Breaking Up with your Girlfriend but not your Friends: A Cyclic Graph Algorithm for Social Network Preservation

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Abstract Tiffany and I broke up. While I am heart broken, thanks for asking, I'm left with an even larger task at the end of any relationship; how do I maintain my social network when we share all of the same friends? I have been with Tiffany for years, so naturally, we have all of the same friends. I would like to keep all of them. But I can't be in the same room as her without getting into another stupid argument because "I don't know how to listen" whenever I'm doing something wrong. She knew this when she started dating me, I'm not a mind reader! I'm not going to know when me and my friends are being too loud, we were playing Warhammer this weekend, everyone knows that game takes like 33 hours and we'd be up that late! It's not like it was the first time. Regardless, it was a messy breakup and to keep my friends and not run into her every other night, this paper develops cyclic graphical representation of all our social network and develops an algorithm so that I don't accidentally run into her so that she'll think "I can't live without her, because I can't take care of myself."

1 Introduction

According to Tiffany, this break up is a long time coming [1]. Apparently, I spend way too much time playing video games [2], don't do enough chores [3], and spend way too much money on my gun collection [4]. She also thinks I don't listen to her or understand how she's feeling even though I've perfectly optimized both processes [5, 6]. Maybe I think SHE's too manipulative, and controlling of my spending habits. She still doesn't want me to buy that speed boat. I'd buy it already if I didn't need her to cosign on the loan.

Tiffany and I have been together since 2015. We met Sophomore year so we have all of the same friends. We have all of the same college friends, a trivia group together, the board game group, we go to the same bars, and the same restaurants with a lot of the same people. as shown in the Venn diagram in Figure 1 there is plenty of intersection each clique as well. Even if we decided to split up our friends, there would be awkward intersections.

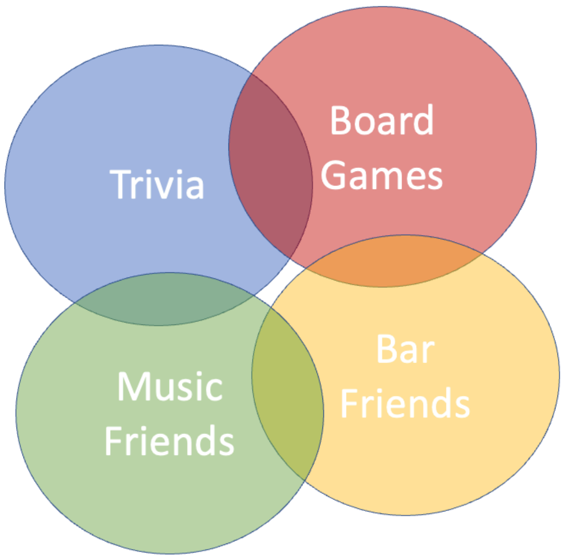

Fig. 1: Venn Diagram of the social structure.

It's all really fresh right now. I'm supposed to move out next week, and I need to restructure my entire social network now before things start to get really awkward. Though some research has been done in this field applying unsupervised machine learning to cluster out and classify friend groups [7], this would be too great a loss for the both of us.

Additionally, if I don't see those same friends, Tiffany's totally gonna talk trash behind my back and that gets around. I can't have her spreading rumors around about my unpopular opinions or some fantasies I've had that are completely normal [8]!

1.1 Background

I have done an extensive mapping of our friend group based on non-intrusive and totally not creepy group text analysis [9]. As shown in figure 2, friends can be structured into the graphical clique structure with a dizzying amount of arrows. The strong couples modeled as pairs are represented with blue double arrows while the weak couple is modeled with a red double arrow. We don't know how Jeff and Lisa are still together. The red dot is of course Trevor. The rest of the dots are weakly bonded together as acquaintances who know me and Tiffany and each other only casually. The clique structures grouped into our trivia night friends, the board game night friends, bar friends, and those that only show up for live music events. Naturally, some board game friends may only want to go to trivia while some only want to go out and drink because trivia night interferes with events such as them not wanting to admit they're bad at trivia. Naturally, none have the aerobic stamina to brave the mosh pits at any live music events. They aren't new-grass festivals in the park.

