GBASE: A Scalable and General Graph Management System

U Kang
Carnegie Mellon University
ukang@cs.cmu.edu

Hanghang Tong
IBM T.J. Watson
htong@us.ibm.com

Jimeng Sun
IBM T.J. Watson
jimeng@us.ibm.com

Ching-Yung Lin
IBM T.J. Watson
chingyung@us.ibm.com

Christos Faloutsos
Carnegie Mellon University
christos@cs.cmu.edu

ABSTRACT

Graphs appear in numerous applications including cyber-security, the Internet, social networks, protein networks, recommendation systems, and many more. Graphs with millions or even billions of nodes and edges are common-place. How to store such large graphs efficiently? What are the core operations/queries on those graph? How to answer the graph queries quickly? We propose GBASE, a scalable and general graph management and mining system. The key novelties lie in 1) our storage and compression scheme for a parallel setting and 2) the carefully chosen graph operations and their efficient implementation. We designed and implemented an instance of GBASE using MAPREDUCE/HADOOP. GBASE provides a parallel indexing mechanism for graph mining operations that both saves storage space, as well as accelerates queries. We ran numerous experiments on real graphs, spanning *billions* of nodes and edges, and we show that our proposed GBASE is indeed fast, scalable and nimble, with significant savings in space and time.

Categories and Subject Descriptors

H.2.8 [**Database Management**]: Database Applications—*Data Mining*

General Terms

Design, Experimentation, Algorithms

Keywords

Graph, Indexing, Compression, Distributed Computing

1. INTRODUCTION

Graphs have been receiving increasing research attention, being applicable in a wide variety of high impact applications, like social networks, cyber-security, recommendation systems, fraud/anomaly detection, protein-protein interaction networks, to name a few. In fact, *any* many-to-many database relationship can be easily treated as a graph, with myriads of additional applications (patients and symptoms; customers and locations they have been to; documents and terms in IR, etc). To add to the challenge of graph mining, even the volume of such graphs is unprecedented, reaching and exceeding billions of nodes and edges.

Problem Definitions.

Our goal is to build a general graph management system in parallel, distributed settings to support billion-scale graphs for various applications. For the goal, we address the following problems:

1. *Storage*. How can we efficiently store and manage such huge graphs in parallel, distributed settings to answer graph queries efficiently? How should we split the edges into smaller units? How should we group the units into files?
2. *Algorithms*. How can we define common, core algorithms to satisfy various graph applications?
3. *Query Optimization*. How can we exploit the efficient storage and general algorithms to execute queries efficiently?

For all the problems, *scalability* is a major challenge. The size of graphs has been experiencing an unprecedented growth. For example, one of the graphs we use here, the *Yahoo Web graph* from 2002, has more than 1 *billion* nodes and almost *7 billion* edges. Similar size, or even larger graphs, exist: the Twitter graph spans several Terabytes; click-streams are reported to reach Petabyte scale [25]. Such large graphs violate the assumption that the graph can be fit in main memory or at least the disk of a single workstation, on which most of existing graph algorithms have been built. Thus, we need to re-think those algorithms, and to develop scalable, parallel ones, to manage graphs that span Tera-bytes and beyond.

Our Contributions.

We propose GBASE, a scalable and general graph management system, to address the above challenges. The main contributions are the following:

1. *Storage*. We propose a novel graph storage method called 'block compression' to efficiently store homogeneous regions of graphs. We also propose a grid based method to efficiently place blocks into files. We run our algorithm on billion-scale graphs and show that the block compression method leads up to $50\times$ less storage and faster running time. Our block compression method is agnostic to the underlying storage mechanism, which can be applied to distributed file systems as well as relational databases.
2. *Algorithms*. We identify a core graph operation, and use it to formulate *seven* different types of graph queries in-

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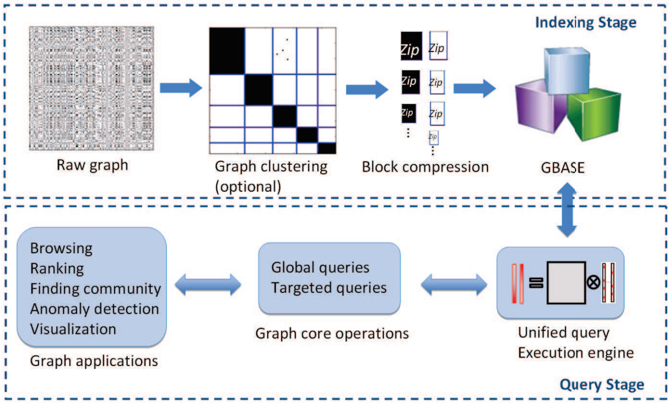


Figure 1: Overall framework of GBASE. 1. Indexing Stage: raw graph is clustered and divided into compressed blocks. 2. Query Stage: global and targeted queries from various graph applications are handled by a unified query execution engine.

cluding neighborhood, induced subgraph, egonet, K-core, and cross-edges. The novelty is in formulating edge-based queries(induced subgraph) as well as node-based queries(neighborhoods) using a unified framework.

3. *Query Optimization.* We propose a grid selection strategy to minimize disk accesses and answer queries quickly. We also propose a MAPREDUCE algorithm to support incidence matrix based queries using the original adjacency matrix, without explicitly building the incidence matrix.

The rest of this paper is organized as follows. We first present the overall framework in Section 2. We describe the storage and indexing method in Section 3, and then the query execution in Section 4. We provide experimental evaluations and comparisons in Section 5. After reviewing the related work in Section 6, we conclude in Section 7.

2. OVERALL FRAMEWORK

The overall framework of our GBASE is summarized in Figure 1. The design objective is to balance storage efficiency and query performance on large graphs. It comprises of two components: the indexing stage and the query stage. In this Section, we give a high level overview of each stage; and we will give more details in Section 3 and 4, respectively.

In the indexing stage, given the original raw graph which is stored as a big edge file, GBASE first partitions it into several homogeneous blocks. Second, according to the partition results, we reshuffle the nodes so that the nodes belonging to the same partition are put nearby. Third, we compress all non-empty block through standard compression such as GZip. Finally, we store the compressed blocks, together with some meta information (e.g., the block row id and column id, and all the encoded node ids), into the graph databases. For many real graphs, such homogeneous blocks, community-like structure, do exist. Therefore, after partition and reshuffling, the resulting blocks are either relatively dense (e.g., the diagonal blocks in Figure 1) or very sparse (e.g., the off-diagonal blocks in Figure 1). Both cases are space efficient for compression (i.e., the compression ratio is high). In the extreme case that a given block is empty, we do not store it at all. Our experiments (See Section 5) show that in some cases, we only need less than 2% storage space of the original after the indexing stage.

