Dota 2 Strategic Evolution Analysis

Overall Goals

Fundamentally, our goal is to shed light on “How can we a) detect and b) quantify the rate of change of strategies in co - evolutionary systems".

This is akin to the classic 'Red Queen hypothesis' in evolutionary biology, but we are interested here in human behaviors where a strategy can be considered most generally as a 'meme' of sorts. As a use-case for this project, we have chosen to analyze data from an online battle arena video game called Defense of the Ancients 2 (Dota 2). Dota 2 is a strategy game between two teams that have to deploy various in - game and between - game tactics, techniques and procedures to achieve a specific measurable objective.

A beginning string of hypothesis :

- a) there exists a mapping between the observables in the game and a set of strategies,
- b) there is a measurable signal from which to ascertain the adoption, stabilization and decay of specific strategy traits
- c) there are changes in strategies over time and
- d) strategy changes are driven (at least in part) from behaviors of the opposing team

The context for this research is to inform the development of a new class of Adaptive Cyber Defense (ACD) technologies (Cybenko et.al. “Adversarial and Uncertain Reasoning for Adaptive Cyber Defense: Building the Scientific Foundation” 10th International Conference, ICISS, 2014). Traditional static cyber defense systems lack the ability to real-time assess changes in an adversaries behavior and require significant lead times to install patch updates. ACD technologies attempt to counter adversarial behaviors through continually changing “attack surfaces and system configurations”. An open question in this domain is “How can the effectiveness of such landscape changes be quantified using objective metrics?” We postulate the development of such measures will require an understanding of the co-evolutionary dynamics of the overall environment.In particular the human behavioral components underlying the adversary/defense team actions will need to be assessed. The use of data from a multiplayer online game for this purpose assumes there is a valid mapping between ‘game-space’ behaviors to ‘cyber-space’ behaviors from which useful inferences can be made. Through this exercise we hope to understand what types of data (if any) are useful for this purpose and how one might develop proxies to characterize strategies. Ultimately we hope that the analysis developed could be applied against realistic data specific to a cyber intrusion.

In what follows, we provide background about the game, a preliminary mapping of the data against the hypotheses and a sample analysis.

DOTA Data Overview

Dota 2 is a competitive 5 vs 5 multiplayer game where teams of 5 individuals compete against each other to complete objectives and destroy the other teams base. The game is played at a variety of skill levels, from people who have just played a few games, to professionals with thousands of hours of experience. There is a professional set of players, who compete for Tens of millions of dollars in prize pools each year. Millions of games of DOTA 2 are played each day. As of December 28th 2015, 2,036,858,090 games have been played.

Each game can be parsed (available for about a week at a time) using open source parsing tools to extract what characters were chosen, how each player performed, and some limited strategic information about how the game progressed. A repository of 500 GB (about 2.5 million games over 1 year) is available as a JSON data file which we have parsed and read into a mongo database.

The data includes about 6000 professional games played by teams competing for up to 15 Million dollars in tournaments, as well as another ~80,000 ticketed semi-pro / amateur league games. Such league games are particularly interesting because there is a pregame “Drafting” phase where the teams take turn picking the characters they will play (as well as banning some from being played by either team). This is done back and forth so each team must design their strategy in real time based on what they believe the other team is trying to accomplish.

Also of note is we have collected the raw replay files from a number of the largest professional tournaments. These can be parsed with a java parser into an event list that contains (potentially) every activity of every player at every “tick” of the game. Thus one could reconstruct all sorts of interesting dynamics about the behavior of players. For instance the current dataset contains some information about where players are on the map for the first 10 minutes of each game. Using these raw replay files one could track players positions (as well as their camera positions) over the entire game and analyze how much time teams spend grouped together and how much time they spend spread apart.

The data we have collected is from one of the websites that tracks games. Three examples of these are given below. They all use the same Java based parser to parse the replay files above that are available from the company who makes the game for about a week after every game is played.

