GeoBlocks: A Query-Driven Storage Layout for Geospatial Data

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ABSTRACT
City authorities need to analyze urban geospatial data to improve transportation and infrastructure. Current tools do not address the exploratory and interactive nature of these analyses and in many cases consult the raw data to compute query results. While pre-aggregation and materializing intermediate query results is common practice in many OLAP settings, it is rarely used to speed up geospatial queries.

We introduce GeoBlocks, a pre-aggregating, query-driven storage layout for geospatial point data that can provide approximate, yet precision-bounded aggregation results over arbitrary query polygons. GeoBlocks adapt to the skew naturally present in query workloads to improve query performance over time. In summary, GeoBlocks outperform on-the-fly aggregation by up to several orders of magnitude, providing the sub-second query latencies required for interactive analytics.

KEYWORDS
geospatial point data, aggregations over polygons, query-driven materialization

1 INTRODUCTION
Current trends of online-booked mobility allow to easily gather data about individual movements in cities, and thereby the data available for city planning and traffic analysis is growing steadily. Tools enabling the visual analysis of these datasets are even available to the public, either from the cities where hired rides where taken, like San Francisco [42], or directly from providers like Uber [44]. In addition to these tools that only allow a small set of predefined queries on predefined regions, there are many more use cases for in-depth analysis, either [33–35] or offering tools for cities and city planners aiding them in their work [3].

But the sheer size of the data prohibits an interactive user experience as current tools that operate with raw data cannot produce the results fast enough [22]. However, the repetitive nature of the queries, often running multiple times on a previously defined and filtered subset of the data, makes it feasible to keep intermediate or even full query results.

Such query-driven materialization and result recycling approaches are widely used and understood in classical OLAP settings [19, 27, 36, 38]. However, these methods do not address multi-dimensional spatial data. While there are approaches to utilize intermediate results and aggregates for spatial workloads, such as nanocubes [17] and the aggregate R-tree (aR-tree) [23, 24], these indices and data structures cannot provide precision guarantees on the results of unknown, arbitrarily shaped query polygon workloads. Both nanocubes and the aR-tree are limited to rectangular query workloads and are further limited by the granularity of their underlying index structures that do not support precision requirements. While nanocubes are error-bound in their output visualizations as they factor in the screen size, the supported drill-down queries need to know the tiling of the resulting area a priori to adhere to these bounds.

We propose GeoBlocks, a novel pre-aggregating storage layout for geospatial point data that guarantees error-bound results for arbitrarily shaped query polygons. GeoBlocks are essentially materialized views on geospatial point data that pre-compute filters and aggregations on pre-defined columns. While the current version is designed for storing historical point data and is therefore write-once/read-only, we also briefly touch upon updates in Section 5. In GeoBlocks, we materialize aggregates of temporal and numerical attributes at a user-defined geospatial granularity to provide the speedup expected of materialization while keeping the error limited to the user-specified granularity. In addition, we propose two trie-like data structures that allow us to collect statistics on the workload and maintain commonly queried regions as aggregates in a compact manner.

To the best of our knowledge, GeoBlocks are the first storage layout to support arbitrary query polygons and still produce results with a bounded error. While existing analysis tools, such as Uber Movement [44], allow the user to retrieve often exact results pre-aggregated for polygons, they limit the number of possible query polygons at aggregation time by pre-defining allowed query regions. This requires a high a priori knowledge of the semantics of the data.
to aggregate meaningful areas and further puts high restrictions on the possible query workloads.

Figure 1 compares our pre-aggregation approach (Blocks) to computing aggregates on the fly from indexed point data, represented as one-dimensional hierarchical cell ids in a sorted vector (BinarySearch) and a secondary index (BTree). Other (non-spatial) columns are stored in a simple columnar format. Note the logarithmic scale on the x-axis. Overall, our approach allows for two orders of magnitude speedup, largely independent from the number of queried aggregates.

The remainder of this paper is structured as follows: In Section 2 we present an overview of related work before we introduce GeoBlocks in Section 3 and describe their data structure, query process, and the two trie-like index structures. Section 4 shows the experimental evaluation of GeoBlocks against our baselines and describes how the configuration options influence the runtime, relative error, and overhead. Section 5 summarizes the key points discovered in the evaluation and discusses updates for GeoBlocks. Finally, we conclude in Section 6.

2 RELATED WORK

To the best of our knowledge, there is no other system that allows for pre-aggregating point data with support for arbitrary query polygons under strict precision guarantees. However, there are several concepts for pre-aggregation and indexing in a general OLAP, as well as a geospatial setting.