In the query stage, our goal is to provide a set of core operations that will be sufficient to support a diverse set of graph applications, e.g., ranking, community detection, anomaly detection, and etc. The key of the on-line query stage is the query execution engine, which unifies the different types of inputs as query vectors. It also unifies the (seemingly) different types of operations on the graph by a unified matrix-vector multiplication which we will introduce in Section 4. By doing so, GBASE is able to support multiple different types of queries simultaneously. Table 1 summarizes the queries (the first column) that are supported by GBASE. These queries construct the main building blocks for a variety of important graph applications (Table 1). For example, the diversity of RWR(Random Walk with Restart [35]) scores among the neighborhood of a given edge/node is a strong indicator of abnormality of that node/edge [34]. The ratio between the number of edges (or the summation of edge weights) and number of nodes within the egonet can help find abnormal nodes on weighted graphs [6]. The K-cores and cross-edges can be used for visualization and finding communities in large graphs.

Query / **Applications**	**Browsing**	**Ranking**	**Finding Community**	**Anomaly Detection**	**Visualization**
Connected Comp.			✓	✓	
Radius				✓	✓
PageRank, RWR	✓	✓		✓	
Induced Subgraph	✓		✓		✓
(K)-Neighborhood	✓		✓		✓
(K)-Egonet	✓		✓	✓	✓
K**-core**			✓		✓
Cross-edges				✓	✓

Table 1: Applications of GBASE. Notice that GBASE answers wide range of both global(top 3 rows) and targeted queries(bottom 5 rows with bold fonts) with applications in browsing[29, 35, 24], ranking[29, 35], finding communities[20, 24], anomaly detection[34, 20, 19, 6], and visualization[24, 7].

Symbol	Definition
$\mathcal{G}$	Graph.
A	Adjacency matrix of the graph $\mathcal{G}$.
B	Incidence matrix of the graph $\mathcal{G}$.
n	Number of nodes.
m	Number of edges.
k	Number of partitions.
p, q	Partition indices, $1 \leq p, q \leq k$.
$I^{(p)}$	Set of nodes belonging to the p-th partition.
$l^{(p)}$	Partition size, $l^{(p)} \equiv \lvert I^{(p)} \rvert, 1 \leq p \leq k$.
$\mathcal{G}^{(p,q)}$	Subgraphs induced by p-th and q-th partitions.
$m^{(p,q)}$	Number of edges in $\mathcal{G}^{(p,q)}$.
$H(.)$	Shannon entropy function.

Table 2: Definitions of symbols

3. GRAPH STORAGE AND INDEXING

In this section, we describe in details the indexing and storage stage of GBASE. We use the symbols in Table 2.

3.1 Baseline Storage Scheme

A typical way to store the raw graph is to use the adjacency list format: for each node, it saves all the out-neighbors adjacent from the node. The adjacency list format is simple and might be good for answering out-neighbor queries. However, it is not efficient format for answering general queries including in-neighbor queries and ego-net queries as we will see in Section 4. For the reason, we instead use the sparse adjacency matrix format, where we save each edge by a (source,destination) pair. The advantage of the sparse adjacency matrix format is its generality and flexibility to enable efficient storage and indexing techniques as we will see later in this and the next sections.

The storage system should be designed to be efficient in both storage cost and on-line query response. To this end, we propose to index and store the graph on the homogeneous block, community-like structure, levels. Next, we will describe how to *form*, *compress* and *store/place* such blocks.

3.2 Block Formulation

The first step is to partition the graph, i.e., re-order the rows and columns, and make homogeneous regions into blocks. Partitioning algorithms form an active research area, and finding optimal partitions is orthogonal to our work. Any partition algorithms, e.g., METIS [22], Disco [30], etc, can be naturally plugged into GBASE.

Graph partitioning can be formally defined as follows. The input is the original raw graph denoted by $\mathcal{G}$. Given a graph $\mathcal{G}$, we partition the nodes into k groups. The set of nodes that are assigned into the p-th partition for $1 \leq p \leq k$ is denoted by $I^{(p)}$. The subgraph or block induced by p-th source partition and q-th destination partition is denoted as $\mathcal{G}^{(p,q)}$. The sets $I^{(p)}$ partition the nodes, in the sense that $I^{(p)} \cap I^{(p')} = \emptyset$ for $p \neq p'$, while $\bigcup_p I^{(p)} = \{1, \ldots, n\}$. In terms of storage, the objective is to find the optimal k partitions which lead to smallest total storage cost of all blocks/subgraphs $\mathcal{G}^{(p,q)}$ where $1 \leq p, q \leq k$. Intuitively, we want the induced subgraphs to be homogeneous (meaning the subgraphs are either very dense or very sparse), which captures not only community structure but also leads to small storage cost.

For many real graphs, the community/clustering structure can be naturally identified. For instance, in Web graphs, the lexicographic ordering of the URL can be used as an indicator of community [10] since there are usually more intra-domain links compared with the inter-domain links. For authorship network, the research interest is often a good indicator to find communities since authors with the same or similar research interest tend to have more collaborations. For patient-doctor graph, the patient information (e.g., geography, disease type, etc) can be used to find the communities (patients with similar disease and living in the same neighborhood have higher chance to visit the same doctor).

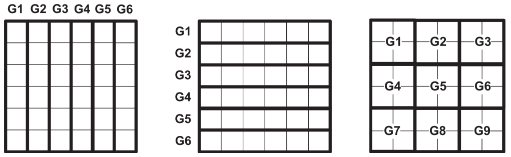
3.3 Block Compression

The homogeneous block representation provides a more compact representation of the original graph. It enables us to encode the graph in a more efficient way. The encoding of a block $\mathcal{G}^{(p,q)}$ consists of the following information:

- source and destination partition ID p and q;
- the set of sources $I^{(p)}$and the set of destinations $I^{(q)}$.
- the payload, the bit string of subgraph $\mathcal{G}^{(p,q)}$.