Sites that track stats:

http://yasp.co/ (open source started by some grad students I think)
http://www.dotabuff.com/ (according to match id’s there have been over 1884579074 games played in total (its over 2 Billion now)
http://www.datdota.com/ (only professional matches)

Java Parser: https://github.com/skadistats/clarity

Dota Background

Here are a number of links for background:

Dota 2 is broadcasted on twitch.tv much like professional sports. Here is a link to a video that starts with a brief overview of the game and then proceeds to a broadcast of the final game of the largest tournament so far:

http://www.twitch.tv/dota2ti_newcomer/v/10164406?t=478m21s

The total prize pool for this tournament 18.4 Million dollars and the winning team took home 6.4 Million dollars.   Interestingly most of this prize pool was crowd-sourced by selling in game items and an interactive “program” that allows players to guess who will win games and other statistical questions. The prize pool started at 1.6 Million dollars and the rest was added by selling these in game items. The company who makes the game (Valve) keeps 75% of the money for each sale, meaning they made over **50 Million dollars selling in game items**

In organized games the 5 players on each team each play a different role. Here are a series of short youtube videos that describe each role:

https://www.youtube.com/watch?v=k7CoR71Vapo&list=PLxkyNsoBqOdBGfqZNbJwcz5UiL7rhrk3h&inde

x=1

A documentary made a few years ago about some professional players:

https://www.youtube.com/watch?v=UjZYMI1zB9s

Here is a new players guide:

https://purgegamers.true.io/g/dota-2-guide/

Strategy and Dota Hypotheses

Observables and Strategies

The easiest way we can directly measure strategies is by examining the drafts of organized and professional games.   More about drafting can be found below in the drafting section

Measurable Signals

Again the easiest measurable signals are the drafts that start organized games. More about that below

Changes in Time

Dota is a game that changes in time across multiple time scales. Within a particular match the game progresses over loosely defined stages. In the beginning players are often fighting the environment more than the enemies. By the end of the game the players have gained strength and are now fighting each other more.

There is also a longer time scale where “meta-game” changes in strategies occur. Teams and players determine new ways to combine the 100+ heros for maximum effectiveness as well as different strategies for how to use the map and when they would like to end the game. This is further complicated by the fact that the game is constantly evolving through a series of patches. These patches introduce new heros and items, change the statistics and skills of all of the heros, as well as make other broad changes to the game in an attempt to keep it “balanced” and to promote certain types of play.

Strategy Changes Driven by behavior of opposing team(s)

A game of DOTA 2 typically takes between 20 and 60 minutes. Over this time, each team must work together to complete their objectives while also defending against the enemy team. For best success, each team enters the game with a plan for how they will win the game (for example how long they want it to last based on the characters they chose and how they position). Over the course of the game this strategy may need to change based on their current level of success and the postures taken by the enemy team.

In addition, in competitive DOTA each game starts with a draft. During the draft each time takes turns picking the characters (heros) they will play as well as banning heros so neither team can pick that particular character. The drafting in itself is an example of how the teams must adaptive their strategies in real time to the behavior of the other team. The drafter must quickly ascertain what strategy the opposing team is attempting to use so as to pick heros that are good against that strategy or ban heros that are key components of the strategy.

Main Dataset

For an example of what the data in the main dataset looks like please have a look at this page:

https://github.com/yasp-dota/yasp/wiki/JSON-Data-Dump

Drafting

As part of the data dump from yasp.co we have created a .csv file that contains drafting information for professional Dota 2 games. Dota 2 is a 5v5 competitive action real time strategy game played by millions of people around the world. It is a complex game (and most likely highly over engineered). There are over 100 heros that players can select to play as, each with unique skills and statistics. In addition there are over 100 items that players may purchase over the game to improve their stats or give their characters new abilities

Each professional game starts with a “draft” where each team selects what heros they would like to play and what heros they would like to remove from consideration by both teams. This is a process of 20 choices that goes in the following order (where B is a ban and P is a pick):

B1 B1 P1 P1 B1 B1 P1 P1 B1 P1

B2 B2 P2 P2 B2 B2 P2 P2 B2 P2

As one can see above the draft starts by each time removing 2 heros from consideration **by either team**. This is done so as to remove either heros that the team considers to be very strong at the current moment overall or heros the other team is particularly good at.

