CS765 Spring 2023 Semester, Assignment-3

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PART-A

Description of DApp and how it will handle the below-mentioned issues

Sybil attack :
The primary objective is to prevent the creation of duplicate identities within the DApp. This is achieved by requiring users to provide either their Aadhaar Number or PAN Number when registering to vote.

Bootstrapping :
At the time of registration, we will be giving some news such that we cover all diverse fields. A Little news on each topic (Physics, Economy, Politics, Sports, Science, etc) Here, we will be calculating the Trustworthiness of the voter in each field based on their selection of the news.

Evaluating or re-evaluating the trustworthiness of voters :
From the Bootstrapping step, we will be having the trustworthiness of voters in each field. Based on the majority of votes, we decide whether the

news is fake or true. Now, whoever gave the right to vote then their Trustworthiness increased

(Trustworthiness of each voter = Correctly predicted votes / Total number of votes).

So, the trustworthiness of each voter gets updated for every newly posted news.

More trustworthy voters should be given more weight :
We will be using the formula,

News Rating = Σ(trustworthiness of voter)*(their vote 1 or 0) / Σ(trustworthiness of voter).

Now if this News value is less than or equal to 0.5 then we are considering it as Fake News else as true news. Now, based on this value we will re-evaluate the trustworthiness of the voters.

Rational voters are to be incentivized:
For every news item, we will be providing a coin as a reward to all voters. If a voter predicts news articles correctly then he/she gets coins credited in their wallet. So, it incentivizes voters to predict correctly and gain more profit.

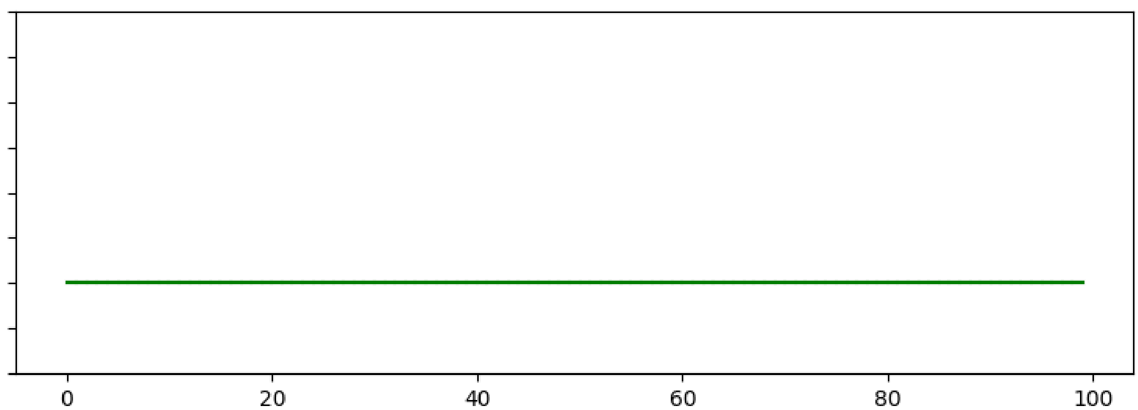
Uploading a news item :
Here, we will maintain some lists of words for each field(technology, health, sports, entertainment, crime, politics,...etc). Now, we will do word matching of words in news with the words in lists. Whichever field gets a high score, then we are classifying that news to that field.

Simulation (PART - C)

Approach:

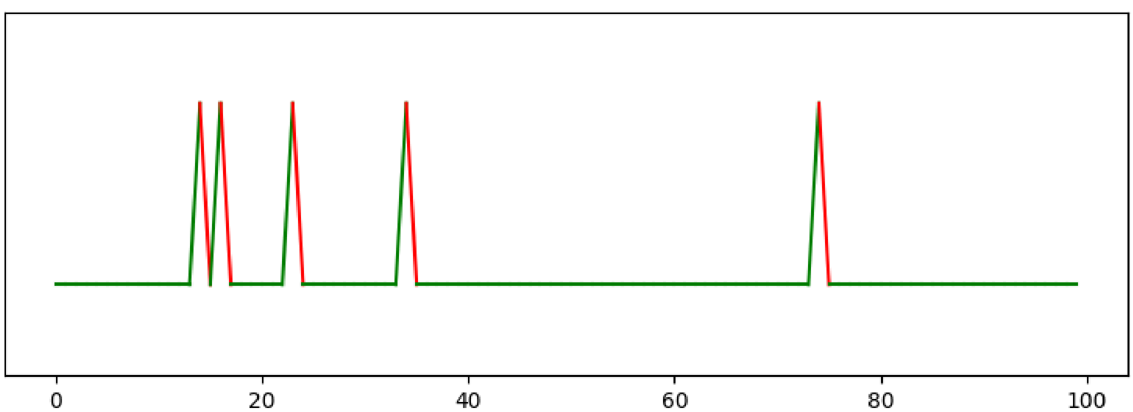
1) Get the number of users, malicious users fraction, and p_fraction of honest users which will have initial trustworthiness=0.9
2) Initially, every user will have trustworthiness=0 and an amount of BTC=0
3) Calculate the no.of malicious users and no.of p_fraction honest users i.e users with trustworthiness=0.9 and remaining honest users with trustworthiness=0.7
4) Randomly select p_fraction honest users and assign them trustworthiness=0.9.
5) Randomly select other 1-p fraction honest users and assign them trustworthiness=0.7.
6) The malicious users will have trustworthiness=0.
7) Randomly create 100 news articles both fake and real.
8) For every news article, get predictions from every user based on the trustworthiness and random probability from uniform distribution.
9) Track the result which got the maximum no.of votes.
10) For every user if he has predicted the majority increase his trust_worthhy_ness and for users who got it wrong decrease the trust_worthy_ness accordingly.
11) For every article predicted block 1 BTC from each user, and based on the no.of users who got correct give the blocked BTC to the correctly predicted users as an incentive.
12) Plot the graph for the real type of article and the type that got the maximum votes.

No.of Users	Malicious Users	P_fraction of honest users	1-P fraction of honest users	No.of articles predicted right.
100	0	100	0	100
100	0	80	20	100
100	0	60	40	100
100	0	40	60	100
100	0	20	80	100
100	0	0	100	100



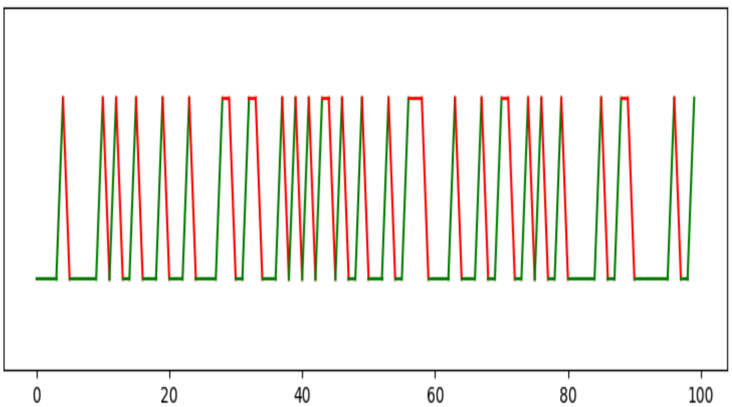
The no.of malicious users is much less compared to the no.of honest users, so every time the predicted news type is the same as the original news type. The green line indicates the instances where the prediction type is the actual news article type.

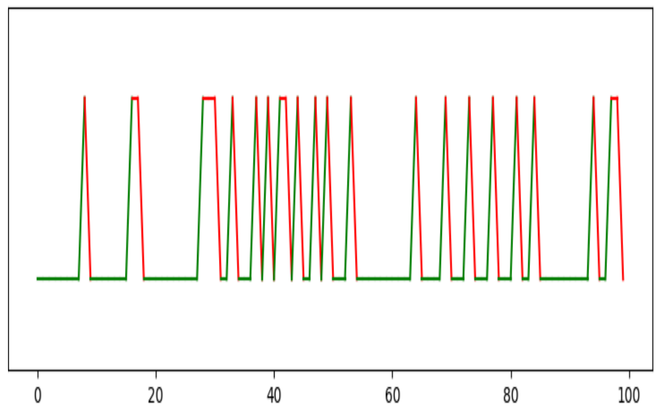
No.of Users	Malicious Users	P_fraction of honest users	1-P fraction of honest users	No.of articles predicted right.
100	20	80	0	100
100	20	60	20	100
100	20	40	40	100
100	20	20	60	100
100	20	0	80	95

