



# XWAVE: Optimal and Approximate Extended Wavelets for Streaming Data

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Sudipto Guha  
Univ. of Penn.

Chulyun Kim  
Seoul Nat'l Univ.

Kyuseok Shim  
Seoul Nat'l Univ.



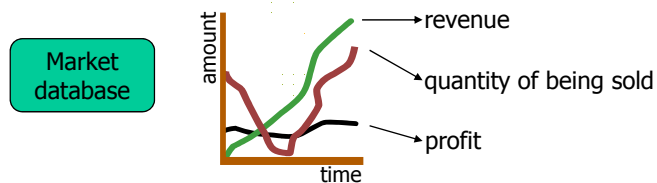
## Outline

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- Introduction
- Preliminaries & Previous Work
- XWAVE Algorithms
  - Optimal Algorithms
  - Approximation Algorithm
  - Adapting to Stream data
- Experimental Result
- Summary

## Introduction

- Decision support system applications
  - Large database with multiple measures are common
  - Stringent response-time is required
  - Approximate query processing can provide a viable solution
  - Approximate wavelet synopses with multiple measures are frequently used



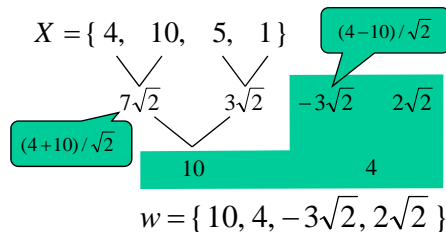
## Wavelet – Haar wavelet

- Decomposition – takes linear time complexity

- Basic operation

$$\begin{array}{c} \boxed{p} \quad \boxed{q} \longrightarrow (p-q)/\sqrt{2} \\ \searrow \\ (p+q)/\sqrt{2} \end{array}$$

- Example



## Wavelet – Haar wavelet (Cont.)

- To Compress the original N data with Minimum  $L_2$  error using  $B(\ll N)$  Haar wavelet coefficients,
  - choose B coefficients with largest absolute value
- For given  $B = 2$  and  $X = \{4, 10, 5, 1\}$ 
  - $w = \{10, 4, -3\sqrt{2}, 2\sqrt{2}\}$
  - Two largest coefficients are  $10, -3\sqrt{2}$
  - $w' = \{10, 0, -3\sqrt{2}, 0\}$
  - $X' = \{2, 8, 5, 5\}$
  - $L_2 \text{ error} = 4^2 + (2\sqrt{2})^2 = 24$

## Traditional Wavelet Methods for Multiple Measures

- Multi-measure coefficients
 

$w = \left\{ \begin{matrix} 0 \\ 4 \\ 1 \end{matrix}, \begin{matrix} 3 \\ 5 \\ 0 \end{matrix}, \begin{matrix} 1 \\ 1 \\ -4\sqrt{2} \end{matrix}, \begin{matrix} 5 \\ 0 \\ 0 \end{matrix} \right\}$
- Individual coefficient method
  - Select individual coefficient independently
  - Individual coefficient:  $\langle \text{coordinate}, \text{measure}, \text{value} \rangle$   
 e.g.  $\langle 2, 1, 3 \rangle$   $\langle 2, 2, 5 \rangle$   $\langle 4, 1, 5 \rangle$

## Traditional Wavelet Methods for Multiple Measures

- Multi-measure coefficients  $w = \left\{ \begin{matrix} 0 \\ 4 \\ 1 \end{matrix}, \begin{matrix} 3 \\ 5 \\ 0 \end{matrix}, \begin{matrix} 1 \\ 1 \\ -4\sqrt{2} \end{matrix}, \begin{matrix} 5 \\ 0 \\ 0 \end{matrix} \right\}$
- Individual coefficient method
  - Select individual coefficient independently
  - Individual coefficient: <coordinate, measure, value>  
e.g. <2, 1, 3> <2, 2, 5> <4, 1, 5>
- Combined coefficient method
  - Select combined coefficient vector
  - Combined coefficient: <coordinate, coefficient-vector>  
e.g. <2, {3,5,0}> <4, {5,0,0}>

## Drawbacks of Traditional Wavelet Methods for Multiple Measures

- Both method may result in suboptimal solutions
  - In individual coefficient method, the same coordinate information may be stored multiple times
  - In combined coefficient method, only a few coefficients in a vector may reduce the error
- Example: 2 coordinates, 3 measures, space of 7 numbers (i.e. store 2 individual or 1 combined coefficients)

Example		Individual	Combined
Coord.	Values	<1,100,1><2,100,2>	<1,{100,50,0}>
1	100 50 0	L <sub>2</sub> Error = 2500	L <sub>2</sub> Error = 10000
2	0 100 0		
Coord.	Values	<1,100,1><1,100,3>	<1,{100,50,100}>
1	100 50 100	L <sub>2</sub> Error = 12500	L <sub>2</sub> Error = 10000
2	0 100 0		