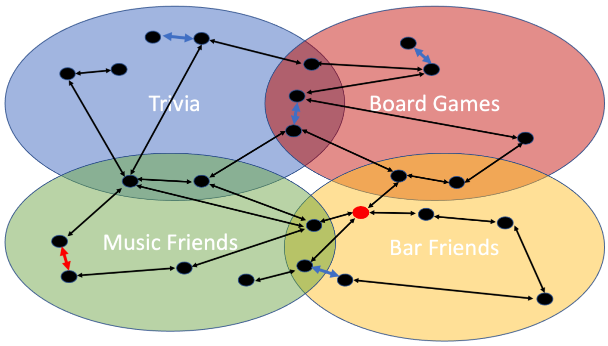

Fig. 2: Graph Representation of Social Network.

After doing extensive forecasting of Tiffany's social calendar, it has become trivial to predict her involvement in any group social outing down to an error level of 0.3 Rain Check Units (RCUs) [10]. By modelling the predictive outcome of her next outing and accounting for the RCU based covariance state transition filter, a pattern has emerged which clique she is more likely to hang out with given a previous hang out. Of course, rules regarding special circumstances do apply. If it's half priced marg night, she will likely be with the bar crew at 11th Street Tavern. Likewise, if *X and Yellow* play, her favorite Cold Play cover band, she will be with the our live music friends. Naturally, hanging out with one clique will create plans with another and so on, through the cyclic graph social network.

While it is important that the algorithm ensures that I will never appear at the same outing as Tiffany, this will not be the only objective. I have a strong suspicion that she will be talking smack about me behind my back and I may need to do some damage control. This algorithm will only be successful if I can maintain my friendships. If they believe her when she talks about my controversial opinion that I don't think Bernie can make it this year, or that Game of Thrones is over rated, I won't get invited back to trivia night. I won't get invited back to the bar if she spills my secret regarding [8] who are hyper critical of furries. They ruined her whole character in the new space jam. I don't have a suit or anything.

2 Methodology

Three algorithms are proposed and tested against the historic Tiffany social outing data. Using the Tiffany Depth-First Search (TDFS) method in [10] a distance can be established for determining the likeliness of Tiffany hanging out with the same clique of friends. One algorithm optimizes the DFS while the others optimizes the TDFS Tiffany Social distance while minimizing either the time before or after her appearance in the social clique. Appearing in a clique shortly after Tiffany may allow me to dispel dangerous rumors she may be spreading. Similarly, making a social appearance before her may get ahead of the story so that she won't be able to spread anything too damaging. This will be estimated using and Expected Tiffany Rumor Damage (ETRD) model given a positive ($ETRD^{+}$) and negative ($ETRD^{-}$) lead rumor control prior developed after a comparative study after I studied my poor handlings of her pregnancy scares with her friends and family [11]. Additional social event maximization algorithms such as the Maximum Fun Model (MFM) or the Time Commitment Minimization (TCM) Technique [12] may eventually be integrated. Finally a normalized Tiffany Social Forecast Error (nTSFE) is estimated as $nTSFE = \sqrt{\Sigma(TSFE^2)/RCU}$. The nTSFE is assumed to be normal and not something scary to work with.

2.1 Maximum Tiffany Distance Algorithm

The Maximum Tiffany Distance Algorithm (MTDA) optimizes staying away over anything else. It does not weight in ETRD and only returns "a stay home tonight" if the minimum nTSFE is below two standard deviations. The algorithm is shown in Algorithm 1.

Algorithm 1 The Maximum Tiffany Distance Algorithm

$NearestCliqueHangOuts = SocialCalendar[Today : Today + 1Month]$
$Y \leftarrow RawDistanceScores$
for all $Eventin(NearestCliqueHangOuts)$ **do**
  $Y = TDFS(Event)$
  $Y = FoodTruckCorrection(Y|Event)$
  if $exists(HalfPricedMargs(Event))$ **then**
    $Y = Y/1.8$
  end if
  if $exists(Trevor(Event))$ **then**
    $Y = 3.3Y$
  end if
end for
$GOTOEvent = Max(Y)$
$nTSFE = \sqrt{\Sigma(TSFE(GOTOEvent)^2)/RCU}$
if $nTSFE < 2$ **then**
  $StayHomeAndWatchForgedInFire \leftarrow FALSE$
else
  $PickUpBeer \leftarrow TRUE$
  $StayHomeAndWatchForgedInFire \leftarrow TRUE$
end if

As shown in the algorithm, after adjusting the TDFS for the constants developed in [10] regarding Food Truck preferences, Marg deals, and Trevor who I swear has been hitting on her for a year now. I don't even think he was really in the Peace Corp.