One way to look at this data is that heros that are picked or banned early in this sequence are the highest valued by the two teams.

Data:

Lets take a look at the data:

```
dota = Import["/Users/dslater/dota_pro.csv", "CSV"];
dota⟦2 ;; -1, 2⟧ = ToExpression[dota⟦2 ;; -1, 2⟧];
header = dota⟦1⟧;
data = SortBy[dota⟦2 ;; -1⟧, Part[#, 4] &];
```

```
header // TableForm
```

```
pickfirst
seq
leagueid
start_time
dota_version
lobby_type
match_id
radiant_name
league_name
radiant_win
dire_name
```

Each entry in the data has the above information in it. Match_ID is the unique identifier for the match. This can be used either with the mongoData base or one of the websites that track games to get more information about that particular game:

```
TableForm[data[[-500]], TableDepth → 1, TableHeadings → {header}]
```

pickfirst	R
seq	{50, 55, 28, 100, 106, 19, 72, 21, 3, 62, 26, 58, 90, 68, 99, 98, 111, 87, 60,
leagueid	4088
start_time	1.45043×10^9
dota_version	6.86
lobby_type	1
match_id	2 010 299 165
radiant_name	Team Secret
league_name	World Cyber Arena 2015 GRAND FINAL
radiant_win	
dire_name	the wings gaming

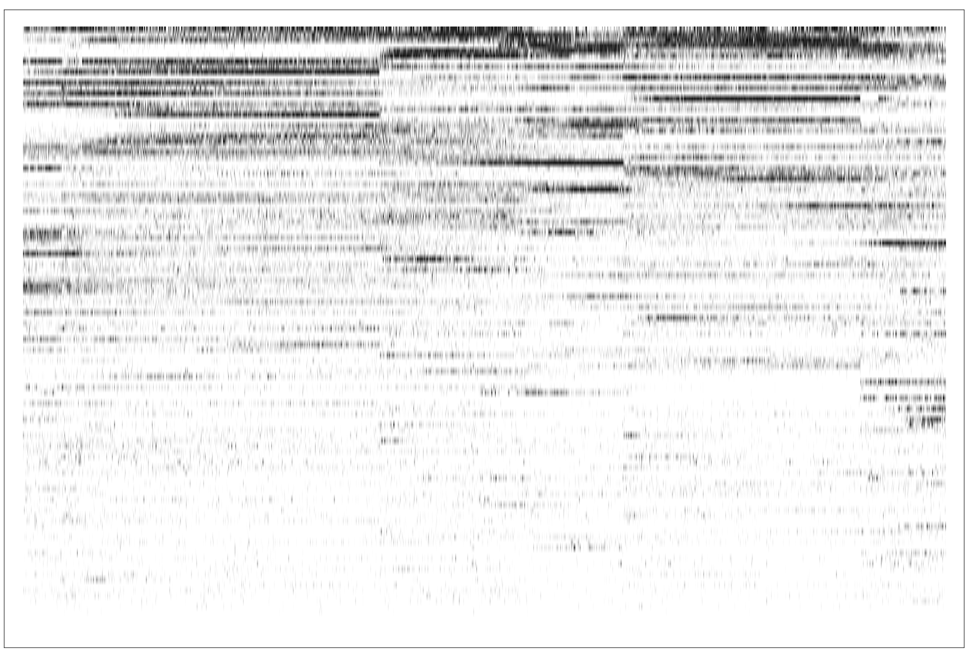
https://yasp.co/matches/2010299165
http://www.dotabuff.com/matches/2010299165
http://www.datdota.com/match.php?q=2010299165

Picks Over Time For The Full Dataset

Lets start by just looking at all picks over time and create a new data structure where each column is a game and each row is a hero. The entry in the row is the importance of the pick, 20 if its banned first, 1 if its picked last, and 0 if it is not picked at all.

```
bb = data[[All, 2]];
fig = ConstantArray[0, {113, Length@bb}];
For[k = 1, k ≤ Length[bb], k++,
  For[j = 1, j ≤ Length[bb[[k]]], j++,
   fig[[bb[[k, j]], k]] = 21 - j;
  ]
 ];
```

```
ArrayPlot[Reverse@SortBy[fig, Total], ImageSize → 500, AspectRatio → 2 / 3]
```