## Extended Wavelet Coefficients

- [Deligiannakis and Roussopoulos: SIGMOD'03]
- A more flexible representation:  $\langle \text{Bit}, i, V \rangle$ 
  - Bit : A bitmap consisting of M bits
  - i : i-th coordinate
  - V : The list of stored coefficient values
  - e.g.  $\langle 110, 2, \{3,5\} \rangle$   $\langle 100, 4, \{5\} \rangle$

Coordinate

measure

$$w = \left\{ \begin{bmatrix} 0 \\ 4 \\ 1 \end{bmatrix}, \begin{bmatrix} 3 \\ 5 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 \\ 1 \\ -4\sqrt{2} \end{bmatrix}, \begin{bmatrix} 5 \\ 0 \\ 0 \end{bmatrix} \right\}$$

## Motivation for Extended Wavelet Coefficients

- For the given 2 coordinates having 3 measures
- Assuming that we have only space to store 7 numbers
  - We can store 2 individual, 1 combined, or 2 extended coefficients

Example	Individual	Combined	Extended
Coord. Values 1 100 50 0 2 0 100 0	$\langle 1,100,1 \rangle \langle 2,100,2 \rangle$ $L_2 \text{ Error} = 2500$	$\langle 1, \{100,50,0\} \rangle$ $L_2 \text{ Error} = 10000$	$\langle 110,1, \{100,50\} \rangle$ $\langle 010,2, \{100\} \rangle$ $L_2 \text{ Error} = 0$
Coord. Values 1 100 50 100 2 0 100 0	$\langle 1,100,1 \rangle \langle 1,100,3 \rangle$ $L_2 \text{ Error} = 12500$	$\langle 1, \{100,50,100\} \rangle$ $L_2 \text{ Error} = 10000$	$\langle 101,1, \{100,100\} \rangle$ $\langle 010,2, \{100\} \rangle$ $L_2 \text{ Error} = 2500$



## Extended Wavelet Coefficients

- [Deligiannakis and Roussopoulos: SIGMOD'03]
- The goal isn't to minimize  $L_2$  error but to maximize  $L_2$  benefit

$$\sum_{i,j:w_{ij} \text{ is stored}} W_j w_{ij}^2$$

- $w_{ij}$ : the coefficient of  $j$ -th measure at  $i$ -th coordinate
- Proposed algorithms
  - DynL2: an optimal alg. with  $O(NMB)$  time and  $O(NMB)$  space
  - GreedyL2: an approximation alg. with  $O(NM^2 \log(NM))$  time and  $O(NM)$  space



## DynL2

- Dynamic programming to get optimal  $L_2$  benefit
- $OPT[u,b]$  is the optimal benefit with upto  $u$ -th coefficient using  $b$  space

- Optimal substructure

$$Opt[u,b].ben = \max \begin{cases} Opt[u-1,b].ben \\ Opt[u-1,b-space(w_{ij})].ben + W_j w_{ij}^2 \end{cases}$$

- $u = (i-1)M+j$  for  $w_{ij}$
- Time complexity :  $O(NMB)$
- Space complexity :  $O(NMB)$



## GreedyL2

- Greedy algorithm to get 2-approximation for L2 benefit
- Greedy choice property
  - Let per space benefit be benefit/required-space
  - Select a subset of a combined coefficient with **maximum per space benefit**
  - Use a data structure guaranteeing logarithmic time per operation (e.g. AVL tree or Heap)
- Time complexity :  $O(NM^2\log(NM))$
- Space complexity :  $O(NM)$



## Drawback of the Previous Work

- Both optimal and approximate algorithms require at least **linear space**
- These algorithms cannot work for **stream data**
- Approximation for benefit doesn't guarantee **error bound**
  - Suppose a 2-approximation of the benefit is 50
  - The error is actually 50 times of optimum error

	benefit	error
optimal	99	1
2-approx.	50	50
$\max(o/a, a/o)$	<b>1.98</b>	<b>50</b>



## Our Contributions

- Propose **faster** optimal and approximation algorithms with **less space**
- Our approximation guarantees that its quality in terms of **L2 error** is at most that of the optimum solution with relaxed space
- Extend our algorithms to **streaming** data
- Experimental result confirms the our algorithms are much faster with less space requirement



## Problem Formulation

- Given a  $N$  data points in  $D$ -dimensions with  $M$  measures, a storage constraint  $B$ , and a set of weights  $W$ ,
- Select the extended wavelet coefficients to be stored within  $B$  space to minimize the error

