

## Proof of theorem 1

We will use the following definitions:

- $\mathcal{V}$ , the set of cache-enabled routers/nodes in the network with cardinality  $V$ .
- $\mathcal{M}$ , a set of  $M$  equally unit sized content items.
- $\zeta$ , the new users' connection rate.
- $\phi$ , the connented user's disconnection rate.
- $z$ , the Zipf distribution exponent of the content items popularity.
- $\vartheta_m$ ,  $m \in \mathcal{M}$  the popularity of item  $m$  in the Zipf distribution.
- $r_m$ , the aggregate incoming request rate for an information item  $m \in \mathcal{M}$ .

where  $r_m$  is given by:

$$r_m = \zeta \vartheta_m = \zeta \frac{1/k^z}{\sum_{i=1}^M 1/i^z}, \quad (1)$$

assuming that the particular item is ranked  $k$ -th out of the  $M$  information items within the Zipf distribution.

### Probability of absorption into state 0

The probability of retrieving a requested item  $m \in \mathcal{M}$  at time  $t > 0$ , assuming that at time  $t = 0$  the network fragments and the content origin for that particular item is not reachable, depends only on the probability that another user has already retrieved that item in the past and is still connected to the network (*i.e.*, assuming zero router cache capacity).

We define as  $\{X_m(t), 0 \leq t < \infty\}$  the Markov process with stationary transition probabilities (where the possible values of  $X_m(t)$  are non-negative integers), that depicts the number of users which have already retrieved item  $m$  and are connected to the network at time  $t$ . Clearly, if at any

time instance  $t' \geq 0$ ,  $X_m(t') = 0$ , the requested item can no longer be retrieved, since (i) it is not cached in the network, (ii) the content origin is not reachable and (iii) there are no connected users who have previously retrieved the item and can assist in content retrieval.

According to the stochastic modelling theory  $X_m(t)$  is a *birth and death* process with one absorbing state. We define as the zero state, the state at which  $X_m(t) = 0$ . This is an absorbing state (no user with a cached copy of item  $m$  is attached at a router of the network), since after that state the requested item cannot be retrieved. The probability of absorption into state 0 is not, a priori, a certain event, since the states of the process may wander forever among the states  $(1, 2, \dots)$  or possibly drift to infinity.

We define as  $\lambda_m(n)$  the birth rate of the process when the process is at state  $n$  ( $n$  connected users in the network who have the content item  $m$ ) and as  $\mu_m(n)$  the death rate of the same process. Clearly  $\lambda_m(0) = 0$ . In our case we have for  $\lambda_m(n)$ :

$$\lambda_m(n) = \begin{cases} 0 & \text{if } n = 0, \\ r_m & \text{if } n > 0. \end{cases} \quad (2)$$

Note that the birth rate of the process is independent of its actual state when  $n > 0$  and it depends only on the popularity of the corresponding item.

For the death rate of the process we have:

$$\mu_m(n) = n\phi. \quad (3)$$

Let  $u_m(n)$   $n = (1, 2, \dots)$  denote the probability of absorption into state 0 from the initial state  $n$ . We will perform a first step analysis and construct a recursion formula for  $u_m(n)$ .

The first transition will entail the following movements:

$$\begin{aligned} n \rightarrow n+1 & \text{ with probability } \frac{\lambda_m(n)}{\mu_m(n) + \lambda_m(n)} \\ n \rightarrow n-1 & \text{ with probability } \frac{\mu_m(n)}{\mu_m(n) + \lambda_m(n)} \end{aligned}$$

Invoking the first step analysis we obtain:

$$u_m(n) = \frac{\lambda_m(n)}{\mu_m(n) + \lambda_m(n)} u_m(n+1) + \frac{\mu_m(n)}{\mu_m(n) + \lambda_m(n)} u_m(n-1) \text{ when } n \geq 1, \quad (4)$$

$$\begin{aligned}
u_m(n) &= \frac{1}{\mu_m(n) + \lambda_m(n)} (\lambda_m(n)u_m(n+1) + \mu_m(n)u_m(n-1)) \\
\lambda_m(n)u_m(n) + \mu_m(n)u_m(n) &= \lambda_m(n)u_m(n+1) + \mu_m(n)u_m(n-1) \\
\lambda_m(n)u_m(n+1) - \lambda_m(n)u_m(n) &= \mu_m(n)u_m(n) - \mu_m(n)u_m(n-1) \\
u_m(n+1) - u_m(n) &= \frac{\mu_m(n)}{\lambda_m(n)} (u_m(n) - u_m(n-1)) \quad (5)
\end{aligned}$$