2.2 Leading Minimum Tiffany Distance Algorithm

Second, the Leading Tiffany Distance Algorithm (LTDA+) determines the closest event in time on the Y^+ shifted estimate and determines the event which maximizes the leading trash talk to nTSFE ratio $ETRD^+/nTSFE$ where the $ETRD^+$ is estimated for a new argument. The full algorithm is shown below in Algorithm 2

Algorithm 2 Leading Tiffany Distance Algorithm

$NearestCliqueHangOuts = SocialCalendar[Today : Today + 1Month]$
$Y \leftarrow RawDistanceScores$
$X \leftarrow ETRD^+$
$Z \leftarrow LeadingTrashTalkRatio$
for all $Eventin(NearestCliqueHangOuts)$ **do**
  $Y = TDFS(Event)$
  $Y = FoodTruckCorrection(Y|Event)$
  if $exists(HalfPricedMargs(Event))$ **then**
    $Y = Y/1.8$
  end if
  if $exists(Trevor(Event))$ **then**
    $Y = 3.3Y$
  end if
  $X = ETRD^+(Event|newarguement)$
  $nTSFE = \sqrt{\Sigma(TSFE(Event)^2)/RCU}$
  $Z(Event) = -X/nTSFE$
end for
$GOTOEvent = Max(Z)$

With algorithm 2, I should be able to ensure that my side of any new argument is heard first. Between our vitriolic texting or issues surrounding being split dog parents of Franky (the catalyst of the heavily biased dish chore optimization problem in [3]), there will likely always be some new argument to get ahead of.

2.3 Lagging Minimum Tiffany Distance Algorithm

Repeating the method shown in Algorithm 2, the Lagging Tiffany Distance Algorithm (LTDA-) operates neary identically with the exception of doing damage control for whatever Tiffany said at the last Clique hang out. This algorithm instead estimates $X = ETRD^-(Event|oldarguement)$ to minimize rumor damage already done.

3 Results

Each algorithm was tested for a month of post breakup social outings. For each event, our entire friend group was given a short 48 question survey to measure the total $ETRD$. For the next iteration, it is highly encouraged to keep the survey under eight questions to avoid inducing further $ETRD$. As shown in figure 3, while the Leading algorithm performed the best at first, it appeared the pettiness of trash talking Tiffany began to alienate some of my friends. While the lagging algorithm did not come off as petty as the leading algorithm, it did not improve my reputation among our friend group over Tiffany's as did the Maximum Distance algorithm in which I gave everyone space and minimized drama.

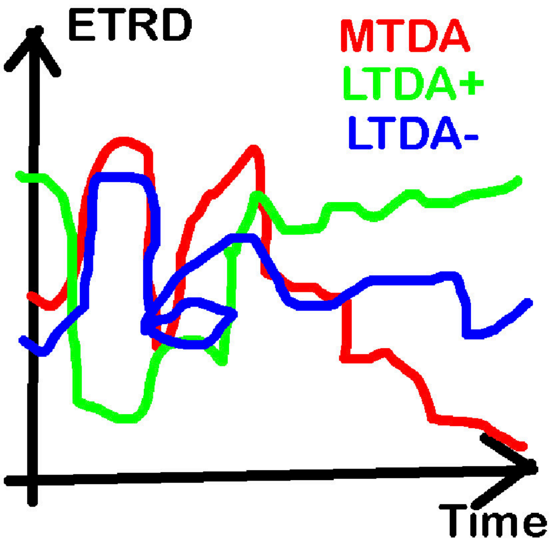

Fig. 3: ETRD Results

Additionally, the LTDA+/- algorithms produced more than an 800 percent increase in the likeliness of accidentally running into Tiffany compared to the MTDA. This may have been responsible for the increase in ETRD. When I got into a very public and loud fight at 11th street when I asked her to leave so she wouldn't taint the results of my survey, that lead to a sharp increase in damage to my social standing and a withdrawn invitation from the *Love is Blind* watch party I didn't want to go to anyway. It didn't help that Trevor was there and their hug-hello lasted a little too long. It appears that the RCU estimates developed in [10] are either under confident or not properly scaled with the ETRD metric.

4 Conclusion

By applying these algorithms, I'm going to win this break up and I won't have to get new friends. Properly tweaking the RCU and ETRD metric for a better implementation of the algorithm will be paramount because I do not see us getting back together, even though she says I won't last a month without her without crawling back and saying I'm sorry. I'm not apologizing for being loud in my own home, I got her noise cancelling head phones for a reason.

5 Acknowledgements

I would like to thank Jack Daniels for helping me through these hard times.

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