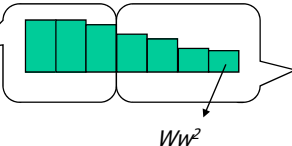
$$\sum_{i=1}^N \sum_{j=1}^M W_j \cdot e_{ij}^2 = \sum_{i,j:w_{ij} \text{ is not stored}} W_j w_{ij}^2$$

in a **single pass** over the data



## OptWaveI – Optimal Algorithm

- We can *independently* select subsets of measures for each coordinate
- To store a subset  $C \subseteq \{1, \dots, M\}$  of  $i$ -th coordinate with  $|C|=p$ 
  - Let  $\text{BOTTOM}[i,j] = \sum_{j \text{ smallest items}} W_k w_{ik}^2$  and  $\text{TOP}[i,j] = \sum_{j \text{ largest items}} W_k w_{ik}^2$
  - $\text{TOP}[i,p]$  gives the maximum benefit
  - $\text{BOTTOM}[i,M-p]$  gives the minimum error

$$\forall C \text{ where } |C|=p, \quad \text{TOP}[i,p] \geq \sum_{j \in C} W_j w_{ij}^2$$


$$\forall C \text{ where } |C|=p, \quad \text{BOTTOM}[i,M-p] \leq \sum_{j \in \{1, \dots, M\} - C} W_j w_{ij}^2$$

$Ww^2$

## OptWaveI (Cont.)

Procedure OptWaveI()

begin

1. for  $i:=1$  to  $N$  do

2. for  $b:=1$  to  $B$  do

3. for  $p:=0$  to  $M$  do

4. if  $b-H-S*p \geq 0$

5.  $\text{NEWOPT}[i,b] := \min(\text{NEWOPT}[i,b],$   
 $\text{NEWOPT}[i-1, b-H-S*p] + \text{BOTTOM}[i, M-p])$

end

space for top  $p$  coefficients

- $O(NMB)$  time
- $O(B^2)$  space
  - To evaluate  $\text{NEWOPT}[i,j]$ , only need the array of  $\text{NEWOPT}[i-1,j]$  for  $1 \leq j \leq B$
  - Each  $\text{NEWOPT}[i,j]$  needs  $O(B)$  space to store chosen coefficients

## OptWaveII – Optimal Algorithm

- We *do not need* to examine all coordinates
- The optimum solution can store at most  $L = \left\lfloor \frac{B}{S+H/M} \right\rfloor$  coefficients
  - Each coefficient  $w_{ij}$  takes up *at least*  $S+H/M$  space
- BEST[p] is the set of coordinate i in top-L largest TOP[i,p]
- There *exists* an optimum solution which has the coefficients in the coordinates only in

$$\bigcup_{p=1}^M BEST[p]$$

## OptWaveII - Example

H: space for Bit and i,  
S: space for a coefficient  
H+S|V|: space for an extended coefficient

When H=2, S=1, and B=5,  
 $L = \left\lfloor \frac{5}{1+2/3} \right\rfloor = 3$

$$\bigcup_{p=1}^3 BEST[p] = \{ 1, 2, 3, 6 \}$$

Candidate Coefficients			
Coord.	Values		
1	100	1	2
2	90	70	50
3	50	50	40
4	10	20	30
5	5	7	4
6	60	20	10
7	10	9	8
8	2	4	6

BEST[1]	BEST[2]	BEST[3]
1 (TOP[1,1]=10000)	2 (TOP[2,2]=13000)	2 (TOP[2,3]=15500)
2 (TOP[2,1]=8100)	1 (TOP[1,2]=10004)	1 (TOP[1,3]=10005)
6 (TOP[6,1]=3600)	3 (TOP[3,2]=5000)	3 (TOP[3,3]=6600)



## OptWaveII (Cont.)

Procedure OptWaveII()

begin

1. for each  $i \in \cup \text{BEST}[p]$

2. for  $b:=1$  to  $B$  do

3. for  $p:=0$  to  $M$  do

4. if  $b-H-S*p \geq 0$

5.  $\text{NEWOPT}[i,b] := \min(\text{NEWOPT}[i,b],$   
 $\text{NEWOPT}[\text{prev\_}i, b-H-S*p] + \text{BOTTOM}[i, M-p]$

end

- $O(NM(\log M + \log L) + M^2LB)$  time
- $O(ML + B^2)$  space
  - Array  $\text{BEST}[p]$  needs  $O(ML)$  space

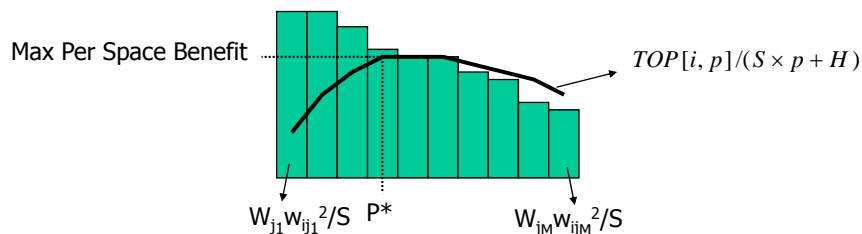


## ApproxWave - Approximate Alg.

- Relax space constraint  $B$  slightly by  $(MS+H)$
- Guarantee the quality in terms of *L2 error*
- Reduce space and time using a  *$O(B)$ -space* heap to store a *solution*
  - c.f. GreedyL2 uses  $O(NM)$ -space heap to store coefficient sets
- Each coefficient is inserted to the heap at most once - allows a single scan

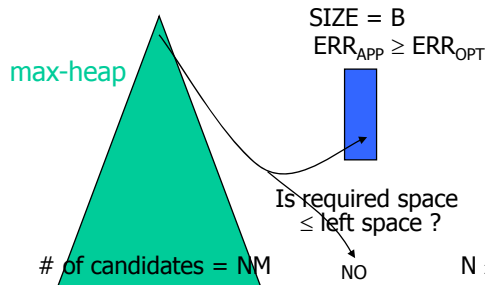
## Approximation Algorithm (Cont.)

