV_a + \sum_{e \in Enemy} EIV_e$$
- Model evolutions
  - TDIPV with Classification
    - Items classified into several categories (Early/Mid/Final/Assist)
    - Learn per hero item category purchase amount
    - Basic items are reserved for better coverage
    - Hero-ally item voting
  - TDIPV with Crafting Tracking (Wei Model)
    - Basic/Consumables/Assistance items are not considered
    - The crafting process of final/intermediate items is tracked and only the goal item is considered
    - New dimensions capturing more specific hero-hero item voting

## Motivation

The current Dota2 game adopts a static item recommender system that suggests hard-coded best-suitable items for heroes based purely on their personalities. The official item recommendations for heroes can be found on:

https://dota2.gamepedia.com/Dota_2_Wiki

However the static approach is limited in the following aspects:

- The current recommender system disregards any other dynamic factors in a game, such as hero selection and item combinations of both camps, which might significantly determine key items for certain heroes.
- The manual efforts of maintaining a static recommendation table need to be updated repeatedly with version changes, gaming strategy evolutions, etc.

## Existing Resource

Thanks to Dota's the huge popularity and community efforts, multiple online resources providing a wide variety of game records have emerged over the past years. Our data were obtained from OpenDota.com, an open source game data platform offering past match information for both professional and amature players.

On OpenDota.com, each match is associated with a serial ID at the API endpoint with the URL:

api.opendota.com/api/matches/<MATCH_ID>

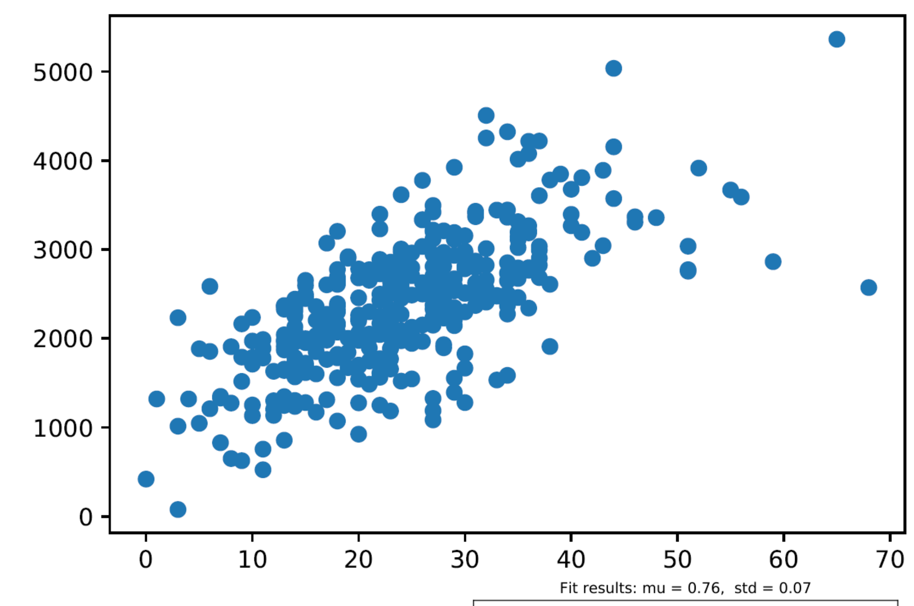
and can be downloaded in JSON format. Running in parallel, we were able to fetch enough match records with item purchase logs.

Apart from the match-related information, OpenDota also provided a direct-query API endpoint, allowing us to performed limited queries to its database directly. We were able to fetch important game metadata from this endpoint, including but not limited to hero information, item details, etc.