Here we can start to see clear times when heros change from being popular (dark) to unpopular (light) and back. This can be overlayed with patches. Dota 2 is continuing being updated with large patches that change hero abilities, hero statistics as well as introduce new heros and items and modify the game in other ways. There are three patch changes int his data:

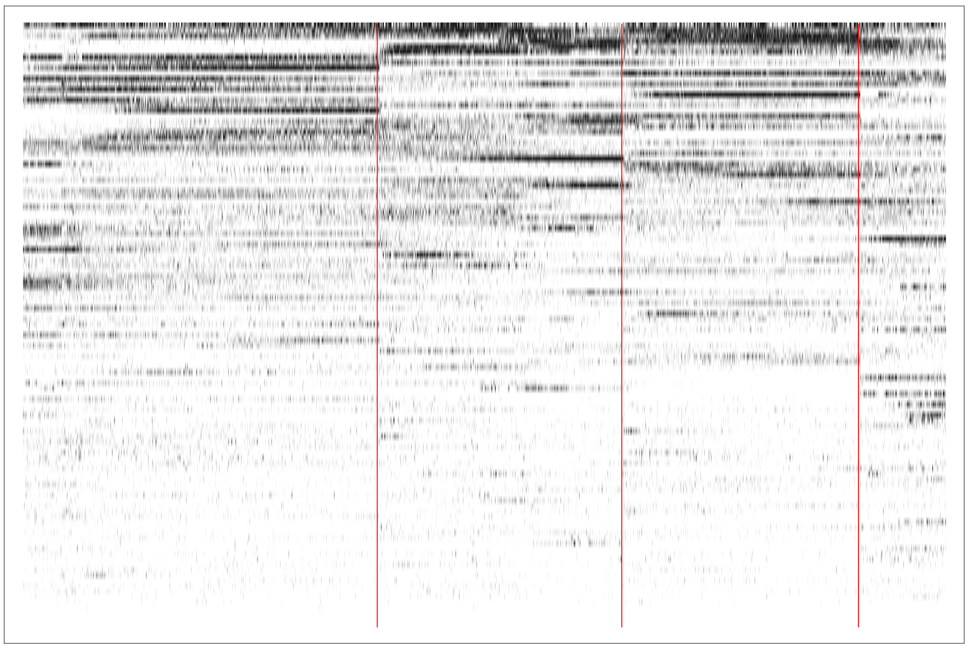
```
DeleteDuplicates[data[[All, 5]]]
patchChanges = Position[Differences[data[[All, 5]]], _?(# ≠ 0 &)] // Flatten
```

```
{6.83, 6.84, 6.85, 6.86}
```

```
{2259, 3825, 5341}
```

We can overlay when this occurs in our data:

```
Show[ArrayPlot[Reverse@SortBy[fig, Total], ImageSize → 500, AspectRatio → 2 / 3],
 Graphics[{Red, Line[{{2259, 0}, {2259, 113}}],
   Line[{{3825, 0}, {3825, 113}}],
   Line[{{5341, 0}, {5341, 113}}]}]]
```



Here we can clearly see that changes in popularity of heros often happens when patches are released, but also happen across the dataset at other times as well.