- In each  $i$ -th coordinate, we find  $TOP[i, p^*]$  with max. per space benefit for  $1 \leq p \leq M$
- If insertion into the heap succeeds, try insertion for rest of the coefficients
- Otherwise, move to the next coordinate



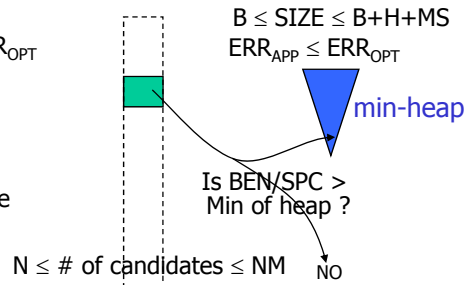
## GreedyL2 vs. ApproxWave

[GreedyL2]



Time Complexity	$O(NM^2 \log(NM))$
Space Complexity	$O(NM)$

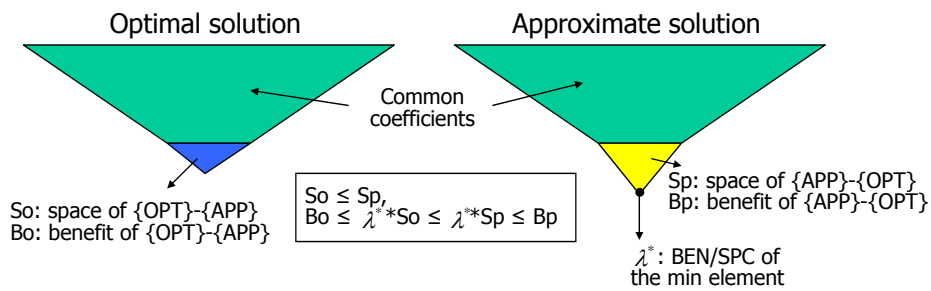
[ApproxWave]



Time Complexity	$O(NM(\log M + \log B))$
Space Complexity	$O(B)$

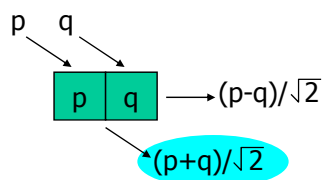
## Approximation Algorithm (Cont.)

- We can show that the benefit of our solution is no less than the benefit of the optimum solution



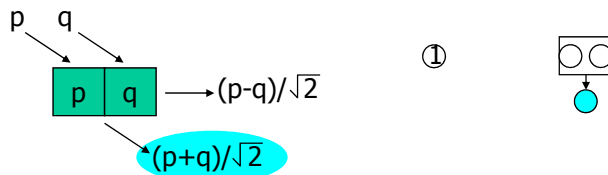
## Adapting to Stream data

- Using  $O(\log N)$  space we can compute the wavelet decomposition in a single pass.
- The order of the output coefficients will correspond to a post-order traversal of the tree



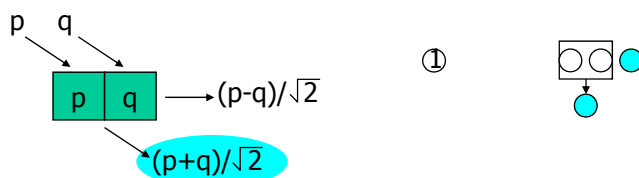
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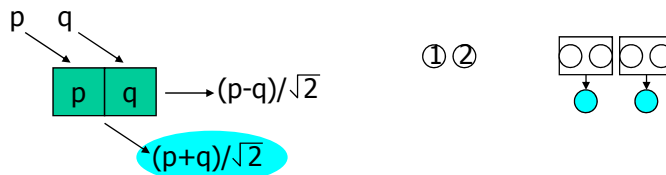
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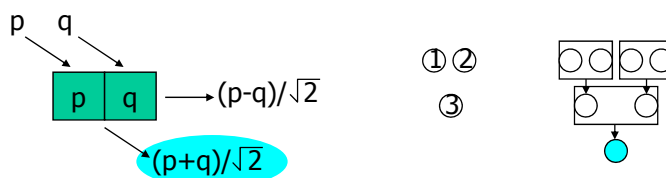
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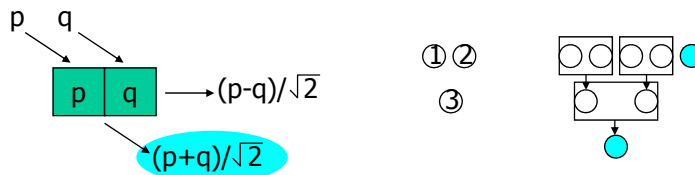
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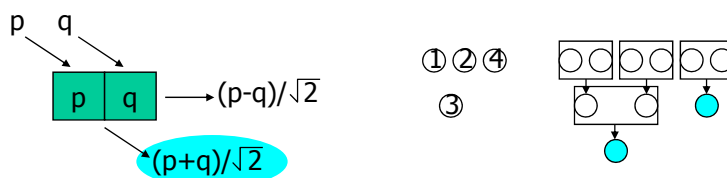
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## Adapting to Stream data

