# Keep Right to Keep "Right"

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**Abstract**

Our goal is a model that can evaluate the performance of the keep-right-except-to-pass rule and other alternatives by simulating the traffic flow on the freeway. We construct models to analyze five influencing factors. Then we integrate multiple criteria to judge the performance of nine rules using a fuzzy synthetic evaluation(FSE).

Our basic lane-changing model focuses on the behavior of a specific vehicle on the freeway. We carefully examine the vehicles lane-changing behavior, an essential component of overtaking.

We extend our model with a cellular-automaton-based approach. We assume that the drivers will change the lane with a probability if the trigger and safety conditions are satisfied. Using periodic boundary conditions, we seek to simulate a section of a long freeway, which is hardly influenced by real boundary conditions. In addition, we can accurately control the occupancy of the freeway. We can simulate the traffic flow under several conditions by varying *the number of lanes, maximum speed limit, minimum speed limit and signaling behavior*.

Four other basic rules such as free-overtaking rule are examined by revising the laws governing the cells in the cellular automaton. Then we design five improved rules based on the basic rules attempting to obtain an optimal rule.

We choose flow rate, average speed as traffic flow criteria, sharp braking frequency as a safety criterion and satisfaction and standard deviation of speed as experience criteria. Then we use a fuzzy synthetic evaluation technique to integrate these criteria to determine the performance of each rule. We find that in a light traffic case, *a partial-assigned-lane-and-keep-right rule* performs the best while in a heavy traffic situation, *a different-speed-limit-on-each-lane rule* is preferred.

We change the probability of lane-changing to adjust our model to a country like Great Britain. Moreover, we change that parameter to simulate a freeway fully controlled by an intelligent system and observe small deviations.

Additionally, we refine our extended model considering the ramps. We adopt open boundary conditions and assume that the vehicles flowing in are Poisson-distributed. Finally, we change parameters to analyze freeways with ramps under different conditions.

# Contents

# 1 Introduction

Understanding process of information getting around society network has attracted increasing attention. Information flow in complex society network is of paramount importance when trying to solve the

## 1.1 literature review

In previous research, scientists usually base their model on the well know susceptible-infected-recovered ($SIR$) model. The advanced methodology of SIHR [?], the further developed SEIQR model[?], inspired other research of this kind, therefore we can find some relatively mature research like the one by $LinyuanLv$ and $Duan-BingChen$, which we based on to obtain our result. The basic idea of their's is to change the continuous SIR model into a discrete-time model to resemble the spreading of news, and introduce four similar situation of node to represent the attitude of people towards news to describe the probalistic spreading of news.

$--------------workinthemodelpart--------------$

Furthermore, there exist a couple of applications of the model or the variants of it, including the description of growth and decline of network service[?], predicting forest fire spreading[?]. But when taking into consideration the details of the real world society, we find there are still things left to be discussed.

The nodes, links, and the information itself differs from that of a pure network.

- We can introduce a memory effect to resemble the actual memory loss[?].
- The information itself, or rather the value of it, determines to which degree people tend to believe it. This is discussed in this paper.
- A link may be strong or weak, and the speed of information getting around differs.

The topology structure is distinguished in the following aspects.

- The change of link between nodes, namely the dynamic social network decribed in previous work[?]. It represents people making new contacts and lose touch with old friends.

- The abidance of $SixDegreesofSeparation$[?] is missed in previous work during simulation.
- The difference of structure entropy, which makes such much difference that the Small World Structure, Random Structure and Regular Structure distinguishes from each other a lot[?]. Furthermore, we witness a change of that when taking into account the historical trend of society, which we will discuss in our work.
- The connection between the nodes are not to be simply described as non-directional link. Some links are . Data could be collected by crawling the real world network[?], and we will give it a thorough consideration in this paper.

Despite of the previous research, there are essential points neglected such as the involvement of social media

$$somethinghere$$

, the change of topology structure and the historical explanation of it, the inherent value of information as mentioned above.

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# 2 Introduction

A more detailed introduction about the background of this problem. Some important terms to narrate this problem and how important it is to solve this problem(which is equivalent to say that our dedication is worthy).

## 2.1 Restatement of the Problem

A little paragraph about what we are trying to solve. In the abstract and introduction, we have given the description of the real-world problem. In this section, we must try to formalize our problem in a more mathematical way which could be directly transformed to either evaluation or regulation or procedure of our model.

## 2.2 Literature Review

This section should give the readers a rough idea about what have already be done. It should at least give the introduction about those works from which you get your inspirations. Moreover, it is better to compare several well known models and give a brief summary about the relative strongness and weakness between them. Then, you could illustrate you own model at the end of this section.

# 3 Assumptions and Justifications

This is a very important section. In this part, you should give all the basic assumption under which you build your model. Every model has its applicable range, so you must figure out what are those assumption at the beginning of building a model. Those assumption should be inspired and concordant with our daily intuition. The form of assumption and justification should be more or less like this:

- **A sentence of assumption** A sentence of justification. Usually, this is a narrative of an intuition from which you derive your assumption. You should depict this intuition and its connection with the assumption.

# 4 Notations

This part is not so important, only provide some convenience for the reader to figure out the meaning of each notation. We can adjust its size according to how many space we have in the real competition.