A naive way of encoding a block is *raw block encoding* which only stores the coordinates of the non-zero entries in the block. Although this method saves the storage space since the nonzero elements within the block can be encoded with a smaller number of bits (log(max($l^{(p)}, l^{(q)}$)) than the original, the savings are not great.

To achieve better compression, we propose *zip block encoding* which converts the adjacency matrix of the subgraph into a binary string and stores the compressed string as the payload. Compared to the raw block encoding, the zip block encoding requires more cpu time to zip and unzip blocks. However, the storage savings and the reduced data transfer size help to improve performance of GBASE as we will see in Section 5.



(a) Vertical Placement (b) Horizontal Placement (c) Grid Placement

Figure 2: Adjacency matrices showing possible placement of blocks into files in HADOOP. The smallest rectangle represents a block in the adjacency matrix. The placement strategy determines which of the blocks are grouped into files G1 to G6 or G9. Vertical placement in (a) is good for in-neighbor queries, but inefficient for out-neighbor or egonet queries. Horizontal placement in (b) is good for out-neighbor queries, but inefficient for in-neighbor or egonet queries. GBASE uses the grid placement, shown in (c), which is efficient for all types of queries.

For example, we have the following adjacency matrix of a graph:

$$\mathcal{G} = \begin{pmatrix} 1 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 1 \end{pmatrix} \qquad (1)$$

raw block encoding will just store the non-zero coordinates $(0, 0)$, $(1, 0)$, $(2, 1)$, and $(2, 2)$ as the payload. Zip block encoding will converts the matrix into a binary string $110, 001, 001$ (in the column major order) and then use the compression of this string as the payload.

Storage Estimation. The storage needed for raw block encoding is $2 * m^{(p,q)} * log(max(l^{(p)}, l^{(q)}))$. The storage needed for zip block encoding is $l^{(p)} l^{(q)} H(d)$, where $d = \frac{m^{(p,q)}}{l^{(p)} l^{(q)}}$ is the density of $\mathcal{G}^{(p,q)}$. $H(\cdot)$ is the Shannon entropy function: $H(X) = -\sum_x p(x) \log p(x)$ where $p(x)$ is the probability that $X = x$. Note that the number of bits to encode an edge in zip block encoding decreases as d increases, while it is constant in raw block encoding.

3.4 Block Placement

After we compress the blocks, we need to store/place them in the file system (e.g., HDFS of HADOOP, relational DB). Here, the main idea is to place several blocks together into a file, and select only relevant files as inputs in the query stage. The question is, how do we place blocks into files? A typical approach is to use vertical placement to place the vertical blocks in a file as shown in Figure 2(a). The other alternative is to use horizontal placement to place the horizontal blocks in a file as shown in Figure 2(b). However, both of the placement techniques are good only for one type of query: for example, horizontal and vertical placement is good for out-neighbor and in-neighbor queries, respectively.

To solve the problem, GBASE uses the grid placement as shown in Figure 2(c). The advantage of the grid placement is that it can answer various types of queries efficiently as we will see in Section 4. Suppose we store all the compressed blocks in K files. With vertical/horizontal placement, we need $O(K)$ file accesses to find the in- and out-neighbors of a given query node. In contrast, we only need $O(\sqrt{K})$ files accesses with grid placement.

4. HANDLING GRAPH QUERIES

In this section, we describe query execution in GBASE. GBASE supports both "global" queries, as well as "targeted" queries for one or a few specific nodes. The answer to global queries requires traversal of the whole graph, like, e.g., diameter estimation. In contrast, "targeted" queries need to access only parts of the graph. GBASE supports seven different queries including neighborhoods, induced subgraphs, egonets, K-core, and cross-edges.

4.1 Global Queries

Global queries are performed by repeated joins of edge blocks and vector blocks. GBASE supports the following graph queries: degree distribution, PageRank, RWR("Random Walk with Restart"), radius estimations, and discovery of connected components. Our contribution here is that our proposed storage and compression scheme reduce the graph storage significantly, and enable faster running time as shown in Figure 5. The global queries also serve as primitives for targeted queries(see 'T6: K-core' in Section 4.2), enabling a variety of applications as shown in Table 1.

4.2 Targeted Queries

Many graph mining operations can be unified as matrix-vector multiplication. Here that matrix is either the adjacency matrix A of size $n \times n$ or the incidence matrix B of size $m \times n$ where n and m are the number of nodes and edges in the graph, respectively. Each row of the incidence matrix corresponds to an edge, and it has two non-zeros whose column ids are the node ids of the edge.

The matrix-vector multiplication observation has the extra benefit that it corresponds to an SQL join. Thus, graph mining could use all the highly optimized join algorithms in the literature (hash join, indexed join etc), while still leverages the proposed block compression storage scheme.

In fact, for each of the upcoming primitives, we shall first give the matrix-vector details, and then the SQL code.

T1: 1-step neighbors.

The first query is to find 1-step in-neighbors and out-neighbors of a query node v.

Matrix-Vector version

Given a query node v, its 1-step in-neighbors can be found by the following matrix-vector multiplication:

$$in^1(v) = A \times e_v, \tag{2}$$

where the matrix is the adjacency matrix of the graph A and the vector is the 'indicator vector' e_v which is the n-vector whose v-th element is 1, and all other elements are 0s. The 1-step in-neighbors of the query node v are those nodes whose corresponding values in $in^1(v)$ are 1s.

The 1-step out-neighbors can be obtained in the similar way by replacing A with its transpose A^T.

SQL version

We can also find 1-step in-neighbors and out-neighbors by the standard SQL. Assume we have a table `E(src, dst)` storing the edges, with attributes 'source' (`src`) and 'destination' (`dst`). The 1-step out-neighbors of a query node 'q' are given by

```
SELECT dst
FROM E
WHERE src='q'
```

without even requiring a join. 1-step in-neighbor can be answered in a similar way.

T2: K-step neighbors.

The next query is to find 'within k-step' neighbors. Let us only consider the k-step in-neighbors. k-step out-neighbors can be found in similar way - we only need to replace the matrix A by its transpose A^T in the matrix-vector multiplication version; and switch `src` and `dst` in the SQL version.

Matrix-Vector version

The k-step in-neighbors $nh^k(v)$ of the query node v is defined recursively by $(k-1)$-step neighbors $nh^{k-1}(v)$ in terms of matrix-vector multiplication as follows:

$$nh^k(v) = A \times nh^{k-1}(v), \tag{3}$$

where the 0-step in-neighbors $nh^0(v)$ is just the indicator vector e_v. After the k multiplications, the k-step in-neighbors are those nodes whose corresponding values in $nh^k(v)$ or $nh^{k-1}(v)$ are 1s.