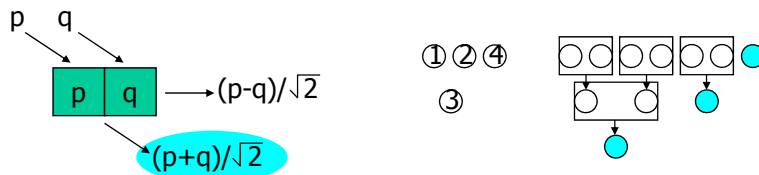
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- The order of the output coefficients will correspond to a post-order traversal of the tree





## Adapting to Stream data

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- The order of the output coefficients will correspond to a post-order traversal of the tree

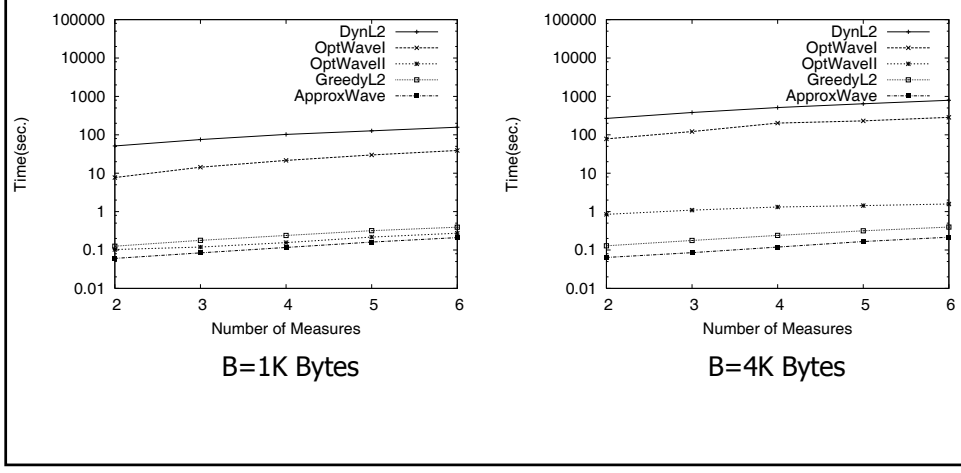


## Experimental Result

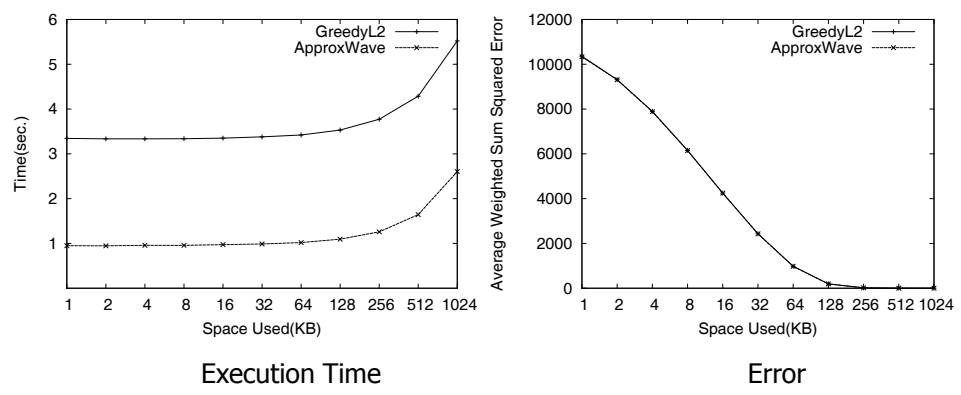
- Environment
  - Pentium-4 2.8 GHz with 512MB running Linux
  - GCC ver. 2.95.3
- Synthetic Data Sets
  - Data generator uses the Zipf functions to distribute values
  - Default parameters

Description	Value
# of dimensions	2
# of measures	30
Cardinality of every dimension	512
# of dense regions	10

