# **APPENDIX**

This appendix provides the mathematical proofs of the theoretical results in our paper "Probabilistic Path Queries in Road Networks: Traffic Uncertainty Aware Path Selection", in Proceedings of the Thirteenth International Conference on Extending Database Technology (EDBT'10), Lausanne, Switzerland, March 22-26, 2010.

#### **Proof of Theorem 1**

PROOF. Since P is a simple path, each edge  $e_i \in P$  (1  $\leq$  $i \leq i$  is only adjacent to  $e_{i-1}$  (if i > 1) and  $e_{i+1}$  (if i < n) in P. Therefore, given  $w_{e_i}$ , the weights  $w_{e_1}, \ldots, w_{e_{i-1}}$  are conditionally independent on  $w_{e_{i+1}}, \ldots, w_{e_n}$ . Equation 2 follows with the basic probability theory.

#### **Proof of Theorem 2**

PROOF.  $P_m$  contains subpath  $P_{m-2}$  and edges  $e_{m-1}$  and  $e_m$ , as illustrated in Figure 11. Therefore,

$$f_{P_m|e_m}(x|y) = Pr[w_{P_{m-1}} = x - y|w_{e_m} = y]$$
  
=  $\sum_{z_1+z_2=x-y} Pr[w_{P_{m-2}} = z_1, w_{e_{m-1}} = z_2|w_{e_m} = y]$ 

Using the basic probability theory,

$$\begin{aligned} & Pr[w_{P_{m-2}} = z_1, w_{e_{m-1}} = z_2 | w_{e_m} = y] \\ & = Pr[w_{e_{m-1}} = z_2 | w_{e_m} = y] \cdot Pr[w_{P_{m-2}} = z_1 | w_{e_{m-1}} = z_2] \end{aligned}$$

Since  $z_1 + z_2 = x - y$ , we have

$$Pr[w_{P_{m-2}} = z_1 | w_{e_{m-1}} = z_2] = Pr[w_{P_{m-1}} = x - y | w_{e_{m-1}} = z_2]$$

Thus, Equation 5 holds. Equation 6 follows with the basic principles of probability theory.

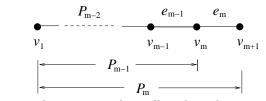
#### Proof of Lemma 2

PROOF. We prove by contradiction. In the worst case, each bucket contains only one value in  $w_{P_m}$ , which means that the probability sum of any two consecutive values in  $w_{P_m}$  is greater than  $\frac{1}{t}$ . Then, if the number of values in  $w_{P_m}$  is greater than 2t, the probability sum of all values in  $w_{P_m}$  will be greater than 1, which contradicts the fact that  $w_{P_m}$  is a discrete random variable.

## **Proof of Lemma 3**

PROOF.  $F'_{P_{m+1}}(l) - F''_{P_{m+1}}(l)$  is the sum of the probabilities in the shaded area in Figures 12(a) and 12(b). In each bucket  $\phi_i$ , the width of the shaded area is  $Pr(\phi_i) < \frac{1}{t}$ . The sum of the lengthes of all pieces of the shaded area is at most 1. Thus, the probability of the shaded area is at most  $\frac{1}{t} \times 1 = \frac{1}{t}. \text{ That is, } F'_{P_{m+1}}(l) - F''_{P_{m+1}}(l) \leq \frac{1}{t}.$ Inequality  $|\widehat{F}_{P_{m+1}}(l) - F_{P_{m+1}}(l)| \leq \frac{1}{2t}$  follows immedi-

ately.



 $(w_{P_{m-2}})$  and  $w_{e_m}$  are conditionally independent given  $w_{e_{m-1}}$ 

#### Figure 11: A path $P_m$ .

### **Proof of Theorem 3**

PROOF. P contains m edges, so m-1 steps of bucket approximation are needed to compute the probability distribution of P. We prove the theorem using mathematical induction.

In the first step (computing the probability of  $P_3$  =  $\langle v_1, v_2, v_3 \rangle$ , we have  $|F_{P_3}(l) - F_{P_3}(l)| \leq \frac{1}{2t}$ , which is shown in Lemma 3.

Assume that the conclusion holds for the j-th step which computes the probability of  $P_{j+2}$   $(j \ge 1)$ . That is,

$$|\widehat{F}_{P_{j+2}}(l) - F_{P_{j+2}}(l)| \le \frac{j}{2t} \tag{10}$$

for any real value l > 0.