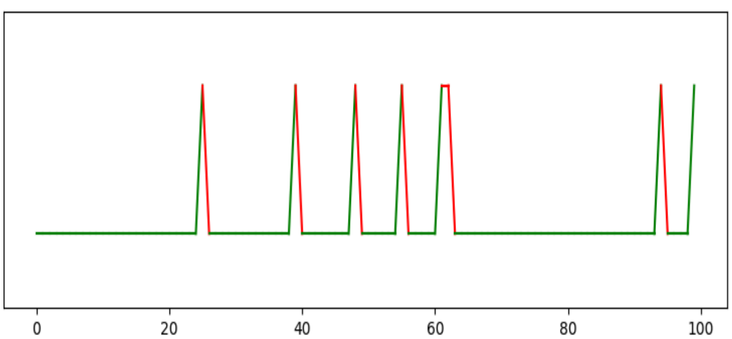


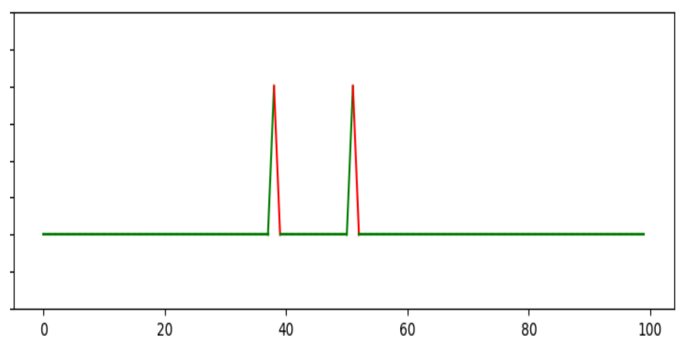
The no.of malicious is much less than the no.of honest users and when we decrease the trustworthiness of the hones users there are some instances where the prediction type is opposite to the actual prediction type. Red indicates the instances where the prediction type is the opposite of the original news type.

No.of Users	Malicious Users	P_fraction of honest users	1-P fraction of honest users	No.of articles predicted right.
100	0.3	1	0	100
100	0.3	0.8	0.2	100
100	0.3	0.6	0.4	98
100	0.3	0.4	0.6	92
100	0.3	0.2	0.8	76
100	0.3	0	1	67



