Impact of Net Neutrality Repeal in the Presence of Malicious Users in HetNets

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Abstract

When determining the effects of the repeal of the Net Neutrality, it is crucial to model not only the relationship between internet users and Internet Service Providers (ISPs), but also the relationship users have amongst each other in the context of ISPs. In the absence of Net Neutrality, there exists the potential for internet users to provide fallacious information on ISP performance in recommendations to one another.

This paper proposes a model by which users provide recommendations based on their experiences, methods for the determination of two classes of fallacious recommendations (existence of liaisons and indifference), and a model for assigning trust metrics from users to recommenders on specific ISPs. These models hinge on statistical information offered by each set of recommendations with respect to each user's experiences and attempt to emulate human decision-making in assigning trust corrections to recommendations.

Nominal results indicate generally successful identification of fallacious behavior. Integration with prior models is recommended in order to provide additional insight into how malicious users affect the churning rates of ISPs.

Net Neutrality

Net Neutrality is the policy that mandates that all users on the same ISP obtain the same level of service to all content providers without throttling, blocking, or paid prioritization [1], regardless of bandwidth requested by each user.

The repeal of Net Neutrality allows for scenarios in which different users on the same provider might receive different quality of service. For example, businesses that provide free WiFi access to customers might prioritize bandwidth allocation to customers who buy a larger volume of their products.

Similarly, ISPs might be encouraged to create liaisons with content providers in which the ISP provides additional bandwidth to users requesting content from said providers in exchange for exorbitant fees. Whereas larger corporations might be able to afford these prices, smaller players will find themselves pushed out of the industry.

The goal of this research is not to make any conclusive comment on the advantages or disadvantages of Net Neutrality, but only to study its effect on user recommendations and the interpretation of said recommendations in the context of internet service providers.

Background of the Model [2]

Preference for user i on ISP j is represented by

$$T_j^i(t+\partial t) = T_j^i(t) + T_j^i(t) D_j^i(t, t+\partial t) + \sum_{i' \neq i} T_j^{i'}(t) R_j^{i',i}(t, t+\partial t)$$

In the **presence of Net Neutrality**, direct experiences $D_j^i(t)$ and recommendations $R_j^{i',i}(t)$ are modeled as additive white Gaussian noise (AWGN).

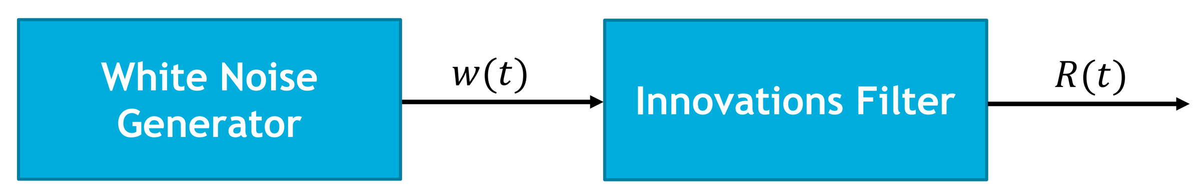
In the **absence of Net Neutrality**, direct experiences $D_j^i(t)$ and recommendations $R_j^{i',i}(t)$ are modeled as bandpass colored noise with impulse responses

$$h_j^i = \sigma_j^i 2\delta\omega_0 e^{-\delta\omega_0 t}\cos(\omega_c t + \theta),$$

where $\delta < 1$ determines a narrow band-pass frequency response, $\omega_c = \omega_0\sqrt{1-\delta^2}$, and $\cos(\theta) = \delta$.

Modeling Recommendations

Recommendations and direct experiences can be modeled as Gaussian noise - white, in the presence of Net Neutrality, and colored in its absence. The colored noise is generated by means of an innovations filter with impulse response dependent on variables unique to each user.