To compute the probability distribution of  $w_{P_{i+3}}$ , the approximate weight of  $w_{P_{i+2}}$  is divided into buckets, such that the probability of each bucket  $\phi_i = [x_{z_i}, x_{z'_i}]$  is at most  $\frac{1}{t}$ . Since the buckets are constructed based on the approximation probability distribution of  $P_{j+2}$ , we have

$$\widehat{Pr}(b_i) = \widehat{F}_{P_{j+2}}(x'_i) - \widehat{F}_{P_{j+2}}(x'_{i-1}) \le \frac{1}{t}.$$

From Inequality 10, we have

$$|\widehat{F}_{P_{j+2}}(x'_i) - F_{P_{j+2}}(x'_i)| \le \frac{j}{2t}$$

and

$$|\widehat{F}_{P_{j+2}}(x'_{i-1}) - F_{P_{j+2}}(x'_{i-1})| \le \frac{j}{2t}.$$

The exact probability of  $\phi_i$  is

$$Pr(\phi_i) = F_{P_{j+2}|e_{i+2}}(x_{z'_i}|y) - F_{P_{j+2}|e_{i+1}}(x_{z_i}|y)$$
  
=  $\frac{1}{t} + \frac{j}{2t} \times 2 = \frac{j+1}{t}.$ 

Similar to the proof of Lemma 3, the approximation quality of  $P_{j+3}$  in the (j+1)-th step can be derived as

$$|\widehat{F}_{P_{j+3}}(x) - F_{P_{j+3}}(x)| \le \frac{j+1}{2t}.$$

To compute the distribution of P, there are overall m-1steps. Thus, the theorem holds.

### **Proof of Theorem 4**

PROOF. The theorem is an immediate application of the well known Chernoff-Hoeffding bound [1].

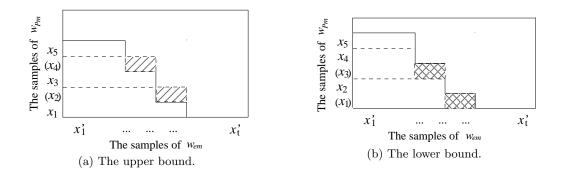


Figure 12: The upper/lower bound of  $F_{P_{m+1}}(l)$ .

# **Proof of Theorem 5**

PROOF. The weight of P is  $w_P = w_{P_1} + w_{P_2}$ . Therefore,

- $F_P(l) = Pr[w_P \le l]$
- $\begin{array}{l} & = & Pr[w_{P_1} + w_{P_2} \le l] \\ = & & \sum_{x_1 + x_2 \le l} Pr[w_{P_1} = x_1, w_{P_2} = x_2] \\ = & & \sum_{x_1 + x_2 \le l} Pr[w_{P_1} = x_1] Pr[w_{P_2} = x_2|w_{P_1} = x_1] \end{array}$

Since  $w_{P_1}$  and  $w_{P_2}$  are conditionally independent given  $w_e$ , we have

$$Pr[w_{P_2} = x_2 | w_{P_1} = x_1] = \sum_{y \le x_1} Pr[w_{P_2} = x_2 | w_e = y]$$

Equation 8 follows directly.

# **Proof of Theorem 6**

PROOF. (Direction if) If for any path P=  $\langle u, \ldots, v_i, \ldots, v \rangle$ ,  $\Delta(v_i, l) \geq F_P(l)$ , P<sup>\*</sup> considers all such paths and evaluates their exact  $F_P(l)$  values. Therefore, P<sup>\*</sup> can return all paths P such that  $F_P(l) \geq \tau$ .

(Direction only-if) We prove by contradiction. Assume that there is a path P such that  $\Delta(v_i, l) < \tau \leq F_P(l)$ . Then, P will not be returned by  $P^*$  but it is actually an answer path.

## **Proof of Theorem 7**

PROOF. Comparing two paths  $P = P_1 + P_{opt}$  and P' = $P_1 + P_{2_i} \ (P_{2_i} \in \mathcal{P}_2)$ , we have

$$Pr[w_P \le l] = \sum_{x \le l} Pr[w_{P_1} = x] \times Pr[w_{P_{opt}} \le l - x]$$

and

$$Pr[w'_P \le l] = \sum_{x \le l} Pr[w_{P_1} = x] \times Pr[w_{P_{2_i}} \le l - x].$$

Since

$$Pr[w_{P_{opt}} \le l - x] \ge Pr[w_{P_{2i}} \le l - x],$$

we have

$$Pr[w_P \le l] \ge Pr[w'_P \le l].$$