## Experiment on Varying M



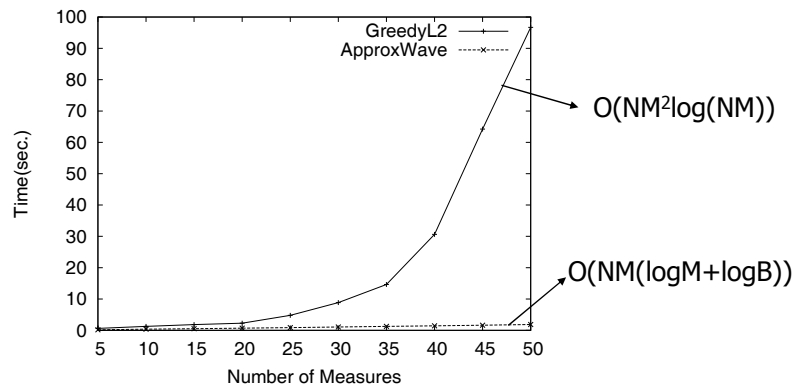
## Experiment on Varying B



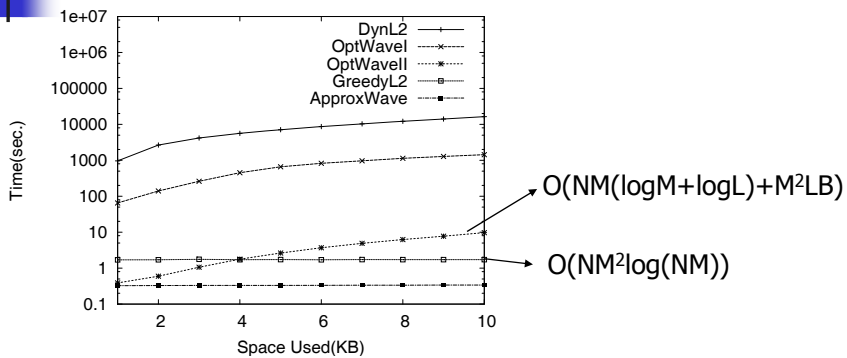


## Experiment on Large Values of M

- B = 1K Bytes



## Experiment on Real-life Dataset



- Pacific Northwest 1-year weather measurement data
  - 525600 tuples and 6 measures (Solar irradiance, wind speed)
  - Weight vector : <3,3,2,2,1,1>



## Summary

- [Deligiannakis and Roussopoulos: SIGMOD'03] gave an optimal algorithm and a 2-approximation algorithm with linear space for L2 benefit
  - Their approximation guarantees on benefit not on error
- We developed two faster optimal algorithms for L2 error with less space requirement
- We provide an approximation algorithm with at most the optimal error using relaxed space
- We demonstrated that our algorithms have significant performance benefits with much less space



## Example: DynL2

Candidate Coefficients				
Coord.	Values			
1	100	1	2	
2	90	70	50	

H: space for Bit and i,  
 S: space for a coefficient  
 H+S|V|: space for an extended coefficient

When H=2, S=1, and B=5,  
 Benefit = 15500, Error = 10005

Opt					Force				
B	2	3	4	5	H+S V	2	3	4	5
i	H	H+S	H+2S	H+3S	i	H	H+S	H+2S	H+3S
1	0	10000	10000	10000	1	0	10000	10000	10000
2	0	10000	10001	10001	2	0	10000	10001	10001
3	0	10000	10004	10005	3	0	10000	10004	10005
4	0	10000	10004	10005	4	0	8100	8100	8100
5	0	10000	13000	13000	5	0	8100	13000	13000
6	0	10000	13000	15500	6	0	8100	13000	15500

## Example: GreedyL2

Candidate Coefficients			
Coord.	Values		
1	100	1	2
2	90	70	50

When  $H=2$ ,  $S=1$ , and  $B=5$ ,  
 Left Space = 5  
 Benefit = 0, Error = 25505

Coeff.	Sp.	Ben./Sp.	Selection
{100}	3	3333.3	-
{100,2}	4	2501	-
{100,2,1}	5	2001	-
{90}	3	2700	-
{90,70}	4	3250	-
{90,70,50}	5	3100	-

## Example: GreedyL2

Candidate Coefficients			
Coord.	Values		
1	100	1	2
2	90	70	50

When  $H=2$ ,  $S=1$ , and  $B=5$ ,  
 Left Space = 2  
 Benefit = 10000, Error = 15505

Coeff.	Sp.	Ben./Sp.	Selection
{100}	3	3333.3	-
{100,2}	4	2501	-
{100,2,1}	5	2001	-
{90}	3	2700	-
{90,70}	4	3250	-
{90,70,50}	5	3100	-

Coeff.	Sp.	Ben./Sp.	Selection
{100}	3	3333.3	1
{2}	1	4	-
{2,1}	2	2.5	-
{90}	3	2700	-
{90,70}	4	3250	-
{90,70,50}	5	3100	-

## Example: GreedyL2

Candidate Coefficients			
Coord.	Values		
1	100	1	2
2	90	70	50

When  $H=2$ ,  $S=1$ , and  $B=5$ ,  
 Left Space = 1  
 Benefit = 10004, Error = 15501

