

Use of patterns in n -tuple combinatorial generation

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Agenda

- 1 Applications
 - Peer-to-peer networks
 - Calendaring
- 2 Combinatorial generation
 - Model
 - Data structures
 - Algorithms
- 3 Running time
 - Theoretical analysis
 - Experimental results

Bibliografia

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-  D. L. Kreher and D. R. Stinson, *Combinatorial algorithms: Generation, enumeration and search*, CRC press LTC, Boca Raton, Florida, 1998.
-  Dmitri Loguinov, Juan Casas, and Xiaoming Wang, *Graph-theoretic analysis of structured peer-to-peer systems: routing distances and fault resilience*, IEEE/ACM Trans. Netw. **13** (2005), no. 5, 1107–1120.
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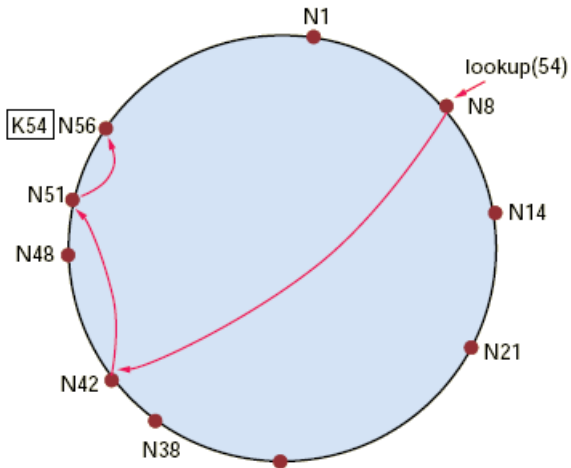
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Chord – definition

- Choose **key space** \mathcal{S} , such that $|\mathcal{S}| = 2^m$.
- Assign a **random key** $k_i \in \mathcal{S}$ to every node in the network
- **Order** nodes such that they form **cyclic list** and $k_i < k_{i+1}$
- Every node v keeps its **routing table** R_v of size m , such that $R_i[j]$ stores address of node in distance 2^j from v

Chord – searching



Distributed Hashtables

Other structured peer-to-peer networks based on DHT use **minimal-change** topologies like

- n -cube
- Butterfly
- de Bruijn graph

What if someone wanted to visit some subset of nodes?

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Software

- Personal Information Mangement (*PIM*): Palm Desktop, Mozilla
- Google Calendar
- CRON

PIM pattern specification

- choose **exclusively** one of the **patterns** (granularity)
- choose **start** and **end** date

Starting 25 marca 2007

Select how often this event should repeat:

None	Day	Week	Month	Year
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Every: Week

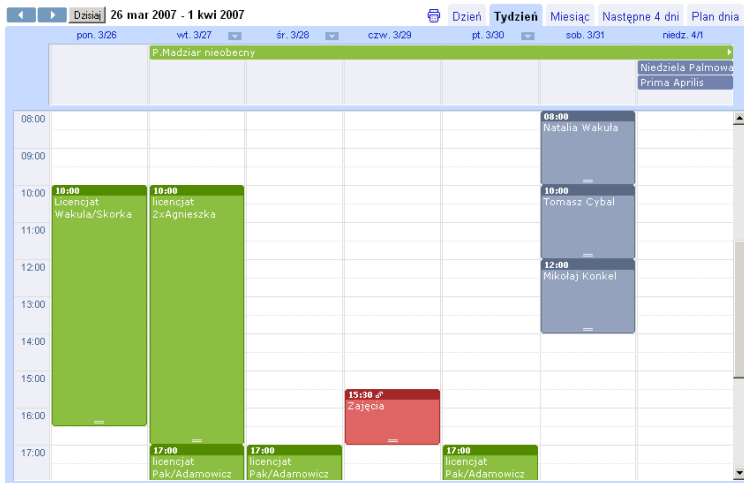
End on: No End Date
 2007-03-25

Repeat on:

M	T	W	T	F	S	S
---	---	---	---	---	---	----------

Every niedziela

PIM views



CRON pattern specification

- 6 fields: year, month, dom, dow, hour, minute
- example: *, *, 1-15, *, 0-23/2, 0
- runs in background checking **every minute** if there is an event matching a pattern

How to generate monthly view for CRON?