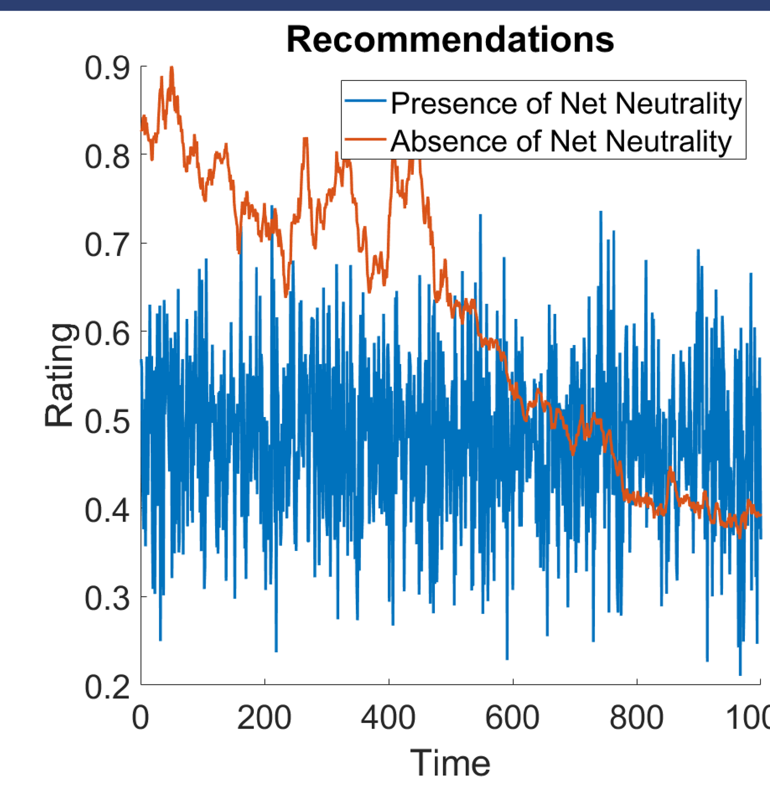
The relationship between a user's direct experiences and recommendations depend on the Lying Coefficient, LC.

- Mean of Recommendations:

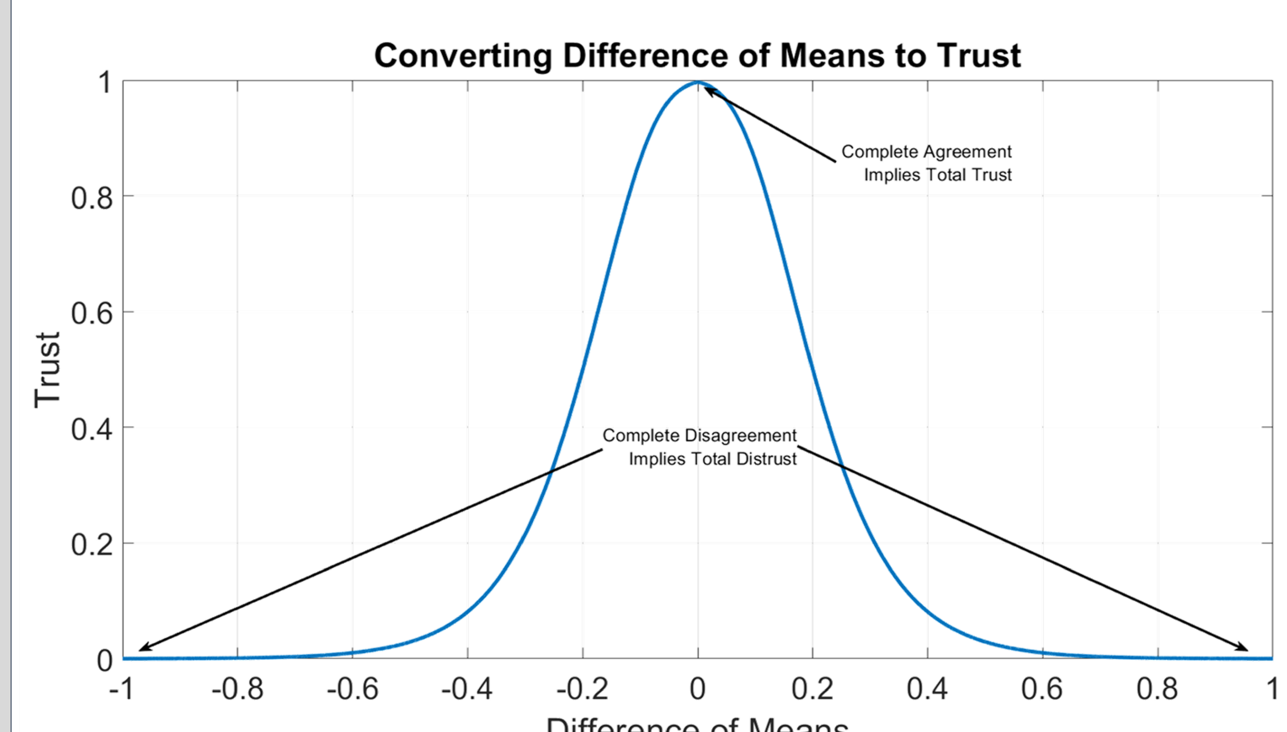
$$\mu_R = \mu_D + (LC \times \sigma_D)$$