Materialized Views and OLAP Cubes. Materializing and maintaining intermediate query results in the form of materialized views is a well-studied problem [10, 37]. GeoBlocks can be thought of as materialized views over geospatial data with support for filters and aggregations. In contrast regular materialized views, GeoBlocks are designed for summarizing historical spatial data and can adapt to the query workload at a micro level (using the two trie structures). Work on materialized view selection [1] also considers the query workload to make materialization decisions, but at a much higher level (e.g., what columns to aggregate). Such adaptation is orthogonal to the one we are proposing.

There has also been a lot of work on data cubes in a classical OLAP setting [9, 13]. These approaches allow for slicing and dicing data on pre-defined dimensions but do not support geospatial data as first-class citizens.

Spatial Point Indexing. Several approaches for indexing geospatial point data have been presented in the past. Most index points using a hierarchy of minimum bounding rectangles (MBRs), most notably the R-tree [11], or by subdividing grid cells into equally-sized children, e.g., the quadtree [8]. Both these index structures rely on minimum and maximum values per dimension to probe the index, reducing them to rectangular query regions for spatial data. Other approaches like the UB-tree [2] assign univariate keys to the indexed regions first and rely on these keys for data access. While the UB-tree does not specify how these keys must be generated, most approaches use space-filling curves like Z order [21].

Based on these concepts more specialized indices have been developed. The PH-tree [46] combines a quadtree with hypercubes to allow splitting of all dimensions in each node, providing a space-efficient index structure for multidimensional data. The space efficiency can be partly attributed to the utilization of prefix sharing, similar to the one used for our proposed trie-like structures. A further recently introduced index structure, the PL-tree [45], aims at reducing the curse of dimensionality by again combining a tree structure with hypercubes. In addition to point and region queries this allows them to additionally support kNN queries. While these structures require the index to be built a priori, there are others like QUASII [26]. In QUASII, the index is built incrementally as a side product of regular query execution by database cracking [14]. Similar to our approach it is therefore able to adapt to the queries at runtime. A fixed-size grid layout to index spatial data has been used already similar to what we propose, recently by Toss et al. [43], albeit without pre-aggregation and limited to rectangular query regions.

Spatial Pre-Aggregation and Warehousing. In addition to the point indexing methods presented above, there has been work on pre-aggregation in spatial data warehousing [12]. Papadias et al. [23, 24] introduce the aR-tree, a version of the R-tree that stores a selected list of aggregates for all elements contained within an MBR alongside it. This way they do not have to traverse each query to the entries but can instead answer it once a MBR is fully enclosed in the query region. Similarly, Rao et al. [29] use a spatial index tree to improve spatial query processing in OLAP environments. Using this spatial hierarchy for aggregation in the datacubes, they can use intermediate node aggregates to answer queries faster, having to resort to the leaf node data fewer times. Several other works for spatial point warehousing have been presented in the past, some surveyed by López et al. [18]. All either storing aggregates integrated into a spatial index like the quadtree or R-tree [16, 23–25], inside a datacube [6, 29] or using sketches [39]. Other works [40, 43] do not pre-aggregate any data but instead use indexing to limit the query space. However, all of these approaches are limited to rectangular queries and most cannot make precision guarantees without using the raw data.

Specialized for visualization, tools like nanocubes [17] combine quadtree-like spatial indexing for the spatial domain with spare coalesced data cubes to provide fast aggregated results. They drill down operations based on map tiles and are limited to rectangular query regions.

3 GEOBLOCKS

3.1 Spatial Subdivision and Data Extraction

We first introduce the concepts required for the geospatial subdivision of the input space that we use to generate our aggregates. In order to map the geospatial, two dimensional input space to a linear one we use Google’s S2 Geometry library [30]. S2 uses a Hilbert curve covering a spherical projection of the Earth to transform latitude and longitude of a point to a single 64-bit integer. Its version of the Hilbert curve has 31 levels, each level subdividing the previous one into four equally-sized parts. The granularity of the cells range from approximately 85 million km² at level 0 to 0.74 cm² at level 30 [31]. S2 further supports calculating the ids of parents from child ids and vice versa, as well as containment checks, using
Apart from sorting, we extract the higher-level grid cells that we value into the raw data in the aggregates if access to the raw data multiple blocks. In addition to the extracted raw data we maintain disjunct parts, or using different filter predicates on the data we only for the same data is possible, either splitting the raw data into start building the GeoBlock. While building multiple GeoBlocks once we completed our extract and reorganize process, we can compute the aggregates in a single pass over the raw data. We prepend the aggregates to the raw data, keeping the same order for the aggregates as we have for the raw data. Grid cells covering no tuples are omitted during aggregation as they would needlessly consume space. In addition, we combine all cell-level aggregates into higher-level aggregates containing information on the whole block and store these in front of all other aggregates. After the build process has been completed, we have our basic storage layout, an overview of which can be seen in Figure 4:

**GeoBlock Header**: The block-wide header stores all grid cell aggregates, the aggregate containing information on the whole block as well as meta data required for querying such as the start of the individual columns in the raw data. We will refer to the data contained in each grid cell as CellBlock and to the aggregate representing such a CellBlock as the CellBlock Header.