Coeff.	Sp.	Ben./Sp.	Selection
{100}	3	3333.3	1
{2}	1	4	2
{1}	1	1	-

Coeff.	Sp.	Ben./Sp.	Selection
{100}	3	3333.3	1
{2}	1	4	-
{2,1}	2	2.5	-
{90}	3	2700	-
{90,70}	4	3250	-
{90,70,50}	5	3100	-

## Example: GreedyL2

Candidate Coefficients			
Coord.	Values		
1	100	1	2
2	90	70	50

When  $H=2$ ,  $S=1$ , and  $B=5$ ,  
 Left Space = 0  
 Benefit = 10005, Error = 15500

Coeff.	Sp.	Ben./Sp.	Selection
{100}	3	3333.3	1
{2}	1	4	2
{1}	1	1	-

Coeff.	Sp.	Ben./Sp.	Selection
{100}	3	3333.3	1
{2}	1	4	2
{1}	1	1	3

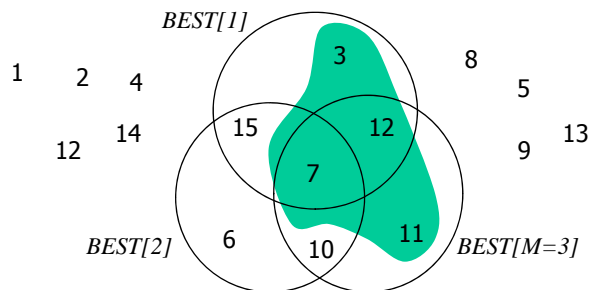
## Example: OptWaveI

Candidate Coefficients			
Coord.	Values		
1	100	1	2
2	90	70	50

When  $H=2$ ,  $S=1$ , and  $B=5$ ,  
Benefit = 15500, Error = 10005

i \ B	0	1	2	3	4	5
	-	-	H	H+S	H+2S	H+3S
0	25505 { }	25505 { }	25505 { }	25505 { }	25505 { }	25505 { }
1	25505 { }	25505 { }	25505 { }	15505 {(0,1)}	15501 {(0,1),(0,3)}	15500 {(0,1),(0,3),(0,2)}
2	25505 { }	25505 { }	25505 { }	15505 {(0,1)}	12505 {(1,1),(1,2)}	10005 {(1,1),(1,2),(1,3)}

## OptWaveII (Cont.)





## Approximation Algorithm (Cont.)

- Suppose  $w_{ij_1}, w_{ij_2}, \dots, w_{ij_M}$  are the coefficients with index  $i$  such that  $w_{ju} w_{iu}^2 \geq w_{jv} w_{iv}^2$  whenever  $u \leq v$ .
- $\text{RATIO}[i].\text{wt} = \max_{p=1, \dots, M} \text{TOP}[i, p] / (S \times p + H)$
- $\text{RATIO}[i].p$  is the smallest value  $p$  of the maximum per space benefit
- If  $\text{RATIO}[i].\text{wt}$  does not enter to the heap,
- We don't need to examine the rest of coefficient index from  $\text{RATIO}[i].p$  to  $j_M$



## Approximation Algorithm (Cont.)

- Keep an approximate solution in a heap with the space  $\leq (B + M * S + H)$
- For each  $i$ -th coordinate, suppose that
  - $w_{ij_1}, w_{ij_2}, \dots, w_{ij_M}$  are the coefficients with index  $i$  such that  $w_{ju} w_{iu}^2 \geq w_{jv} w_{iv}^2$  whenever  $u \leq v$ .
  - $\text{wt} = \max_{p=1, \dots, M} \text{TOP}[i, p] / (S \times p + H)$
  - $p$  is the smallest value  $j_k$  with the above  $\text{wt}$
- If  $w_{ip}$  cannot be inserted into the heap, the coefficients  $\{w_{i(p+1)}, w_{ij_2}, \dots, w_{ij_M}\}$  are guaranteed not to be inserted
- Otherwise, we put  $\{w_{ij_1}, w_{ij_2}, \dots, w_{ip}\}$  into the heap and examine the rest of coefficients  $\{w_{i(p+1)}, w_{ij_2}, \dots, w_{ij_M}\}$



## Approximation Algorithm (Cont.)

- Abstract pseudo code

Procedure ApproxWave()

begin

1. for i:=1 to N do
  2.   if Free  $\geq$  0
  3.     Insert  $\text{RATIO}[i].p$  to heap
  4.   else if  $\text{RATIO}[i].wt >$  min of heap
  5.     Delete overflow elements and Insert  $\text{RATIO}[i].p$  to heap
  6.   for u:= $\text{RATIO}[i].p+1$  to M
  7.     if Free  $\geq$  0
  8.       Insert  $Ww_u/S$  to heap
  9.     else if  $Ww_u/S >$  min of heap
  10.      Delete overflow elements and Insert  $Ww_u/S$  to heap
  11. Include all the coefficients stored in the heap
- end