- Standard Deviation of Recommendations:

$$\sigma_R = \sigma_D$$



Developing a Trust Metric



$$\tau_j^{i,i'} = 1 - a e^{-b e^{-c(|\mu_D - \mu_R| - d)}}$$

The recommendations give to user i by user i' on ISP j can be corrected by a trust factor, $\tau_j^{i,i'}$:

$$\tilde{R}_j^{i,i'} = \underbrace{R_j^{i,i'}\tau_j^{i,i'}}_{\text{Trust Component}} + \underbrace{(1 - R_j^{i,i'})(1 - \tau_j^{i,i'})}_{\text{Distrust Component}}$$

Intuitively:

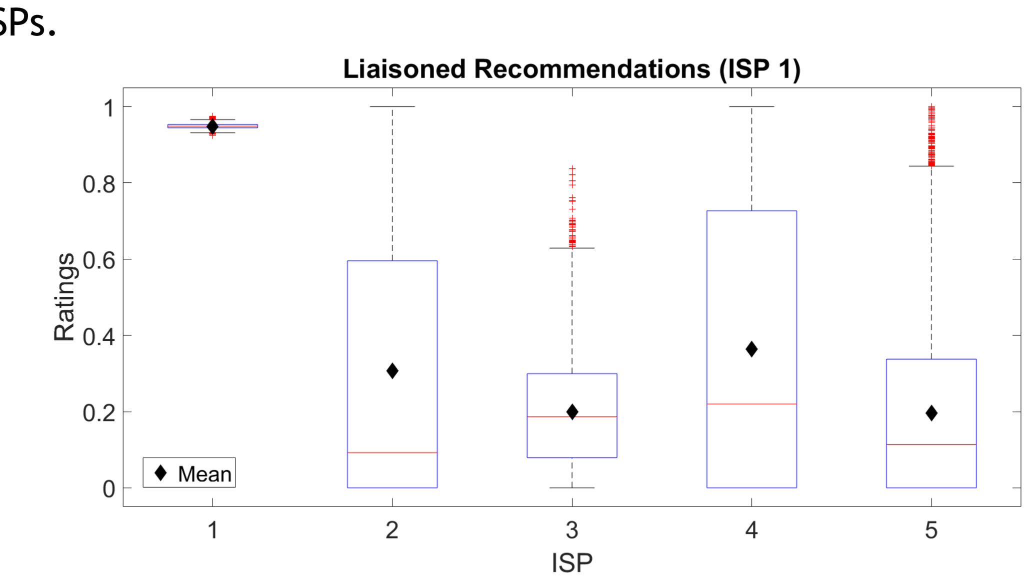
- When the recommendations are wholly trusted, their values are accepted as given.
- When the recommendations are wholly not trusted, the opposite of their values is accepted.
- Otherwise, a weighted sum is taken.

Statistical significance for the difference of means can be determined by Welch's T-Test, as the variances are not guaranteed to be equal for the two data sets.

Identifying Fallacious Information

Liaisons

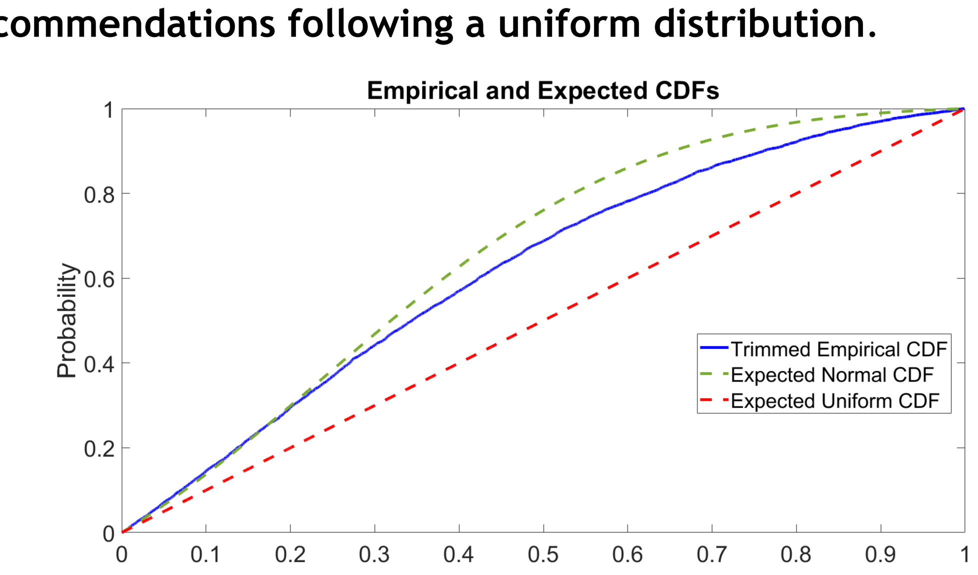
A user under a preferential contract with a single ISP would be able to receive a higher quality of service (QoS) and more bandwidth than possible with other ISPs. As the user's bandwidth requests increase, the percentages of the desired bandwidth that other ISPs can provide decrease. Therefore, a liaisoned user can be expected to provide ratings in which **a single ISP has a significantly higher mean and lower variance** than all other ISPs.



