# Get a Sample for a Discount

## Sampling-Based XML Data Pricing

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# Introduction

- In most data pricing literature (e.g., [Koutris et al., 2012a, Koutris et al., 2012b, Koutris et al., 2013, Li and Miklau, 2012]), data prices are prescribed and not negotiable, and give access to the best data quality that the provider can achieve.

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- In our previous work [Tang et al., 2013], we proposed a pricing framework for **relational** data, in which **accuracy** can be traded for discounted prices.
- In this paper, we propose a pricing framework for **XML** data, in which **completeness** can be traded for discounted prices.

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    - she has a limited budget
    - she wants to explore the document before the full purchase
  - Data market owner:
    - she negotiates with the data provider a *pricing function* to decide the *completeness* of a sample that should be returned, according to a proposed price
    - she samples a rooted subtree of the requested document with the decided completeness **uniformly at random**.

# Weight and Completeness of a rooted subtree

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- The **weight of a tree** ($\text{weight}(t)$) is intuitively, the sum weight of all the nodes.
- **Completeness** of $t'$ with respect to a tree $t$ ($t'$ is a rooted subtree of $t$) is $c_t(t') = \frac{\text{weight}(t')}{\text{weight}(t)}$.

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# Pricing Function

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- Non-decreasing. The more complete a rooted subtree is, the more expensive it should be, i.e., $c_1 \geq c_2 \Rightarrow \phi_t(c_1) \geq \phi_t(c_2)$.

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- Non-decreasing. The more complete a rooted subtree is, the more expensive it should be, i.e., $c_1 \geq c_2 \Rightarrow \phi_t(c_1) \geq \phi_t(c_2)$.
- Arbitrage-free. Buying a rooted subtree of completeness $c_1 + c_2$ should not be more expensive than buying two subtrees with respective completeness $c_1$ and $c_2$, i.e., $\phi_t(c_1) + \phi_t(c_2) \geq \phi_t(c_1 + c_2)$. This property is useful when considering repeated requests.

# Pricing Function

- Minimum and maximum bound. We should have $\phi_t(0) = pr_{\min}$ and $\phi_t(1) = pr_t$, where $pr_{\min}$ is the minimum cost that a data consumer has to pay using the data market and $pr_t$ is the price of the whole tree $t$.

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- All these properties can be satisfied, for instance, by functions of the form $\phi_t(c) = (pr_t - pr_{\min})c^p + pr_{\min}$ where $p \leq 1$.

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- We consider the problem of uniform sampling a rooted subtree with prescribed weight (instead with prescribed completeness). The problem of **sampling a rooted subtree**, given a tree $t$ and a weight $k$, is to sample a rooted subtree $t'$ of $t$, such that $\text{weight}(t') = k$, *uniformly at random*.

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- Why "uniformly at random"? To be fair to the data consumer, there should be an equal chance to explore every possible part of the XML document that is worth the proposed price.

# Tractability of the Sampling Problem

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- Tractable cases:
  - Unweighted Sampling: $\mathrm{w}(n) = 1$ for all $n$.
  - $0/1$-weights Sampling.: $\mathrm{w}(n) \in \{0, 1\}$ for all $n$.

# Unweighted Sampling for Binary Trees

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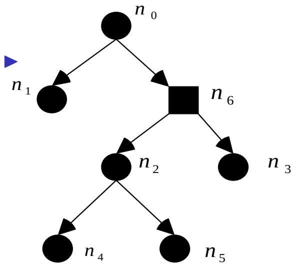
- **First phase: Subtree Counting.** We start by computing a matrix $D$ such that, for every node $n_i$ of the input tree $t$ and any value $0 \leq k \leq \text{size}(t)$, $D_i[k]$ is the number of subtrees of size $k$ rooted at node $n_i$.

# Unweighted Sampling for Binary Trees



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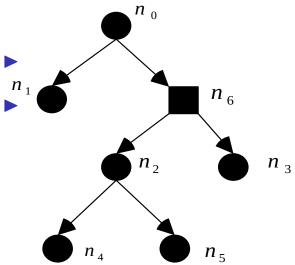


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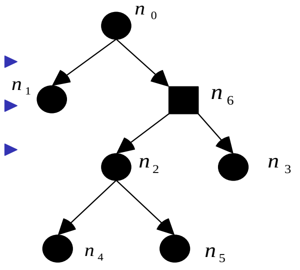


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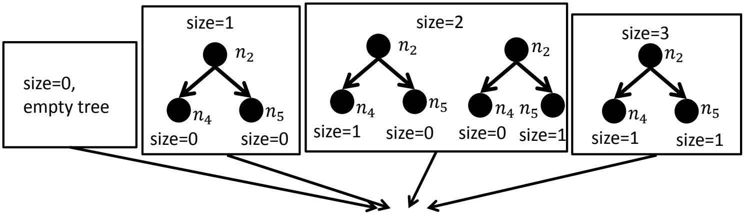


$D_2 = (1,1,2,1)$

# Unweighted Sampling for Binary Trees

- **Second phase: Uniform Sampling.** We sample a rooted subtree from $t$ in a recursive top-down manner, based on the matrix $D$ computed.
- The basic idea is that to sample a rooted subtree at node $n_i$, we decide on the size of the subtrees rooted at each child node, biased by the number of outcomes as counted in $D$, and then sample rooted subtrees of the desired sizes recursively.