# 5 Model

## 5.1 Basic Model

### 5.1.1 Overview

This is a fundamental model which will give us some insight into the network. Inspired by [?], we use $N$ nodes to simulate $N$ identical users in reality and each node stochastically links to other $k$ nodes. When a given event occurs at a node in this graph, we use a dynamic probabilistic information propagation model (DPIP), discussed in details as follows, to simulate the spreading of information. This model only depicts the case that all users are the same, with no existence of influencial social media famous people or h...(

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### 5.1.2 Assumption and Justification

- **All nodes are identical** In this model, we do not consider famous people or huge media company, therefore, all nodes are equally important in the sense that they all have $k$ edges connecting with them.
- **Each node has four states** Since we use a node to represent a person, a node has four states corresponding with a person has four attitudes towards an information, 'Unknown', 'Known', 'Approved' and 'Unconcerned'[?].
- **Transferring from 'Known' to 'Approved' is a probabilistic event** Once a node heard a piece of news from its neighbor, it has a probability to transfer from 'Known' to 'Approved'. The more times it hears the same news, the higher probability it has to approve this news.

### 5.1.3 Methodology

Our model is a time-discrete network model. We have a set of laws which update the parameters of the model every time-step. Those laws are based on previous assumptions and observations. In this part, we formalize those laws in a mathematical way, and explain how they could update parameters from time $t$ to time $t + 1$.

**Step 1: Initializing the network**

(a) Randomly constructing the network

Our network is a randomly connecting network. It has $N$ nodes. Then we randomly connect nodes with edges and make sure that, for each node, there is always $k$ edges connected with it.

(b) Initializing the states

To begin with, every nodes should be unknown to a piece of news except the node which originates this news. Therefore, we set every nodes in our network to the 'Unknown' state.

(c) Generating news

We randomly choose a node to be the news producer, transferring its state from 'Unknown' to 'Approved'. This indicates that this node approves this news and is willing to tell its neighbors. The other nodes remain in the 'Unknown' state.

**Step 2: Propagating information**

(a) Spreading news

We traverse all nodes and find out those nodes with state 'Approved'. For each 'Approved' node, it is willing to spreading this news to its neighbors. If the neighbor is unknown about this news, it shift to known states. If the neighbor is already in known state but not approved state, it will memorize this event and has higher probability to transfer to approved state in later time.

Formalizing this step mathematically, we denote $m_i(t)$ to be how many times the $i^{th}$ node has heard this news from its neighbor until time $t$. For each 'Approved' node $A$ in our network, we manipulate the states of all its neighbors. Suppose node $B$ is one of its neighbor. If $B$ is in the state 'Unknown', we set $B$ to the state 'Known' and let

$$m_i(t+1) = 1.$$

If $B$ is already in the state 'Known', we remain it at 'Known' and let

$$m_i(t+1) = m_i(t+1) + 1.$$

If $B$ is in the state 'Unconcerned'...(line truncated)...

(b) Transferring from Known to Approved

Based on our observation, once an individual hears a piece of news, he will choose to believe in or not depending on how many times he has heard it. The more times it is, the more willingly he is to trust it. Therefore, we use a probability model to describe this phenomenon.

For each 'Known' node, if it hears the news from its neighbor at time $t$, it has a probability to approve this news. Denoting $P(m)$ as the probability of a node transferring from 'Known' to 'Approved', we have

$$P(m) = (\lambda - T)e^{-b(m-1)} + T,$$

where $m$ is $m_i(t)$ and $\lambda$, $T$, $b$ are network parameters.Once a node transfers to 'Approved', it will spread the news at next time-step, namely, at time $t + 1$.

We need to mention that if a node does not hear news from its neighbors at time $t$, it will definitely not transfer to 'Approved', even though it may have heard the news once before $t - 1$. This is in accordance with our intuition that one will not abruptly change his mind as long as he does not hear anything new.

(c) Iterating

In previous steps, we have updated states and $m_i(t + 1)$ for each nodes. By iterating those previous two steps, we could simulate the propagation of information.

### 5.2 Model 2

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## 6 Results

1)All results we have

2)What criteria we should use to evaluate our model and why

3)Discussion and comparison of result and each model(Better if we could compare the result of our model and previous one, demonstrating our model is better in some sense).

4)If we use different parameter value, is there any difference? How should we choose our parameter value?

5)Can we use external data or proof(searching on Internet) to demonstrate our model is satisfactory?

6)Any more specific discussion about model(par example, is there any probability distribution similar to our result?and why? Can we use a statistical way to evaluate our result(variance etc). If we aggrandize our data size, will our result be more convincible? Is our model computational friendly and in what extent it is? )

## 7 Sensitivity Analysis

This is actually the concern about whether our model is statistical robust to some outliers. Those outliers could be change in data, could be change in assumptions, could be change in parameter value. We should try our best to test under different outlier conditions, what are the behaviors of our model and compare them in details.

## 8 Further Discussions

I think this part is more adaptable to the problem requirement, namely we could find what the problem expect us to discuss in this part. Nevertheless, except those specific topic, there are some general things we should discuss no matter what the problem is. They are,
1)Strengthness and weakness.

2)What else can we do in the future.

## References

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