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Sequence spaces

Definition (Consecutive sequence space)

Space Ω_n is called **consecutive sequence space** iff for some $n \in \mathbb{N}$, $s_j \in \mathbb{N}$, $e_j \in \mathbb{N}$ we have

$$\Omega_n = \{(a_n) : s_j \leq a_j \leq e_j, 1 \leq j \leq n, a_j \in \mathbb{N}\}.$$

Definition (Pattern sequence space)

Space Ψ_n is called **pattern sequence space** iff for some $n \in \mathbb{N}$ and characteristic functions $\chi = (\chi_n)$, where $\chi_j : \mathbb{N} \mapsto \{0, 1\}$ for all $1 \leq j \leq n$, we have

$$\Psi_n = \{(a_n) : \chi_j(a_j) = 1, 1 \leq j \leq n, a_j \in \mathbb{N}\}.$$

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Sequence ranges

Definition (Sequence range)

A pair $((f_n), (t_n))$ is called **sequence range** iff $(f_n) \in \Omega_n$, $(t_n) \in \Omega_n$ and $(f_n) \preceq_{\Omega_n} (t_n)$.

Definition (Sequence space subrange)

Sequence range $((f_n), (t_n))$ generates **sequence space subrange** $\Phi_n^{f,t}$ for some sequence space Φ_n where

$$\Phi_n^{f,t} = \{(a_n) \in \Phi_n : (f_n) \preceq (a_n) \preceq (t_n)\}$$

and by Φ_n we may take pattern sequence space Ψ_n or consecutive sequence space Ω_n .

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Not so easy task

Definition (Pattern sequence rookie)

Sequence $(r_n) \in \Psi_n^{f,t}$ is called **pattern sequence rookie** iff

$$\forall (a_n) \in \Psi_n^{f,t} : (r_n) \preceq (a_n).$$

Solution: find pattern sequence rookie!

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Pattern

Definition (Pattern)

Let $\Gamma = (\Gamma_n)$ be a **pattern** defined as $(\Gamma_j) = \text{supp}\{\chi_j\}$ for all $1 \leq j \leq n$.

Definition (Filtered pattern)

For sequence range $((f_n), (t_n))$ we define $\Gamma^f = (\Gamma_n^f)$ to be a **filtered pattern**, where $\Gamma_j^f = \Gamma_j \cap \{f_j, \dots, \infty\}$ for all $1 \leq j \leq n$.

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Naive generate

Algorithm 2.1: NAIVEGENERATE($(f_n), (t_n), (\chi_n)$)

global ε

$(c_n) \leftarrow (f_n)$ (1)

while $(c_n) \preceq (t_n)$ (2)

do { **if** $\chi((c_n)) \equiv 1$ (3)

then output $((c_n))$ (4)

$(c_n) \leftarrow (c_n) \oplus \varepsilon$ (5)

JSUCCESSOR()

Algorithm 2.2: JSUCCESSOR($j, (c_n), (\Gamma_n)$)**global** (λ_n) $i \leftarrow j$ **while** $i > 0$ **and** $\lambda_i = |\Gamma_i|$ (1) **do** $i \leftarrow i - 1$ **if** $i = 0$ **then return** ("*undefined*") $(s_n) \leftarrow (c_n)$ (2) $\lambda_i \leftarrow \lambda_i + 1$ $s_i \leftarrow \Gamma_{i, \lambda_i}$ **for** $k \leftarrow i + 1$ **to** j (3) **do** $\begin{cases} \lambda_k = 1 \\ s_k \leftarrow \Gamma_{k, 1} \end{cases}$ **return** $((s_n))$ (4)

More definitions

Definition (Favorite subsequence)

Subsequence $(u_j) = (u_1, u_2, \dots, u_j)$ for $1 \leq j \leq n$ is called **favorite subsequence** of sequence space subrange $\Psi_n^{f,t}$ iff (u_j) is a pattern sequence rookie of sequence space subrange $\Psi_j^{f,t}$.