where  $u_m(0) = 1$ . If we now let  $v_m(n) = u_m(n+1) - u_m(n)$  the above formula becomes

$$v_m(n) = \frac{\mu_m(n)}{\lambda_m(n)} v_m(n-1), \quad n \geq 1.$$

Let us iterate on this formula

$$\begin{aligned}
v_m(n) &= \frac{\mu_m(n)}{\lambda_m(n)} v_m(n-1) \\
v_m(n) &= \frac{\mu_m(n)}{\lambda_m(n)} \frac{\mu_m(n-1)}{\lambda_m(n-1)} v_m(n-2) \\
v_m(n) &= \frac{\mu_m(n)}{\lambda_m(n)} \frac{\mu_m(n-1)}{\lambda_m(n-1)} \frac{\mu_m(n-2)}{\lambda_m(n-2)} v_m(n-3) \\
&\dots \\
v_m(n) &= \frac{\mu_m(n)}{\lambda_m(n)} \frac{\mu_m(n-1)}{\lambda_m(n-1)} \frac{\mu_m(n-2)}{\lambda_m(n-2)} \dots \frac{\mu_m(1)}{\lambda_m(1)} v_m(0)
\end{aligned}$$

If we let

$$\rho_m(n) = \frac{\mu_m(1)\mu_m(2)\dots\mu_m(n)}{\lambda_m(1)\lambda_m(2)\dots\lambda_m(n)} = \frac{\phi \cdot 2\phi \dots n\phi}{\lambda_m\lambda_m \dots \lambda_m} = \left(\frac{\phi}{r_m}\right)^n \cdot n! \quad (6)$$

and  $\rho_m(0) = 1$ , we can obtain

$$v_m(n) = \rho_m(n) v_m(0)$$

If now we return  $v_m(n)$  to  $u_m(n+1) - u_m(n)$ , then

$$\begin{aligned}
u_m(n+1) - u_m(n) &= \rho_m(n) (u_m(1) - u_m(0)) \\
u_m(n+1) - u_m(n) &= \rho_m(n) (u_m(1) - 1)
\end{aligned}$$

Let us sum both sides from  $n = 1$  to  $n = s - 1$ ,

$$\sum_{n=1}^{s-1} (u_m(n+1) - u_m(n)) = \sum_{n=1}^{s-1} \rho_m(n) (u_m(1) - 1)$$

$$\begin{aligned} & (u_m(2) - u_m(1)) + (u_m(3) - u_m(2)) + \cdots + (u_m(s-1) - u_m(s-2)) + \\ & + (u_m(s) - u_m(s-1)) = (u_m(1) - 1) \sum_{n=1}^{s-1} \rho_m(n) \quad (7) \end{aligned}$$

$$u_m(s) - u_m(1) = (u_m(1) - 1) \sum_{n=1}^{s-1} \rho_m(n) \quad (8)$$

where  $u_m(0) = 1$ . Now, in order to solve for  $u_m(1)$ , we let  $s \rightarrow \infty$ . In such a case,  $u_m(s) \rightarrow 0$ . Thus

$$\begin{aligned} u_m(s) - u_m(1) &= (u_m(1) - 1) \sum_{n=1}^{s-1} \rho_m(n) \\ 0 - u_m(1) &= (u_m(1) - 1) \sum_{n=1}^{\infty} \rho_m(n) \\ 0 &= u_m(1) \sum_{n=1}^{\infty} \rho_m(n) - \sum_{n=1}^{\infty} \rho_m(n) + u_m(1) \\ \sum_{n=1}^{\infty} \rho_m(n) &= u_m(1) \left( \sum_{n=1}^{\infty} \rho_m(n) + 1 \right) \\ u_m(1) &= \frac{\sum_{n=1}^{\infty} \rho_m(n)}{1 + \sum_{n=1}^{\infty} \rho_m(n)} \quad (9) \end{aligned}$$