SQL version

As before, assume we have a table `E` with attributes `src` and `dst`. The k-step in-neighbors can also be found by SQL join. In general, the k-step in-neighbors is a $(k-1)$-way join. For example, the 2-step in-neighbors of a query node 'q' is given by the following SQL join:

```
SELECT E2.src
FROM E as E1, E as E2
WHERE E1.dst='q'
   AND E1.src = E2.dst
```

T3: Induced subgraph.

Given a set of nodes V_q in a graph $\mathcal{G}$, the induced subgraph is defined to be a graph whose nodes are V_q and an edge between two nodes v_1 and v_2 exist if they are adjacent in $\mathcal{G}$.

Matrix-Vector version

Let B be the $m \times n$ incidence matrix where m and n are the number of edges and nodes of the graph, respectively. Let e_{vq} be the n-vector, whose corresponding elements for V_q are 1s, and 0s otherwise.

Then, the induced subgraph $S(V_q)$ from V_q is expressed by the following matrix-vector multiplication:

$$S(V_q) = B \times e_{vq}, \tag{4}$$

where the resulting vector $S(V_q)$ is m-vector and the elements in $S(V_q)$ have values of 0, 1, or 2. The induced subgraph is given by those edges whose corresponding values in $S(V_q)$ are 2s since it means that the incident nodes (both the source and the target) of the edges are in V_q.

SQL version

Assume we have an incidence matrix as table B, with attributes *eid*, *srcid*, and *dstid*, representing the edge id, the source node id, and the destination id of a row in the incident matrix, respectively. Also assume we have a query vector table Q with an attribute *nodeid*. Then the induced subgraph is given by the following join:

```
SELECT B.eid, B.srcid, B.dstid
FROM B, Q as Q1, Q as Q2
WHERE B.srcid=Q1.nodeid
   AND B2.dstid=Q2.nodeid
```

T4: 1-step egonet.

Informally, the 1-step-away egonet (or just 'egonet') of a node v is its 1-step-away vicinity. Formally, it is defined as the induced subgraph that includes v and its 1-step neighbors. Extracting the egonet of a query node v is a special case of extracting induced subgraph. That is, the set of nodes V_q is defined to be the v and its 1-step in-neighbors and out-neighbors.

The details are omitted, since we can combine earlier expressions (for both the matrix-vector case, as well as for the SQL case).

T5: K-step egonet.

K-step egonet of a node v is defined to be the induced subgraph from v and its within-k step neighbors. Extracting the k-step egonet of a query node v is also a special case of extracting induced subgraph. That is, the set of nodes V_q is defined to be the v and its within-k step neighbors. Thus, the same expression for the k-step neighbors and the induced subgraph can be used for extracting k-step egonet.

T6: K-core.

K-core of a graph is a maximal connected subgraph in which all vertices have degree at least K [7]. K-core is useful for finding communities and visualizing graphs. Although it seems complicated at first, all K-cores of a large graph can be enumerated by GBASE using primitives defined before:

1. Compute degrees of all nodes. Let C be the set of nodes with degree >= K.
2. Compute induced subgraph G' using C.
3. Find connected components of G'. The resulting components are the K-core.

T7: Cross-edges.

Given two disjoint sets V_1 and V_2 of nodes, how can we find the cross edges connecting the two sets? Cross-edges are useful for visualizing the interaction of two distinct sets of nodes, as well as anomaly detection (e.g., a set of nodes having few edges to the rest of the world are suspicious). Cross-edges can be computed by GBASE using induced subgraph queries:

1. Computed induced subgraphs $S(V_1)$, $S(V_2)$, $S(V_1 \cup V_2)$ using nodes in V_1, V_2, and $(V_1 \cup V_2)$, respectively.
2. Let E_1, E_2, and E_{12} be the set of edges in $S(V_1)$, $S(V_2)$, and $S(V_1 \cup V_2)$, respectively. The cross edges are exactly the edges in $E_{12} - E_1 - E_2$.

4.3 Query Execution Engine

We describe the query execution engine of GBASE built on the top of HADOOP, an open source implementation of MAPREDUCE which is a distributed large scale data processing platform.

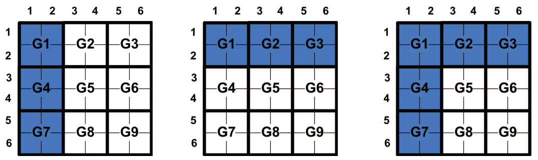
Overview.

As described in previous sections, the main operation of GBASE is the matrix-vector multiplication. GBASE handles queries by executing appropriate block matrix-vector multiplication modules. The global queries are typically handled by multiple matrix-vector multiplications since the answer to the queries is often a fixed point of the multiplication(e.g., the first eigenvector in case of PageRank). The local queries require one or few multiplications.

Most of the operations require the adjacency matrix of the graph. Thus, GBASE uses the adjacency matrix directly as its input. However, some operations including the induced subgraph require the incidence matrix which is different from the adjacency matrix. We will see how to handle the queries requiring incidence matrix efficiently at the end of this subsection.

Grid Selection.

Before running the matrix-vector multiplication, GBASE selects the grids containing the blocks relevant to the queries. Only the files corresponding to the grids are fed into HADOOP jobs that GBASE executes. For global queries, we need to select all the grids since all the blocks are relevant. For targeted queries, however, we can select only relevant grids. For in-neighbor queries, we select grids whose column range contains the query node as shown in Figure 3(a). For out-neighbor queries, we select grids whose row range contains the query node as shown in Figure 3(b). For egonet queries, we select grids whose row or column range contains the query. As we will see in Section 5, this grid selection has advantages of decreasing the running time.



(a) 1-step in-neighbors (b) 1-step out-neighbors (c) 1-step in- and out-neighbors

Figure 3: Grid selection in 6 by 6 blocks where the query node belongs to the second block. The smallest rectangle corresponds to a block, and a bigger rectangle containing 4 blocks is a grid which is saved in a file. Notice that GBASE selects different grids based on the type of the query and the query node id. For example, GBASE selects G1, G4, and G7, instead of all the grids for in-neighbors query. This reduced input size results in the decreased running time.