## Evaluation

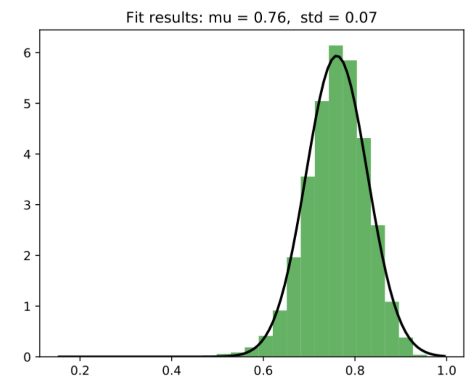
Item Classification

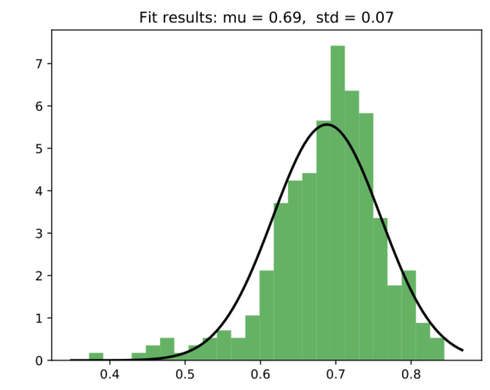
- Overweight in basic/intermediate items
  - Actual Frequency (weighted or not)
    *Freq(basic) > Freq(intermediate) > Freq(final synthesis)*
  - Importance in reality
    *Imp(basic) < Imp(intermediate) < Imp(final synthesis)*
- Need classification
- Learning to assign
  - Problems: total item purchases differ too much among heroes. Short matches may have up to 20 items per hero on average, while longer matches may have more than 50 items per hero on average.
  - How many Early/Mid/Final/Assist item to assign for each hero
  - Final is unknown due to noise and too less data available
  - Learn E/M/A item average count among all games the hero has x final items in the end (few cases where player buy cheap items after the first final items) for ideal match duration prediction.
    *F = FTIC – ( E + M + A )*
    Final Total Item Count (FTIC) = total item count 90% percentile among all matches.

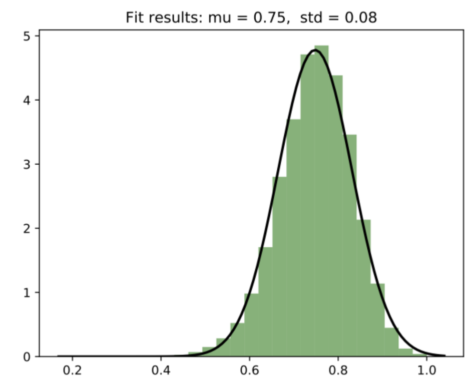


▲ Correlation between match during (Y axis, in seconds) and average item count (X axis)

▶ (Top) TDIPV Model
(Bottom)Wei Model
▼ Baseline




Evaluation Metric

- Similarity Distribution: measurement of predicted vs. actual items of winning teams: $\dfrac{\sum_{m \in M} \sum_{h \in P} sim_h}{|M|}$
- Conditional winning rate
  - Drawbacks:
    - Unfit for noisy and incomprehensive data
    - Sudden changes due to rare cases
  - Compactness of recommendation
    - More items in rec, more chances of hit: rec all items->100% hit rate
    - Too less recommendation->less flexibility for users

Result

We split our 65000 match json data into 50000 for training set and 15000 for testing set. The evaluation result gives us:

- Baseline: 0.69
- Wei: 0.75
- TDIPV with Classification: 0.76

Depending on the testing set, we have variations on the similarities:

| Model | Baseline | Wei | TDIPV |
|---|---|---|---|
| Similarity Range | 0.65-0.71 | 0.74-0.78 | 0.75-0.83 |

## Future Work

Capture temporal effects

- Item purchase count: linear relation with time
- Similar normal distribution pattern between purchase count and time
- Even more: capture E/M/F/A purchase proportion varying by time

## Project Website

dota2rec.github.io
Project information page, detailed information about our algorithms, techniques, examples and evaluations.

dota2rec.github.io/interactive
Get item recommendations for your team by selecting the heroes. View detailed, accurate item descriptions to learn your team's best combinations, and see what the opponents might use against you.