We can now plug in  $u_m(1)$  to solve for a general state  $s$ :

$$\begin{aligned}
u_m(s) - u_m(1) &= (u_m(1) - 1) \sum_{n=1}^{s-1} \rho_m(n) \\
u_m(s) &= u_m(1) \sum_{n=1}^{s-1} \rho_m(n) - \sum_{n=1}^{s-1} \rho_m(n) + u_m(1) \\
u_m(s) &= \left( \frac{\sum_{n=1}^{\infty} \rho_m(n)}{1 + \sum_{n=1}^{\infty} \rho_m(n)} \right) \sum_{n=1}^{s-1} \rho_m(n) - \sum_{n=1}^{s-1} \rho_m(n) + \frac{\sum_{n=1}^{\infty} \rho_m(n)}{1 + \sum_{n=1}^{\infty} \rho_m(n)} \\
u_m(s) &= \frac{\sum_{n=1}^{\infty} \rho_m(n) - \sum_{n=1}^{s-1} \rho_m(n)}{1 + \sum_{n=1}^{\infty} \rho_m(n)} \\
u_m(s) &= \frac{\sum_{n=s}^{\infty} \rho_m(n)}{1 + \sum_{n=1}^{\infty} \rho_m(n)}
\end{aligned}$$

Concluding we have for the probability of absorption into state 0 from the initial state  $s$

$$u_m(s) = \begin{cases} 1 & \text{if } \sum_{n=1}^{\infty} \rho_m(n) = \infty, \\ \frac{\sum_{n=s}^{\infty} \rho_m(n)}{1 + \sum_{n=1}^{\infty} \rho_m(n)} & \text{if } \sum_{n=1}^{\infty} \rho_m(n) < \infty. \end{cases} \quad (10)$$

where

$$\rho_m(n) = \begin{cases} 1 & \text{if } n = 0, \\ \frac{\mu_m(1) \cdots \mu_m(n)}{\lambda_m(1) \cdots \lambda_m(n)} = \frac{\phi \cdot 2\phi \cdots i\phi}{\lambda_m \lambda \cdots \lambda_m} = \left( \frac{\phi}{r_m} \right)^n \cdot n! & \text{if } n > 0. \end{cases} \quad (11)$$

We can obtain similar results by considering an “embedded random walk” associated with this process. In particular we can derive Eq.(4) by considering the “embedded random walk” associated with a given birth and death process. Specifically, we examine the birth and death process only at the transition times. The discrete time Markov chain generated in this manner is denoted by  $\{Y_k\}_{k=0}^{\infty}$ , where  $\{Y_0\} = \{X_0\}$  is the initial state and  $\{Y_k\}$ ,  $k \geq 0$  is the state at the  $k^{\text{th}}$  transition. Obviously, the transition

probability matrix has the form

$$\mathbf{P} = \begin{pmatrix} 1 & 0 & 0 & 0 & \cdots \\ q_m(1) & 0 & p_m(1) & 0 & \cdots \\ 0 & q_m(2) & 0 & p_m(2) & \cdots \\ \vdots & \vdots & & & \ddots \end{pmatrix}$$

where

$$p_m(n) = \frac{\lambda_m(n)}{\lambda_m(n) + \mu_m(n)} = 1 - q_m(n), \quad n \geq 1.$$

The probability of absorption into state 0 for the embedded random walk is the same as for the birth and death processes, since both processes execute the same transitions.

### Mean time until absorption

Here we will compute the mean time to absorption starting from state  $s$ . We assume that condition  $\sum_{n=1}^{\infty} \rho_m(n) = \infty$  holds, and that absorption is certain. Let  $T_m(n)$  be the mean absorption time starting from state  $n$  (*i.e.*, this could be an infinite state). Considering the possible states following the first transition, instituting a first step analysis, and recalling the fact that the mean waiting time in state  $n$  is  $(\lambda_m(n) + \mu_m(n))^{-1}$  (it is actually exponentially distributed with parameter  $\lambda_m(n) + \mu_m(n)$ ), we deduce the recursion relation.

$$T_m(n) = \frac{1}{\lambda_m(n) + \mu_m(n)} + \frac{\lambda_m(n)}{\lambda_m(n) + \mu_m(n)} T_m(n+1) + \frac{\mu_m(n)}{\lambda_m(n) + \mu_m(n)} T_m(n-1), \quad n \geq 1, \quad (12)$$

where  $T_m(0) = 0$ .  $T_m(n)$  is the mean absorption time from state  $n$ , and was extracted by taking into account the waiting (sojourn) time in the state  $n$ .