Handling Incidence Matrix Queries.

While the majority of operations use the adjacency matrix, the induced subgraph queries use the incidence matrix. Thus, GBASE need to access the incidence matrix to support the queries. A naive approach is to build the incidence matrix $B^{m \times n}$ by numbering edges sequentially. However, it requires the storage to save B which is twice the size of the original adjacency matrix. The question is, can we answer incidence matrix queries efficiently without the additional storage?

Our proposed main idea is to derive the incidence matrix from the original adjacency matrix as required. That is, an adjacency matrix element (src, dst) can be interpreted as $([src, dst], src)$ and $([src, dst], dst)$ of the incidence matrix where $[src, dst]$ is the edge id. Thus, the query execution algorithm for handling incidence matrix can work on the original adjacency matrix by treating each adjacency matrix element as two incidence matrix elements.

The HADOOP algorithm for the induced subgraph, which reflect the main idea, is shown in Algorithm 1. The algorithm is composed of two stages. In the first stage, the elements in the incidence matrix and the query vector are grouped together to generate partial results. Notice that two incidence matrix elements are generated (line 6,7 of Algorithm 1) for an adjacency matrix element. In the second stage, the partial results are summed to get the final result. Note that only edges having the sum 2 are included in the egonet since it means that the two incidence nodes of the edges are contained in the query node set.

5. EXPERIMENTS

To evaluate our GBASE system, we perform experiments to answer the following questions:

Q1 How much does our zip block encoding reduce the data size?
Q2 How do our algorithms scale up with the graph sizes and the number of machines?
Q3 How do our indexing and query execution methods save query response time?

Datasets. We use large graph datasets summarized in Table 3 . The YahooWeb dataset is a web graph from Yahoo! with 1.4 billion

Algorithm 1: HADOOP algorithm for Induced Subgraph

```
Input  : Edge $E = \{(src, dst)\}$ of a graph $G = (V, E)$,
         Query Node Set $V_q = \{nodeid\}$
Output: Edges belonging to the subgraph induced from $V_q$
InducedSubgraph-Map1(Key k, Value v);
begin
    if $(k, v)$ is of type $E$ then
        $(src, dst) \leftarrow (k, v)$;
        // Emit incidence matrix elements
        Output($src$, $[src, dst]$);
        Output($dst$, $[src, dst]$);
    else if $(k, v)$ is of type $V_q$ then
        $(nodeid) \leftarrow (k, v)$;
        Output($nodeid$,'1');
    end
end
InducedSubgraph-Reduce1(Key k, Value
v[1..r]);
begin
    if v[] contains '1' then
        Remove '1' from v[];
        foreach $p \in v[1..r-1]$ do
            $[src, dst] \leftarrow p$;
            // Emit partial multiplication result
            Output($[src, dst]$, 1);
        end
    end
end
InducedSubgraph-Map2(Key k, Value v);
begin
    Output($k, v$); // Identity Mapper
end
InducedSubgraph-Reduce2(Key k, Value
v[1..r]);
begin
    $sum \leftarrow 0$;
    foreach $num \in v[1..r]$ do
        $sum = sum + num$;
    end
    // Select edges whose incident nodes belong to the query
    node set
    if $sum$=2 then
        $[src, dst] \leftarrow k$;
        Output($src, dst$);
    end
end
```

nodes, 6.6 billion edges, and 120GB in space. YahooWeb is one of the largest real graph which helps us test the scalability of our GBASE system on real workload. In order to show the performance across different data scales, we use two synthetic data generators: Kronecker [23] and Erdős-Rényi [14] to generate multiple realistic graphs with different sizes.

Storage Schemes. We use the following notations to distinguish different storage and indexing methods:

- GBASE RAW(original RAW encoding): raw encoding which is the original adjacency matrix format.
- GBASE NNB(No clustering, No compression, Blocking): raw block encoding without compression and clustering.
- GBASE NZB(No clustering, Zip compression, Blocking): zip block encoding without clustering.
- GBASE CZB(Clustering, Zip compression, Blocking): zip block encoding with clustering.
- GBASE CZB+GS(CZB with Grid Selection): grid selection as described in Section 4.3.

Graph	Nodes	Edges	File Size
YahooWeb	1,413 M	6,636 M	0.12 TB
Kronecker	177 K	1,977 M	25 GB
	120 K	1,145M	13.9 GB
	59 K	282 M	3.3 GB
	20 K	6 M	439 MB
Erdős-Rényi	177 K	1,977 M	25 GB
	120 K	1,145M	13.9 GB
	59 K	282 M	3.3 GB
	20 K	6 M	439 MB

Table 3: Order and size of networks. M: millon. YahooWeb: http://webscope.sandbox.yahoo.com Kronecker, Erdős-Rényi: http://www.cs.cmu.edu/∼ukang/dataset

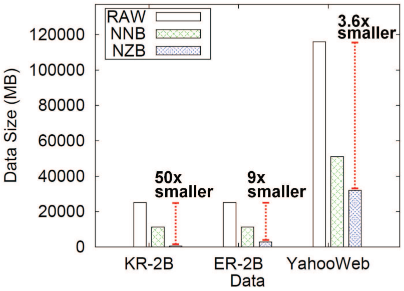


Figure 4: Effect of different encoding methods for GBASE. KR-2B: Kronecker graph with 2 billion edges. ER-2B: Erdős-Rényi random graph with 2 billion edges. Notice our proposed zip block encoding(NZB) decreases the input sizes significantly, reducing to 50× smaller than the original(RAW). The Kronecker and the Erdős-Rényi graphs have better performance gain than the YahooWeb graph since the first two are denser than the last and thus take advantage of the compression. The Kronecker graph has better compression than the Erdős-Rényi graph since it has a block-like structure from the construction.

We deploy our GBASE HADOOP implementation onto the M45 HADOOP cluster by Yahoo!. The cluster has total 480 machines with 1.5 Petabyte total storage and 3.5 Terabyte memory.

5.1 Space Efficiency Comparison

We show the data size over three different graphs across different storage schemes in Figure 4: 1) KR-2B is a graph of 177K nodes and about 2 billion edges generated using Kronecker generator; 2) ER-2B is of the same size as KR-2B but generated by Erdős-Rényi generator; 3) YahooWeb is the real Yahoo web graph of 1.4 billion nodes and 6.6 billion edges. We have the following observations:

Size Reduction. The zip block encoding(NZB) reduces the raw data size significantly (50×, 9×, and 3.6× smaller than the original(RAW) size for Kronecker, Erdős-Rényi, and YahooWeb graphs, respectively). In contrast, the raw block encoding(NNB) decrease the size at most 2.3× smaller than the original(RAW).