Favorite subsequence lemma

Lemma

- If $(u_{j-1}) \in \Psi_{j-1}^{f,t}$ is a **favorite subsequence** of $\Psi_n^{f,t}$ for $1 < j \leq n$ and pattern sequence rookie $(r_n) \in \Psi_n^{f,t}$ exists then:
 - (T1) $(u_1, u_2, \dots, u_{j-1}, \Gamma_{j,1}^f, \Gamma_{j+1,1}, \Gamma_{j+2,1}, \dots, \Gamma_{n,1})$ is a pattern sequence rookie of $\Psi_n^{f,t}$ **when $f_j < \Gamma_{j,1}^f$** ,
 - (T2) $(v_1, v_2, \dots, v_{j-1}, \Gamma_{j,1}, \Gamma_{j+1,1}, \dots, \Gamma_{n,1})$ is a pattern sequence rookie of $\Psi_n^{f,t}$ **when $\Gamma_{j,1}^f$ does not exist**, where $(v_{j-1}) \in \Psi_{j-1}^{f,t}$ is a **successor** of $(u_{j-1}) \in \Psi_{j-1}^{f,t}$,
 - (R) $(u_1, u_2, \dots, u_{j-1}, \Gamma_{j,1}^f) \in \Psi_j^{f,t}$ is a favorite subsequence of $\Psi_n^{f,t}$ **when $f_j = \Gamma_{j,1}^f$** .
- If $j = 1$ and pattern sequence rookie $(r_n) \in \Psi_n^{f,t}$ exists, then $(\Gamma_{1,1}^f)$ is a favorite subsequence of $\Psi_n^{f,t}$.

Auxiliary array (λ^f)

Definition

$$\lambda_j^f = \begin{cases} 0, & (\Gamma_j^f) = \emptyset \\ z : \Gamma_{j,z} = \Gamma_{j,1}^f, & (\Gamma_j^f) \neq \emptyset \end{cases}$$

GETFIRST()

Algorithm 2.3: GETFIRST($(f_n), (t_n), (\Gamma_n)$)

```
for  $j \leftarrow 1$  to  $n$ 
  if  $\lambda_j^f = 0$ 
  then  $\left\{ \begin{array}{l} (r_n) \leftarrow \text{JSUCCESSOR}(j-1, (r_n), (\Gamma_n)) \\ \text{break} \end{array} \right.$ 
do  $\left\{ \begin{array}{l} r_j \leftarrow \Gamma_{j, \lambda_j^f} \\ \lambda_j \leftarrow \lambda_j^f \\ \text{if } f_j < \Gamma_{j, \lambda_j^f} \\ \text{then } \left\{ \begin{array}{l} j \leftarrow j + 1 \\ \text{break} \end{array} \right. \end{array} \right.$ 
for  $i \leftarrow j$  to  $n$ 
  do  $r_i \leftarrow \Gamma_{i, 1}$ 
return  $((r_n))$ 
```

GETFIRST() validity

Theorem

Algorithm GETFIRST() returns **pattern sequence rookie** (r_n) of sequence space subrange $\Psi_n^{f,t}$, if (r_n) exists.

Pattern generate

Algorithm 2.4: PATTERNGENERATE($(f_n), (t_n), (\Gamma_n)$)

$(c_n) \leftarrow \text{GETFIRST}((f_n), (t_n), (\Gamma_n))$

while $(c_n) \neq \text{"undefined"}$

do $\left\{ \begin{array}{l} \text{output } ((c_n)) \\ (c_n) \leftarrow \text{JSUCCESSOR}(n, (c_n), (\Gamma_n)) \end{array} \right.$

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Granularity

Definition (Pattern granularity)

