

# DMS First draft

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## 1 Data required

We need the *AREA* where a *CLIENT* visits during each *TIMESLOT* of current *TIMESTEP*.

We will use this data to find the probabilities for the *CLIENT* to be in an *AREA* a given *TIMESLOT* in the next *TIMESTEP*.

We might also need a confirmed observation about the state of the *CLIENT*. We can use this to learn the location factors of an area in particular timeslots.

## 2 EQUATIONS

### Equation for updating fever count

$$f_p(t) = \delta f_p(t-1) + \sum_{i=1}^k \epsilon_i(t-1) f_i(t-1) \quad (1)$$

Where:

- $f_p(t)$ : fever count of person  $p$  with after the timestep  $t$
- $k$ : Number of encounters of the person during timestep  $t$
- $x_i$  : fever count of  $i^{th}$  encounter
- $\epsilon_i$  : location factor of the  $i^{th}$  encounter

### Equation for calculating fever in an area

$$F_{mn}(t) = \sum_{i=1}^N P_{mn}^i(t-1) * f_i(t-1) \quad (2)$$

Where:

- $F_{mn}(t)$ : Fever count of an area  $n$  at timeslot  $m$  after timestep  $t$

- $P_{mn}^i(t)$ : Probability that a person  $i$  will visit area  $n$  during timeslot  $m$  after time step  $t$
- $f_i(t)$  : fever count of a client  $i$  after timestep  $t$
- $N$  : total number of clients

**Equation for predicting the fever count of person after next timeslot**

$$f_p(t+1) = \delta f_p(t) + \sum_{n=1}^{24} \sum_{m=1}^M \epsilon_{mn}(t) * P_{mn}^i(t) * F_{mn}(t) \quad (3)$$

Where:

- $F_{mn}(t)$ : Fever count of an area  $n$  at timeslot  $m$  after timestep  $t$
- $P_{mn}^i(t)$ : Probability that a person  $i$  will visit area  $n$  during timeslot  $m$  after time step  $t$
- $f_p(t)$  : fever count of a client  $p$  after timestep  $t$
- $M$  : total number of arears being monitored
- $\epsilon_{mn}(t)$ : Location factor for area  $n$  during the timeslot  $m$  after timestep  $t$

### 3 Can this be possible?

By using the data whether a *CLIENT*s state is *FEVER/NOFEVER*, can we learn the probabilities of spreading of fever in the *AREAS* on the particular *TIMESLOTS*. For Example, we know that a *CLIENT* took leave from office and is staying at home. He gets affected by fever. This can make us learn about the *AREA* "client's home" and the location factor  $\epsilon$  for his house.

## 4 Modeling as a markov chain

### 4.1 Modeling

State: fever count of each *CLIENT* say  $f_1 f_2 f_3 \dots f_N$

Transition: a transition is an interaction. An interaction is of form  $[p_1, p_2, A, TS]$ . This represents the meeting of person  $p_1$  with person  $p_2$  in an *AREA*  $A$  during *TIMESLOT*,  $TS$ .

Transition probability: Equation for transition probability is yet to find. But this depends upon the following factors.

- probability that a person  $p_1$  goes to an *AREA*  $A$  at a *TIMESLOT*  $TS$  after the previous timestep.  $P_{TS,A}^{p_1}(t)$

- probability that a person  $p_2$  goes to an *AREA* A at a *TIMESLOT*  $TS$ .  $P_{TS,A}^{p_2}(t)$
- depends on the location factor for the *AREA* A in the *TIMESLOT*  $TS$
- depends on the fever counts of the clients in the previous *TIMESTEP*.  $f_i(t-1)$

## 4.2 Difficulty

Since the states of the markov chain are continuous as the fever count is a continuous variable. We are searching for ways to model the continuous distribution. If we consider a discrete distribution, say with four states for each *CLIENT* instead of the fever count. The problem is that we get a very high number of states.  $4^N$  if we consider three states. We still are figuring out how to get the transition probability in terms of current state  $f_1 f_2 f_3 \dots f_N$  and the next state  $f'_1 f'_2 f'_3 \dots f'_N$