Density and Compression. The zip block encoding compression ratio is better for the dense graphs(Kronecker and Erdős-Rényi) than the sparse YahooWeb graph. The reason is that the

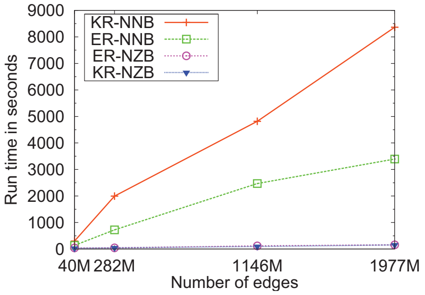


Figure 5: Scalability of indexing in GBASE. KR-NNB: Kronecker graph with raw block encoding. ER-NNB: Erdős-Rényi graph with raw block encoding. ER-NZB: Erdős-Rényi graph with zip block encoding. KR-NZB: Kronecker graph with zip block encoding. Notice that the indexing time is linear on the number of edges. Also notice that the zip block encoding(NZB) takes 50× smaller time than the raw block encoding(NNB), since the output size is smaller.

number of nonzero blocks is much smaller in the dense graphs and thus it results in more storage savings by compression.

Block Structure and Compression. The Kronecker graph has more than 5× better compression ratio than the Erdős-Rényi graph. The reason is that the Kronecker graph is block structured from the construction, and thus it benefits the compression algorithm better than its random counterpart.

To summarize, zip block encoding has shown great space savings across all datasets, which confirms the design objective of GBASE.

5.2 Indexing Time Comparison

So far, we have compared the resulting space efficiency of different methods. Next, we evaluate the indexing time required by each methods. In Figure 5, we show the running time of GBASE indexing process vs. the number of edges for graphs generated by both Kronecker(KR) and Erdős-Rényi(ER) generators.

Running Time. Seemingly to our surprise, zip block encoding(NZB) requires much less time compared to raw block encoding(NNB), despite the additional compression step: NZB performs 50× faster than NNB for 1977M edges. The reason is because the resulting compressed block is much smaller than straightforward block encoding without compression. Thus, the running time for writing the compressed blocks to disks is much smaller than the uncompressed block.

Linear Scalability. The indexing times for both zip (NZB) and raw block encoding (NNB) increase linearly as the number of edges for both Kronecker and Erdős-Rényi graphs. This confirms the scalability of our encoding schemes.

Thanks to the great storage benefit, additional compression step of zip block encoding(NZB) is worthwhile. In YahooWeb graph, we observe a similar trend as Kronecker and Erdős-Rényi graphs.

5.3 Global Query Time

So far, we confirmed the scalability and efficiency of the indexing phase. Next we evaluate the performance of different schemes on the query phase. Here, we show the scalability of GBASE global queries in Figure 6(a,b). We run the PageRank queries on Kronecker and Erdős-Rényi graphs. All the experiments except NZB are performed on Kronecker graphs. We use the zip blocked Kronecker graphs for the CZB experiment since the Kronecker graphs are block structured from its construction. For NZB experiment, we use the zip blocked Erdős-Rényi graph with the same number of nodes and edges since the Erdős-Rényi graph has nonzeros randomly distributed in the adjacency matrix.

Running Time. We see that CZB, which combines the clustering and the zip block encoding, performs the best. It outperforms RAW, NNB, NZB by 14×, 4.6×, and 2.6×, respectively, for 10 machines. The main reason of the better performance is the decreased I/O time due to reduced storage.

Machine Scalability. All the methods scale up near-linearly with the number of machines as we see in Figure 6(a).

Edge Scalability. The methods also scale up near-linearly with the number of edges as we see in Figure 6(b).

5.4 Targeted Query Time

We show the performance on targeted queries in Figure 6(c). Since the targeted queries are often against a small subset of the data, increasing the number of machines does not matter here for improving an individual query. Therefore, we only demonstrate the result with fixing the number of machines to 100. All the experiments report the average running time of 5 randomly selected query nodes. The node ids in the YahooWeb graph is encoded in a clustered manner since all the pages in a domain are numbered sequentially. Thus, we use the zip blocked YahooWeb graph for the CZB experiment.

Grid Selection. We see that GBASE CZB+GS, which combined the clustering, the zip block encoding, and the grid selection, works the best for all the targeted queries. Especially, it works the best for 1-neighborhood query outperforming all other competitors from 1.6× to 4×. The reason is that the grid selection method works better if the portion of the relevant grids is small. For 1-neighborhood query, the portion is the smallest($\sqrt{K}$ for total K grids), while other queries can have many relevant grids depending on the number of neighbors of the query node.

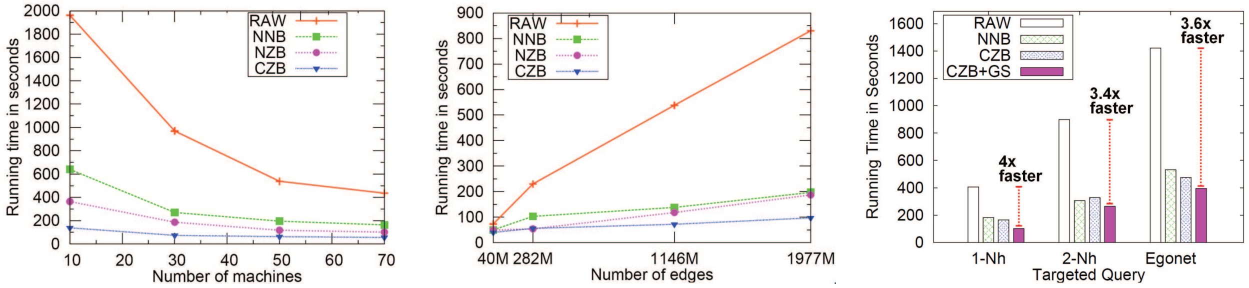
Effect of Zip Block Encoding. The clustered zip block encoding(CZB) performs slightly better than the raw block encoding(NNB) for 1-neighborhood and egonet queries, while it worked slightly worse than NNB for the 2-neighborhood query. The reason is that the size gain of the zip block encoding in CZB is not big enough to overshadow the increased running time for the zip compression. However, the performance of zip block encoding will continuously increase as better clustering algorithm is developed, as shown in the well clustered graph results of Figure 6(a,b). Moreover, the zip block encoding enjoys additional benefits of less storage and indexing time.