Liaison detection is achieved through outlier detection on the set of sample means of each set of recommendations. For a HetNet including a large number of ISPs ($n > 10$), the parametric Z-score method can be employed for this purpose.

Indifference

It is natural to expect that not all users are partial to giving recommendations about all ISPs. An indifferent user, instead of providing recommendations that follow a truncated normal distribution, will instead be expected to provide **recommendations following a uniform distribution.**



Indifference of a user's recommendations to an ISP can be determined by calculating the average deviations from the empirical CDF - trimmed to the interval (0,1) - to the expected CDFs of a uniform distribution and a truncated normal distribution (determined by the sample mean and sample variance).

Implementation

Simulations were performed using MATLAB R2017b on an Intel® Core™ i7-6700HQ CPU @ 2.60GHz with 16.0GB RAM. Optimization through the use of n-dimensional matrix storage and operations has been performed where possible; nonetheless, some operations (including the generation of direct experiences and recommendations by convolution with an innovations filter) remains loop-based. Preliminary results indicate generally successful identification of liaisons and indifference; however, further experimentation and expansion of the model to account for a greater number of users and ISPs is recommended.

Sample Output Logs

```
--- BEGIN POPULATION OF MEANS & SD ---
Elapsed time is 0.524295 seconds.
--- END POPULATION OF MEANS & SD ---

--- BEGIN POPULATION OF FILTERS ---
Elapsed time is 0.566445 seconds.
--- END POPULATION OF FILTERS ---

--- BEGIN GENERATING RATINGS ---
Elapsed time is 0.787500 seconds.
--- END GENERATING RATINGS ---
```

Note: These sample output logs were generated from a simulation of a system with 3 users and 3 ISPs.
Standard simulations were performed on systems of 20 users and 20 ISPs.

```
--- BEGINNING OF TEST ---
User: 1
Recommender: 3
- BEGIN SKEW TEST -
Skew of ISP 1: -0.144265
Skew of ISP 2: -0.547348
Skew of ISP 3: -0.265229
Elapsed time is 2.523195 seconds.

- END SKEW TEST -
- BEGIN INDIFFERENCE TEST -
Recommender 3's Indifference to ISP 1: 1
Recommender 3's Indifference to ISP 2: 0
Recommender 3's Indifference to ISP 3: 0
Elapsed time is 3.090244 seconds.

- END INDIFFERENCE TEST -
Elapsed time is 3.090467 seconds.
--- END OF TEST ---
```

Future Work

While the methods for modeling recommendations, determining trust, and identifying fallacious information listed here have shown to be effective, additional modelling and simulation is recommended to ascertain whether or not there are more efficient methods of simulating such inter-user dynamics.

It is also desirable to incorporate the methodologies described herein to the model of user preference in the presence and absence of Net Neutrality developed by Bar-Yosef et al. in order to observe the effects of malicious users on the churning rate of ISPs.

Future research can also focus on identification of the lying coefficient between two users, as well as designing game-theoretic models in which malicious agents attempt to bypass the tests described herein when providing recommendations.

References

[1] Richard T. B. Ma, Jingjing Wang, and Dah Ming Chiu. Paid Prioritization and Its Impact on Net Neutrality. *IEEE Journal on Selected Areas in Communications*, 35(2):367-379, 2017.

[2] Guy Bar-Yosef and S Anand. Impact of Net Neutrality Repeal on the User Experience in HetNets. 2018.

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