Picks Over Time For One Team

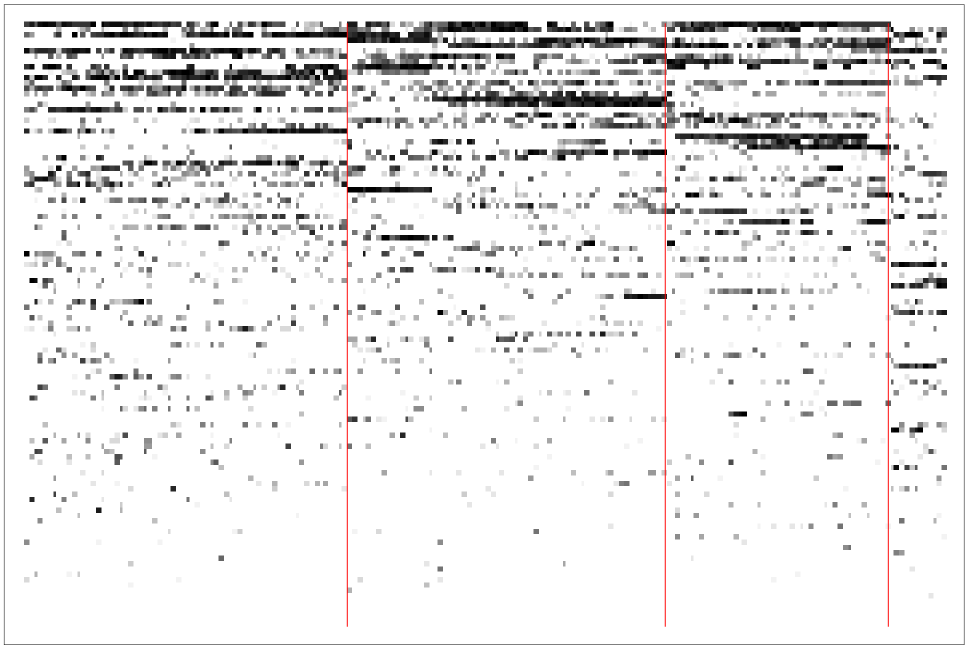
Now we can start asking questions about teams over time. Lets look at evil geniuses the top North American Team

```
egGames = Select[data, (#[[8]] == "Evil Geniuses" || #[[11]] == "Evil Geniuses" &)];

bb = egGames[[All, 2]];
figEG = ConstantArray[0, {113, Length@bb}];
For[k = 1, k ≤ Length[bb], k++,
  For[j = 1, j ≤ Length[bb[[k]]], j++,
   figEG[[bb[[k, j]], k]] = 21 - j;
  ]
 ];
```

Now we can plot hero picks over time, sorting by the most popular heros. Not that as above we are not separating by which team is picking (that is future work to be done) but simply looking at the popularity of heros in games that Evil Geniuses played:

```
patchChangesEG = Flatten@Position[Differences[egGames⟦All, 5⟧], _?(# ≠ 0 &)];
Show[ArrayPlot[Reverse@SortBy[figEG, Total], ImageSize → 500, AspectRatio → 2 / 3],
 Graphics[{Red, Line[{{patchChangesEG⟦1⟧, 0}, {patchChangesEG⟦1⟧, 113}}],
   Line[{{patchChangesEG⟦2⟧, 0}, {patchChangesEG⟦2⟧, 113}}],
   Line[{{patchChangesEG⟦3⟧, 0}, {patchChangesEG⟦3⟧, 113}}]}]]
```



Again we see patches significantly impacting picks, but also other changes in strategies that do not match up with patches

Measuring Change Over Time

One of our goals is to be able to measure how strategies change over time (both for all teams and for individual teams). Here is a first attempt at this.