6. RELATED WORK

In this section, we review the related work, which can be categorized into four parts: (1) graph indexing techniques, (2) graph queries, (3) column store and (4) parallel data management.

Graph Indexing. Graph indexing is very active in both databases community as well as data mining community in the recent years. To name a few, Trißl et al [36] proposed to index the graph using pre- and postorder number to answer the reachability queries. Chierichetti et al [12] explored link reciprocity for adjacency queries. Aggarwal et al [5] proposed using edge sampling to handle graph connectivity queries. Sarkar et al [32] explored the clustering properties to proximity queries on graphs. Maserra et al [27] proposed a Eulerian data structure for neighborhood queries.

Despite of their success, there are two major limitations of these work. First, all the indexing techniques are designed for *one* particular type of queries. Therefore, their performance might be highly optimized for that particular type of query, but they are far sub-optimal for the remaining, vast majority types of queries. Second, they are implicitly designed for the centralized computa-



(a) Global query: machine scalability

(b) Global query: edge scalability

(c) Targeted query: running time

Figure 6: (a,b): Running time and scalability in one iteration of global queries in GBASE on Kronecker and Erdős-Rényi graphs. The CZB method which combines the clustering and the zip block encoding outperforms the RAW method by 14×. Notice also that all the methods scale up near-linearly on the number of machines and edges. (c): Running time of targeted queries over different storage and indexing methods, on YahooWeb graph. K-Nh denotes K step neighborhood query. Note that the CZB+GS(grid selection method combined with the clustered zip block encoding) outperforms the others by 4× at maximum.

tional mode, which limits the size of the graph such indexing techniques can support. These limitations are carefully addressed in the GBASE, which supports multiple different types of queries simultaneously and is naturally applicable to the distributed computing environment.

Finally, there are works on indexing *many small* graphs using frequent subgraph [37, 39] or significant graph patterns [38], which is quite different from our setting where we have *one large* graph.

Graph Queries. There are numerous different queries on graphs. To name a few, graph-level queries answer some global statistics of the whole graph, e.g., estimating diameters [19], counting connected components [20], etc. Node-level queries, on the other hand, focus on the relationship among individual nodes. Representative queries include neighborhood [27], proximity [35], PageRank [29], centrality [9], etc. Between the graph-level and individual node-level, there are also queries on the sub-graph level, e.g., community detection [21, 8], finding induced subgraph [4], etc. GBASE covers a wide range of queries, including the global and the node-level ones, by a unified matrix-vector multiplication framework.

Column Store. Column-oriented DBMS has gained its popularity in the recent years, due to (among other merits) its excellent I/O efficiency for read-extensive analytical workloads. From research community, some representative works include [33, 3, 2, 18, 16]. A notable work of column store database from industrial side is HBase(http://hbase.apache.org/). HBase is designed for large sparse data, built on the top of HADOOP core. Different from HBase, our GBASE partitions the data in two dimensions (both columns and rows) and it is tailored for large real graphs. By leveraging the block and community-like property which exists in many real graphs, GBASE enjoys the advantages of both row-oriented and column-oriented storages.

Parallel Data Management. Parallel data processing has attracted a lot of industrial attention recently due to the success of MAPREDUCE, a parallel programming framework [13], and its open source version HADOOP [1]. Due to its excellent scalability, ease of use, and cost advantage, MAPREDUCE and MAPREDUCE-like systems have been extensively explored for various data processing. Representative work include Pregel [26], PEGASUS [20], SCOPE [11], Dryad [17], PIG Latin [28], Sphere [15], and Sawzall [31], etc. Among them, both PEGASUS and Pregel focus on large graph querying/mining and are most related to our work. The proposed GBASE provides an even lower-level support in terms of storage cost by indexing the graph on the homogeneous block levels, which are ignored in either PEGASUS or Pregel. In addition, both PEGASUS and Pregel essentially perform node/vertex-centralized computation. Our GBASE is more flexible in the sense that it also supports edge-centralized processing (e.g., induced subgraphs, ego-net, etc) in addition to node-centralized processing.

7. CONCLUSION

In this paper, we propose GBASE, a scalable and general graph management system. The main contributions are the followings.

1. *Storage*. We carefully design GBASE to efficiently store homogeneous regions of graphs in distributed settings using a novel 'block compression'. Experiments on billion-scale graphs show that the storage and running time reduced up to 50× of the original.
2. *Algorithms*. We unify node-based and edge-based queries using matrix-vector multiplications on the adjacency and the incidence matrices. As a result, we get *seven* different types of versatile graph queries supporting various applications.
3. *Query Optimization*. We propose a fast graph query execution algorithm using a grid selection. Also, we provide a efficient MAPREDUCE algorithm to support incidence matrix based queries using the original adjacency matrix, without explicitly building the incidence matrix.

Researches on large graph mining can benefit significantly from GBASE's efficient storage, widely applicable primitive operations, and fast query execution engine. Future research directions include query optimization for multiple, heterogeneous queries, and better support for time evolving graphs.

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8. REFERENCES

[1] Hadoop information. http://hadoop.apache.org/.

[2] Daniel J. Abadi, Peter A. Boncz, and Stavros Harizopoulos. Column oriented database systems. *PVLDB*, 2009.

[3] Daniel J. Abadi, Samuel Madden, and Nabil Hachem. Column-stores vs. row-stores: how different are they really? In *SIGMOD Conference*, pages 967–980, 2008.

[4] Louigi Addario-Berry, W. Sean Kennedy, Andrew D. King, Zhentao Li, and Bruce A. Reed. Finding a maximum-weight induced k-partite subgraph of an i-triangulated graph. *Discrete Applied Mathematics*, 158(7):765–770, 2010.

[5] Charu C. Aggarwal, Yan Xie, and Philip S. Yu. Gconnect: A connectivity index for massive disk-resident graphs. *PVLDB*, 2(1):862–873, 2009.

[6] Leman Akoglu, Mary McGlohon, and Christos Faloutsos. oddball: Spotting anomalies in weighted graphs. In *PAKDD (2)*, pages 410–421, 2010.