Letting  $y_m(n) = T_m(n) - T_m(n+1)$  and rewriting (12) leads to

$$y_m(n) = \frac{1}{\lambda_m(n)} + \frac{\mu_m(n)}{\lambda_m(n)} y_m(n-1), \quad n \geq 1. \quad (13)$$

Iterating (13) we get

$$\begin{aligned}
y_m(1) &= \frac{1}{\lambda_m(1)} + \frac{\mu_m(1)}{\lambda_m(1)} y_m(0) \\
y_m(2) &= \frac{1}{\lambda_m(2)} + \frac{\mu_m(2)}{\lambda_m(2)} y_m(1) = \frac{1}{\lambda_m(2)} + \frac{\mu_m(2)}{\lambda_m(1)\lambda_m(2)} + \frac{\mu_m(1)\mu_m(2)}{\lambda_m(1)\lambda_m(2)} y_m(0) \\
y_m(3) &= \frac{1}{\lambda_m(3)} + \frac{\mu_m(3)}{\lambda_m(2)\lambda_m(3)} + \frac{\mu_m(2)\mu_m(3)}{\lambda_m(1)\lambda_m(2)\lambda_m(3)} + \frac{\mu_m(1)\mu_m(2)\mu_m(3)}{\lambda_m(1)\lambda_m(2)\lambda_m(3)} y_m(0)
\end{aligned}$$

and finally

$$y_m(s) = \sum_{n=1}^s \frac{1}{\lambda_m(n)} \prod_{j=n+1}^s \frac{\mu_m(j)}{\lambda_m(j)} + \left( \prod_{j=1}^s \frac{\mu_m(j)}{\lambda_m(j)} \right) y_m(0)$$

Assuming the product  $\prod_{s+1}^s \frac{\mu_m(j)}{\lambda_m(j)} = 1$  and using the notation in (11) the expression for  $y_m(s)$  becomes

$$y_m(s) = \sum_{n=1}^s \frac{1}{\lambda_m(n)} \frac{\rho_m(s)}{\rho_m(n)} + \rho_m(s) y_m(0),$$

and since  $y_m(s) = T_m(s) - T_m(s+1)$  and  $y_m(0) = T_m(0) - T_m(1) = -T_m(1)$ , then:

$$\frac{1}{\rho_m(s)} (T_m(s) - T_m(s+1)) = \sum_{n=1}^s \frac{1}{\lambda_m(n)\rho_m(n)} - T_m(1). \quad (14)$$

If  $\sum_{n=1}^{\infty} \frac{1}{\lambda_m(n)\rho_m(n)} = \infty$ , then inspection of (14) reveals that necessarily  $T_m(1) = \infty$ . Indeed, it is probabilistically evident that  $T_m(s) < T_m(s+1) \forall s$ , and this property would be violated for large  $s$  if we assume to the contrary that  $T_m(1)$  is finite.

Now assume that  $\sum_{n=1}^{\infty} \frac{1}{\lambda_m(n)\rho_m(n)} < \infty$ , then letting  $s \rightarrow \infty$  in (14) gives

$$T_m(1) = \sum_{n=1}^{\infty} \frac{1}{\lambda_m(n)\rho_m(n)} - \lim_{s \rightarrow \infty} \frac{1}{\rho_m(s)} (T_m(s) - T_m(s+1)).$$

It is more involved but still possible to prove that

$$\lim_{s \rightarrow \infty} \frac{1}{\rho_m(s)} (T_m(s) - T_m(s+1)) = 0,$$

and then

$$T_m(1) = \sum_{n=1}^{\infty} \frac{1}{\lambda_m(n)\rho_m(n)}.$$

From the above analysis the corresponding time to absorption for the initial state  $s$  is:

$$T_m(s) = \begin{cases} \infty & \text{if } \sum_{n=1}^{\infty} \frac{1}{\lambda_m(n)\rho_m(n)} = \infty, \\ \sum_{n=1}^{\infty} \frac{1}{\lambda_m(n)\rho_m(n)} + \\ + \sum_{k=1}^{s-1} \rho_m(k) \sum_{j=k+1}^{\infty} \frac{1}{\lambda_m(j)\rho_m(j)} & \text{if } \sum_{n=1}^{\infty} \frac{1}{\lambda_m(n)\rho_m(n)} < \infty, \end{cases} \quad (15)$$