- Once we reach Free  $<$  0

- We keep  $-(M*S+H) \leq \text{Free} < 0$  in all step

## ApproxWave - Example

Candidate Coefficients			
Coord.	Values		
1	100	1	2
2	90	70	50

When  $H=2$ ,  $S=1$ , and  $B=5$ ,  
 $\text{RATIO}[1].p = 1$ ,  $\text{RATIO}[1].wt = 3333.3$   
 $\text{RATIO}[2].p = 1$ ,  $\text{RATIO}[2].wt = 3250$   
 Free space = 5

Heap $\langle i, m, wt, IS\_RATIO[.P] \rangle$



## ApproxWave - Example

Candidate Coefficients			
Coord.	Values		
1	100	1	2
2	90	70	50

When  $H=2$ ,  $S=1$ , and  $B=5$ ,  
 RATIO[1].p = 1, RATIO[1].wt = 3333.3  
 RATIO[2].p = 1, RATIO[2].wt = 3250  
 Free space = 2

Heap <i, m, wt, IS_RATIO[].P>
<1, 1, 3333.3, YES>



## ApproxWave - Example

Candidate Coefficients			
Coord.	Values		
1	100	1	2
2	90	70	50

When  $H=2$ ,  $S=1$ , and  $B=5$ ,  
 RATIO[1].p = 1, RATIO[1].wt = 3333.3  
 RATIO[2].p = 1, RATIO[2].wt = 3250  
 Free space = 1

Heap <i, m, wt, IS_RATIO[].P>
<1, 2, 1, NO>
<1, 1, 3333.3, YES>



## ApproxWave - Example

Candidate Coefficients			
Coord.	Values		
1	100	1	2
2	90	70	50

When  $H=2$ ,  $S=1$ , and  $B=5$ ,  
 RATIO[1].p = 1, RATIO[1].wt = 3333.3  
 RATIO[2].p = 1, RATIO[2].wt = 3250  
 Free space = 0

Heap <i, m, wt, IS_RATIO[].P>
<1, 2, 1, NO>
<1, 3, 4, NO>
<1, 1, 3333.3, YES>



## ApproxWave - Example

Candidate Coefficients			
Coord.	Values		
1	100	1	2
2	90	70	50

When  $H=2$ ,  $S=1$ , and  $B=5$ ,  
 RATIO[1].p = 1, RATIO[1].wt = 3333.3  
 RATIO[2].p = 1, RATIO[2].wt = 3250  
 Free space = -4

Heap <i, m, wt, IS_RATIO[].P>
<1, 2, 1, NO>
<1, 3, 4, NO>
<2, 2, 3250, YES>
<1, 1, 3333.3, YES>



## ApproxWave - Example

Candidate Coefficients			
Coord.	Values		
1	100	1	2
2	90	70	50

When  $H=2$ ,  $S=1$ , and  $B=5$ ,  
 RATIO[1].p = 1, RATIO[1].wt = 3333.3  
 RATIO[2].p = 1, RATIO[2].wt = 3250  
 Free space = -3

Heap <i, m, wt, IS_RATIO[].P>
<1, 3, 4, NO>
<2, 2, 3250, YES>
<1, 1, 3333.3, YES>



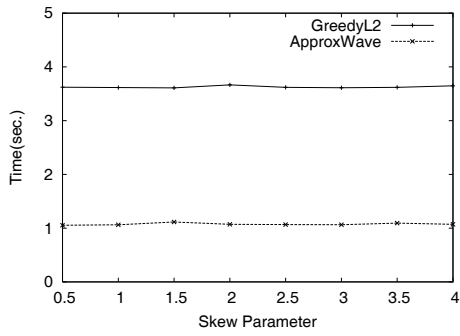
## ApproxWave - Example

Candidate Coefficients			
Coord.	Values		
1	100	1	2
2	90	70	50

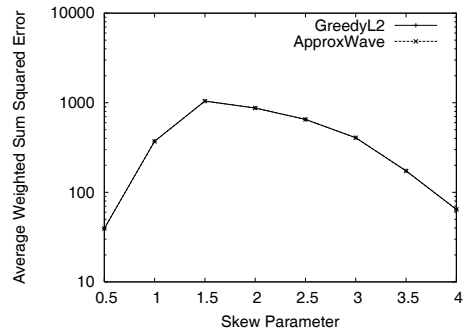
When  $H=2$ ,  $S=1$ , and  $B=5$ ,  
 RATIO[1].p = 1, RATIO[1].wt = 3333.3  
 RATIO[2].p = 1, RATIO[2].wt = 3250  
 Free space = -4, Used Space = 9  
 Benefit = 25505, Error = 1

Heap <i, m, wt, IS_RATIO[].P>
<1, 3, 4, NO>
<2, 3, 2500, NO>
<2, 2, 3250, YES>
<1, 1, 3333.3, YES>

# Experiment on Varying Skew



Execution Time



Error