[7] I. Alvarez-Hamelin, L. Dall'Asta, A. Barrat, and A. Vespignani. k-core decompositions: A tool for the visualization of large scale networks. *http://arxiv.org/abs/cs.NI/0504107*.

[8] Periklis Andritsos, Renée J. Miller, and Panayiotis Tsaparas. Information-theoretic tools for mining database structure from large data sets. In *SIGMOD*, 2004.

[9] David A. Bader, Shiva Kintali, Kamesh Madduri, and Milena Mihail. Approximating betweenness centrality. *WAW*, 2007.

[10] Paolo Boldi and Sebastiano Vigna. The webgraph framework i: compression techniques. In *WWW*, 2004.

[11] Ronnie Chaiken, Bob Jenkins, Per-Ake Larson, Bill Ramsey, Darren Shakib, Simon Weaver, and Jingren Zhou. Scope: easy and efficient parallel processing of massive data sets. *VLDB*, 2008.

[12] Flavio Chierichetti, Ravi Kumar, Silvio Lattanzi, Michael Mitzenmacher, Alessandro Panconesi, and Prabhakar Raghavan. On compressing social networks. In *KDD*, 2009.

[13] Jeffrey Dean and Sanjay Ghemawat. Mapreduce: Simplified data processing on large clusters. *OSDI'04*, December 2004.

[14] P. Erdős and A. Rényi. On random graphs. *Publicationes Mathematicae*, 6:290–297, 1959.

[15] Robert L. Grossman and Yunhong Gu. Data mining using high performance data clouds: experimental studies using sector and sphere. *KDD*, 2008.

[16] Sándor Héman, Marcin Zukowski, Niels J. Nes, Lefteris Sidirourgos, and Peter A. Boncz. Positional update handling in column stores. In *SIGMOD*, 2010.

[17] Michael Isard and Yuan Yu. Distributed data-parallel computing using a high-level programming language. In *SIGMOD Conference*, pages 987–994, 2009.

[18] Milena Ivanova, Martin L. Kersten, Niels J. Nes, and Romulo Goncalves. An architecture for recycling intermediates in a column-store. In *SIGMOD*, 2009.

[19] U Kang, C.E Tsourakakis, Ana Paula Appel, C Faloutsos, and Jure Leskovec. Radius plots for mining tera-byte scale graphs: Algorithms, patterns, and observations. *SIAM International Conference on Data Mining*, 2010.

[20] U Kang, C.E Tsourakakis, and C. Faloutsos. Pegasus: A peta-scale graph mining system - implementation and observations. *ICDM*, 2009.

[21] G. Karypis and V. Kumar. Parallel multilevel k-way partitioning for irregular graphs. *SIAM Review*, 41(2):278–300, 1999.

[22] George Karypis and Vipin Kumar. Multilevel -way hypergraph partitioning. In *DAC*, pages 343–348, 1999.

[23] Jure Leskovec, Deepayan Chakrabarti, Jon M. Kleinberg, and Christos Faloutsos. Realistic, mathematically tractable graph generation and evolution, using kronecker multiplication. *PKDD*, pages 133–145, 2005.

[24] Ching-Yung Lin, Nan Cao, Shixia Liu, Spiros Papadimitriou, Jimeng Sun, and Xifeng Yan. Smallblue: Social network analysis for expertise search and collective intelligence. In *ICDE*, pages 1483–1486, 2009.

[25] Chao Liu, Fan Guo, and Christos Faloutsos. Bbm: bayesian browsing model from petabyte-scale data. In *KDD*, 2009.

[26] Grzegorz Malewicz, Matthew H. Austern, Aart J. C. Bik, James C. Dehnert, Ilan Horn, Naty Leiser, and Grzegorz Czajkowski. Pregel: a system for large-scale graph processing. In *SIGMOD Conference*, pages 135–146, 2010.

[27] Hossein Maserrat and Jian Pei. Neighbor query friendly compression of social networks. In *KDD*, 2010.

[28] Christopher Olston, Benjamin Reed, Utkarsh Srivastava, Ravi Kumar, and Andrew Tomkins. Pig latin: a not-so-foreign language for data processing. In *SIGMOD '08*, pages 1099–1110, 2008.

[29] Lawrence Page, Sergey Brin, Rajeev Motwani, and Terry Winograd. The PageRank citation ranking: Bringing order to the web. Technical report, Stanford Digital Library Technologies Project, 1998.

[30] Spiros Papadimitriou and Jimeng Sun. Disco: Distributed co-clustering with map-reduce. *ICDM*, 2008.

[31] Rob Pike, Sean Dorward, Robert Griesemer, and Sean Quinlan. Interpreting the data: Parallel analysis with sawzall. *Scientific Programming Journal*, 2005.

[32] Purnamrita Sarkar and Andrew W. Moore. Fast nearest-neighbor search in disk-resident graphs. In *KDD*, pages 513–522, 2010.

[33] Michael Stonebraker, Daniel J. Abadi, Adam Batkin, Xuedong Chen, Mitch Cherniack, Miguel Ferreira, Edmond Lau, Amerson Lin, Samuel Madden, Elizabeth J. O'Neil, Patrick E. O'Neil, Alex Rasin, Nga Tran, and Stanley B. Zdonik. C-store: A column-oriented dbms. In *VLDB*, 2005.

[34] Jimeng Sun, Huiming Qu, Deepayan Chakrabarti, and Christos Faloutsos. Neighborhood formation and anomaly detection in bipartite graphs. In *ICDM*, pages 418–425, 2005.

[35] Hanghang Tong, Christos Faloutsos, and Jia-Yu Pan. Fast random walk with restart and its applications. In *ICDM*, pages 613–622, 2006.

[36] Silke Trißl and Ulf Leser. Fast and practical indexing and querying of very large graphs. In *SIGMOD*, 2007.

[37] D. Xin, J. Han, X. Yan, and H. Cheng. Mining compressed frequent-pattern sets. In *VLDB*, pages 709–720, 2005.

[38] Xifeng Yan, Hong Cheng, Jiawei Han, and Philip S. Yu. Mining significant graph patterns by leap search. In *SIGMOD Conference*, pages 433–444, 2008.

[39] Peixiang Zhao, Jeffrey Xu Yu, and Philip S. Yu. Graph indexing: Tree + delta >= graph. In *VLDB*, 2007.