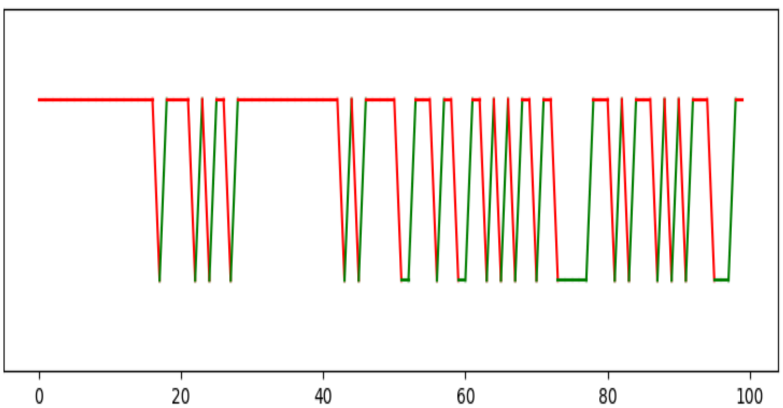


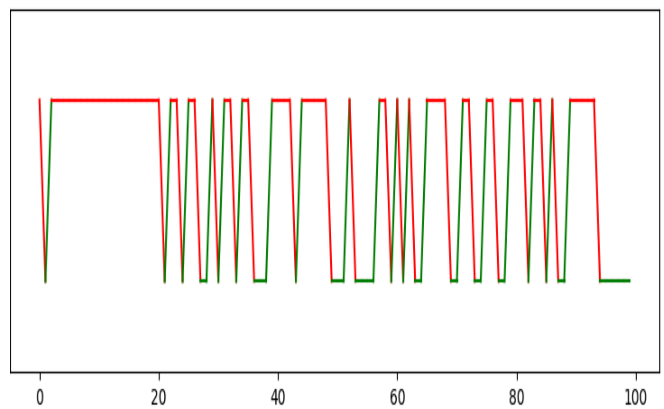


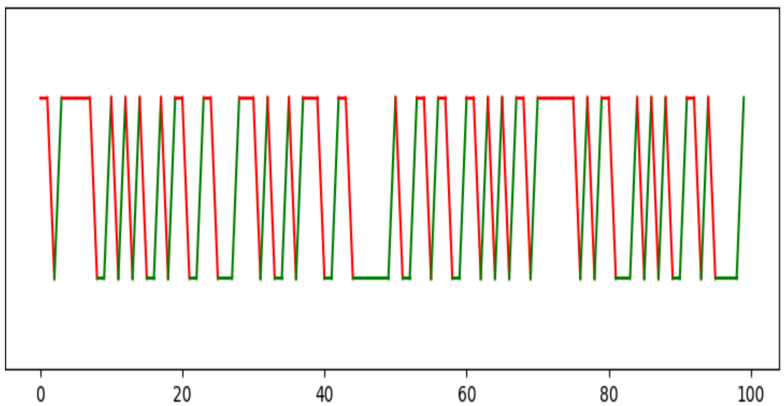


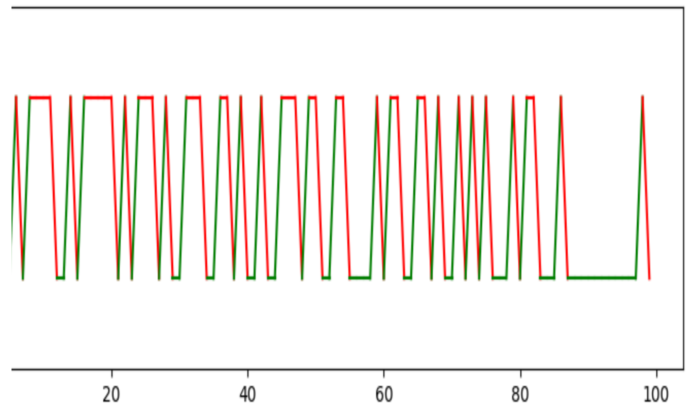
The no.of malicious users fraction is 0.3, when we keep on decreasing the p fraction of users i.e. honest users with trustworthiness=0.9, the no.of instances where the prediction got wrong increases gradually.

No.of Users	Malicious Users	P_fraction of honest users	1-P fraction of honest users	No.of articles predicted right.
100	40	1	0	94
100	40	0.8	0.2	75
100	40	0.6	0.4	53
100	40	0.4	0.6	48
100	40	0.2	0.8	38
100	40	0	1	28






0
20
40
60
80
100


20
40
60
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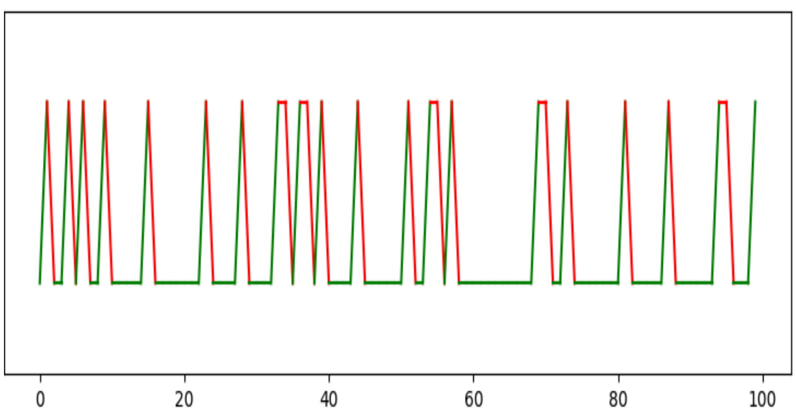
100