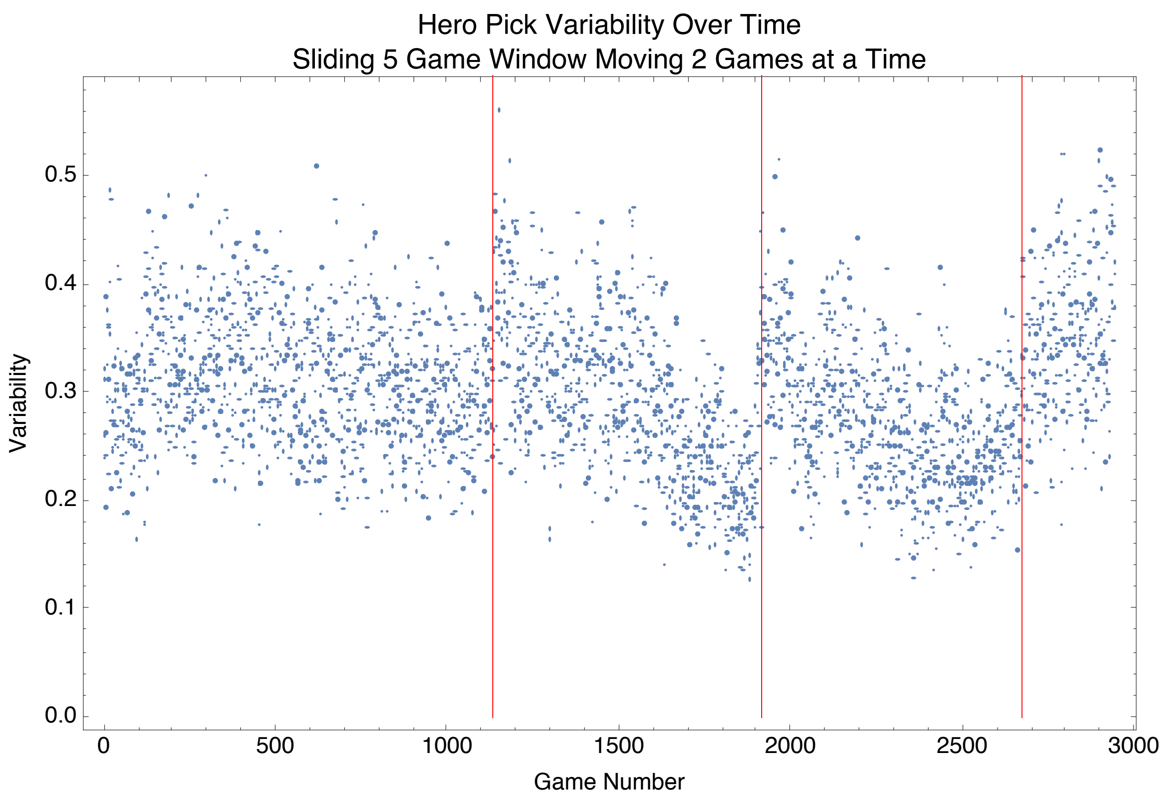
Break the sequence of games into overlapping windows of N games. Then for each pair of overlapping windows, compute the difference in “score” across all heros. Here is a brief example:

Suppose over the first 5 games hero X was always banned first. The score for that hero is then $20*5 = 100$ for that window. Suppose then the second window the hero was banned first twice and then last picked three times. The score for that hero in this window is then $20 + 20 + 1 + 1 + 1 = 43$. The difference is then $| 100 - 43 | = 57$. The total variability between these two windows is the sum of this calculation over all heros. The maximum variability is numHeros * Total[Range[20]] * windowSize

```
explore = Transpose[fig];
variability = {};
step = 2;
win = 5;
overlap = 2;
patchPos = {};
For[k = 1, k ≤ Length@explore - overlap - win, k = k + step,
 one = explore[[k ;; k + win - 1]];
 two = explore[[k + overlap ;; k + overlap + win - 1]];
 If[MemberQ[patchChanges, k],
  AppendTo[patchPos, Length@variability];
 ];
 AppendTo[variability,
  (Total@Abs[Total@one - Total@two]) / (Total[figAll[[All, 1]]] * win // N)];
]

patchChanges
Show[ListPlot[variability, PlotRange → All, BaseStyle → 12,
  ImageSize → 600, FrameLabel → {"Game Number", "Variability"},
  Frame → True, PlotLabel → "Hero Pick Variability Over
     Time\nSliding 5 Game Window Moving 2 Games at a Time",
  Epilog → {Red, Line[{{patchPos[[1]], 0}, {patchPos[[1]], 1}}],
    Line[{{patchPos[[2]], 0}, {patchPos[[2]], 113}}],
    Line[{{patchPos[[3]], 0}, {patchPos[[3]], 113}}]}]]
```

```
{2259, 3825, 5341}
```



Here we do start to see one of our hypothesis that within a patch the variability of picks decreases as teams figure out the strongest heros.

Sample Future Analysis To Do (Brainstorming)

1. Break out analysis by team.
2. Analyze the pick order to understand how good the various teams are at adapting to what the other team picks / bans.
3. Teams often play best of 3 or best of 5 series. We could look at how well they adapt to what each other do within these environments