Let us take sequence range $((f_n), (t_n))$ and pattern Γ . We define **pattern granularity** as

$$\text{gran}(\Gamma) = \frac{|\Psi_n^{f,t}|}{|\Omega_n^{f,t}|}$$

Naive generate running time

Algorithm 3.1: NAIVEGENERATE($(f_n), (t_n), (\chi_n)$)

global ε

$(c_n) \leftarrow (f_n)$ (1)

while $(c_n) \preceq (t_n)$ (2)

do $\left\{ \begin{array}{l} \text{if } \chi((c_n)) \equiv 1 \quad (3) \\ \quad \text{then output } ((c_n)) \quad (4) \\ (c_n) \leftarrow (c_n) \oplus \varepsilon \quad (5) \end{array} \right.$

$$\frac{1}{\varepsilon} O(n|\Omega_n^{f,t}|) = O(n \frac{1}{\varepsilon} |\Omega_n^{f,t}|)$$

Pattern generate running time

Algorithm 3.2: PATTERNGENERATE($(f_n), (t_n), (\Gamma_n)$)

$(c_n) \leftarrow \text{GETFIRST}((f_n), (t_n), (\Gamma_n))$

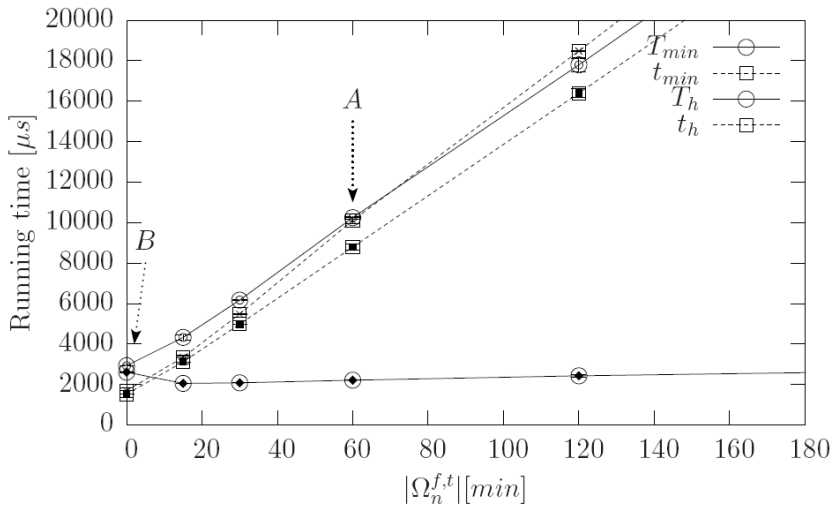
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do $\left\{ \begin{array}{l} \text{output } ((c_n)) \\ (c_n) \leftarrow \text{JSUCCESSOR}(n, (c_n), (\Gamma_n)) \end{array} \right.$

$$O(n \log n + n \text{ gran}(\Gamma_n) |\Omega_n^{f,t}|) = O(n \text{ gran}(\Gamma_n) |\Omega_n^{f,t}|).$$

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$ \Omega_n^{f,t} $	T_h	t_h	T_{min}	t_{min}
0'	2.61ms	1.53ms	2.94ms	1.7ms
15'	2.06ms	3.12ms	4.33ms	3.35ms
30'	2.09ms	4.99ms	6.18ms	5.49ms
1h	2.22ms	8.79ms	10.25ms	10.11ms
2h	2.44ms	16.4ms	17.79ms	18.48ms
4h	2.75ms	31.79ms	33.3ms	35.6ms
8h	3.96ms	62.54ms	63.68ms	70.5ms
16h	4.9ms	125.82ms	125.36ms	140.74ms
1m	129.28ms	6.01''	5.71''	6.82''
2m	243.82ms	11.85''	10.83''	12.89''
4m	502.85ms	23.55''	22.14''	26.41''
8m	1''	48.11''	44.97''	54.19''
1y	1.5''	1.21'	1.12'	1.37'
2y	3''	2.44'	2.26'	2.76'
4y	6.03''	4.88'	4.51'	5.5'

Summary

- Define $\text{RANK}()$ and $\text{UNRANK}()$ for **lexicographic** ordering
- Define **all** algorithms for **minimal-change** ordering
- **Apply** to **peer-to-peer** structured networks

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