0
20
40
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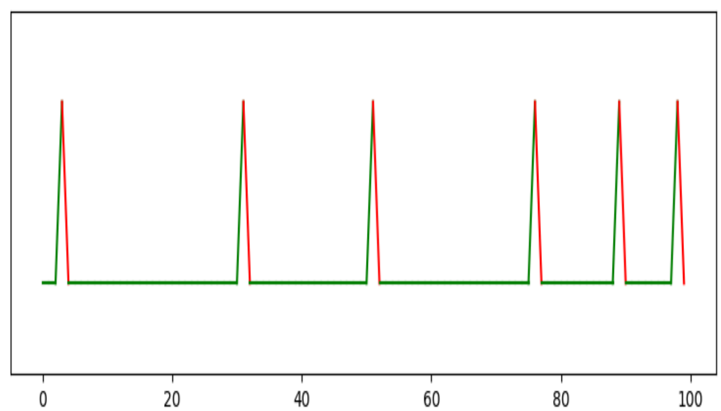
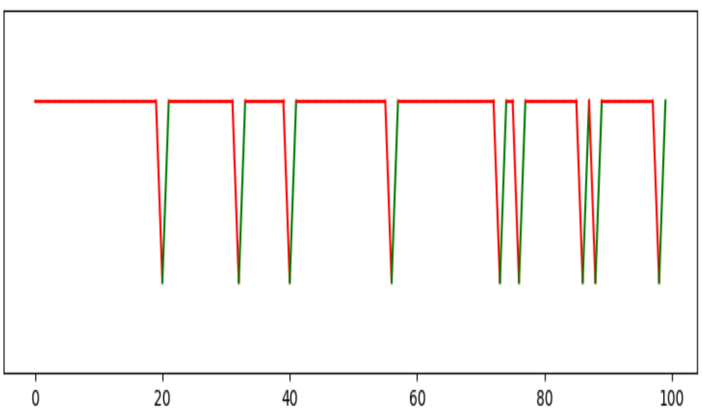
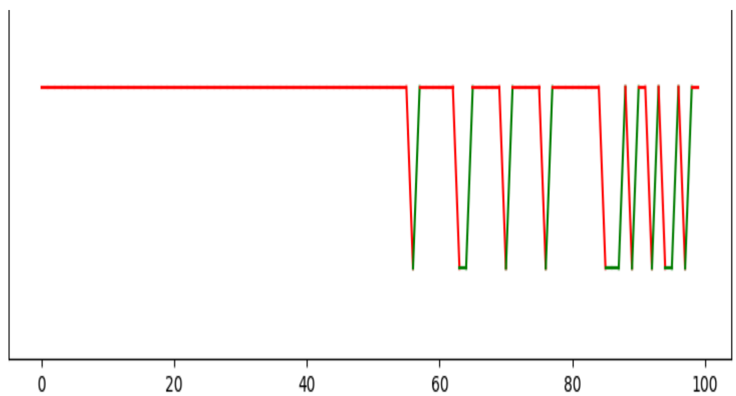
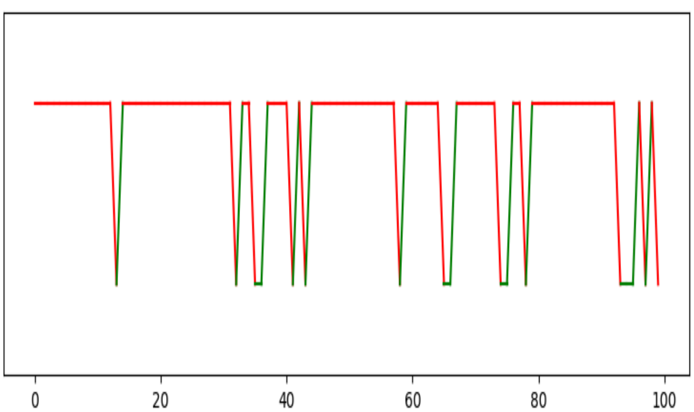
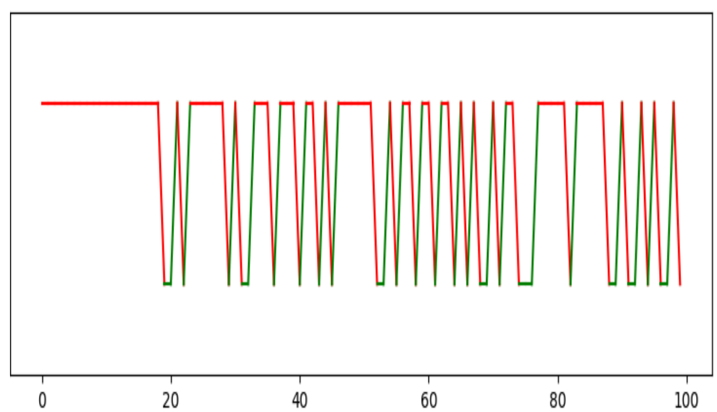

0
20
40
60
80
100

No.of Users	Malicious Users	P_fraction of honest users	1-P fraction of honest users	No.of articles predicted right.
100	50	1	0	32
100	50	0.8	0.2	26
100	50	0.6	0.4	20
100	50	0.4	0.6	17
100	50	0.2	0.8	13
100	50	0	1	9









Final observations:

1) When the malicious user's fraction is much less like 0 or 0.2 the no.of times the prediction goes wrong is much less.
2) With the increase in the fraction of malicious users fraction no.of times the prediction going wrong is increased gradually.
3) With the same fraction of malicious users, if we keep on decreasing the p fraction of users the no.of times prediction going wrong is increased as the trustworthiness of users is decreasing.