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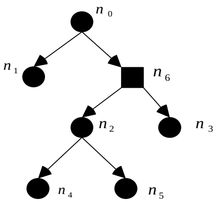
- 

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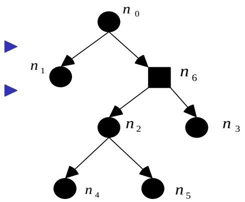


$$D_1 = D_4 = D_5 = D_3 = (1,1)$$
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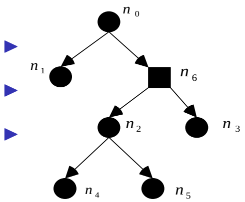


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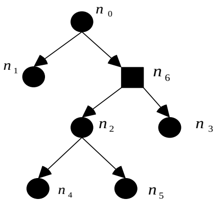


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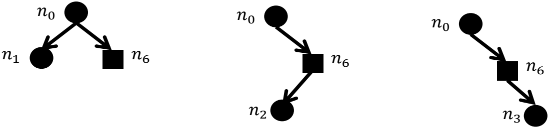

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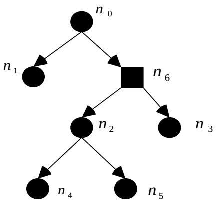


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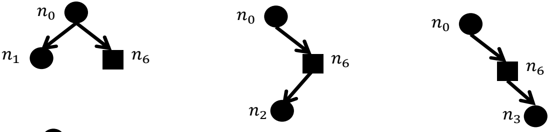
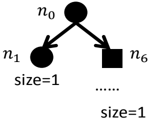
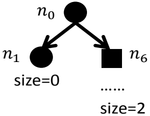



$$\boxed{D_1[1] \times D_6[1] = 1}$$

$$p_1 = \frac{1}{3}$$




$$\boxed{D_1[0] \times D_6[2] = 2}$$

$$p_2 = \frac{2}{3}$$

# Unweighted Sampling for Binary Trees

- Complexity of Phase 1 (the size of $t$ is $n$) is $O(n^3)$.
  - Each $D_i$ has size at most $n$. Therefore computing the convolution sum of two such $D_i$'s is in $O(n^2)$.
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  - We need to compute at most $n$ convolution sums. Therefore the overall complexity is $O(n^3)$.
- Complexity of Phase 2 (the size of $t$ is $n$) is $O(n^2)$.
  - At each node $n_i$, the number of possibilities to consider is $O(n)$, since $n_i$ has at most two children.
  - There are $n$ nodes, hence the overall complexity is $O(n^2)$.

# Unweighted Sampling for Unranked Trees

- The sampling algorithm for binary trees can be adapted for unranked trees, thanks to the associativity of the convolution sum.

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- Based on this idea, we introduce "dummy node" to represent a set of (more than two) nodes. An unranked tree can be transformed to a binary tree by adding such "dummy nodes".

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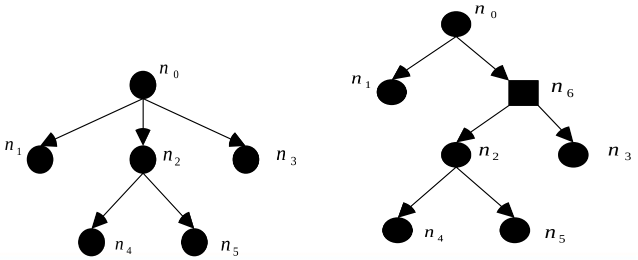
- For instance, $n_6$ is a "dummy node".
- 

# 0/1-weights Sampling

- 0/1-weights sampling problem can be resolved by adapting the sampling algorithm of unweighted sampling for unranked trees, since nodes of 0 weight are similar to dummy nodes. (Details refer to the paper)

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# 0/1-weights Sampling

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- We have presented the algorithms of sampling problem for a single request. Next, we are going to discuss the case of multiple requests from a data consumer.

# Repeated Requests

- Motivation: after having bought incomplete data, the data consumer may realize that she needs additional data, in which case she would like to obtain more incomplete data that is not redundant with what she already has.

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  - This problem is NP-hard.
  - The unweighted version of this problem is tractable. We can set the weights of nodes that a data consumer already has to 0. Then this sampling problem is similar to 0/1-weights sampling problem with slight adaption. (Details refer to the paper)

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- We proposed a framework for a data market in which data quality can be traded for a discount.
- We studied the case of XML documents with completeness as the quality dimension.
- The data consumer proposes a price but may get only a sample if the proposed price is lower than that of the entire document.
- A sample is a rooted subtree of prescribed weight, as determined by the proposed price, sampled uniformly at random.

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- We proved that if nodes in the XML document have arbitrary non-negative weights, the sampling problem is intractable.

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- We identified tractable cases, namely the unweighted sampling problem and 0/1-weights sampling problem, for which we devised P-TIME algorithms. We also considered repeated requests and provided P-TIME solutions to the unweighted cases.

# Conclusion and Future Work

- The more general issue that we are currently investigating is that of sampling rooted subtrees uniformly at random under more expressive conditions than size restrictions or $0/1$-weights. In particular, we intend to identify the tractability boundary to describe the class of tree statistics for which it is possible to sample rooted subtrees in P-TIME under a uniform distribution.

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# Thank you! Questions?