**CellBlock Header**: Each CellBlock Header stores all information on the CellBlock required for querying. In the beginning it has the corresponding spatial key, the offset of the first tuple contained in the raw columns, and the number of contained tuples. While we could calculate the number of tuples from the offsets of two adjacent cells, we still store it separately. For one this saves us checks to see if we are at the last CellBlock Header, and this can be also used to build multiple GeoBlocks with different filter predicates on top of the same data which we plan as future work. If the offset difference is used on unfiltered data, the calculated count would include all contained tuples, not only those qualifying under the given predicates. Following this data-independent information, we maintain the available aggregates for all columns in the raw data. For both numeric and temporal values we store the minimum, maximum, and sum of all values contained. While the sum of temporal values seems useless at first, we use it, together with the tuple count, to compute the average. Furthermore, we store the minimum and maximum key of the spatial column. When saying storing aggregates, we always mean all available aggregates for all columns.

### 3.2 Storage Layout

Once we completed our extract and reorganize process, we can start building the GeoBlock. While building multiple GeoBlocks for the same data is possible, either splitting the raw data into disjunct parts, or using different filter predicates on the data we only consider a single GeoBlock for now (cf. Section 5 for use cases of multiple blocks). In addition to the extracted raw data we maintain aggregates on a pre-defined granularity level corresponding to cell levels (cf. Section 3.1). This level is currently specified by the user at block-creation time, but as we still have access to the raw data choosing a new level later on is possible as well. The input space is subdivided into grid cells at the specified level and we compute a number of aggregates (i.e., MIN, MAX, SUM, and COUNT) on the selected columns. As the data is sorted, and therefore the tuples contained in contiguous grid cells are also stored contiguously, we can compute the aggregates in a single pass over the raw data. We prepend the aggregates to the raw data, keeping the same order for the aggregates as we have for the raw data. Grid cells covering no tuples are omitted during aggregation as they would needlessly consume space. In addition, we combine all cell-level aggregates into higher-level aggregates containing information on the whole block and store these in front of all other aggregates. After the build process has been completed, we have our basic storage layout, an overview of which can be seen in Figure 4:

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![Figure 2: Hierarchical cell subdivision](image1)

![Figure 3: Example polygon covering with maximum error](image2)

![Figure 4: GeoBlock- and CellBlockHeader layout](image3)
3.3 Querying

For querying a GeoBlock, we support two basic types of queries. On the one hand, we offer regular SQL SELECT queries that can produce a user-defined subset of the available aggregates for a given query polygon. On the other hand, we offer specialized COUNT queries. These promise even faster response times as they do not need to combine all CellBlock Headers contained, but only inspect the first and last header contained in the queried region. The number of tuples contained in a polygon is sufficient for some analytical queries, especially in the context of visualization.

Both query types share parts of their logic, especially in the first phase. Therefore we will describe those steps before we go into more detail on the query-specific ones. At first we need to map the query polygon to grid cells of our GeoBlock. For this we utilize the functionality provided by the S2 library [30]. It provides either exterior or interior coverings of polygons using S2 cells and allows to specify a minimum and maximum cell level. As we can only answer queries on the basis of our CellBlocks, we require the maximum level to be at most that of our CellBlock cells. We are not limited in regards to the minimum cell level as larger cells can be split up very easily. This covering of the polygon is the only part in our process that introduces the mentioned (bounded) error. Once we have the covering represented by S2 cells, the remaining parts of the query process are exact in regard to these cells. An example covering of a query polygon can be seen in Figure 3. The polygon is represented as all cells it intersects with, marked in blue. As can be easily seen, the maximum error, marked for one cell in red, is bound by the diagonal of a grid cell.

For each of the cells we perform the following steps and combine the results to get the query result for the whole polygon. To skip the query process for cells entirely not overlapping with the GeoBlock, we first check if there are in fact possible results within the GeoBlock. This is done using the minimum and maximum keys stored within the block-wide aggregates. If this check passes, we continue with the steps specific for each query type.

**COUNT Queries.** We first look at COUNT queries. They differ from SELECT queries as they do not have to look at all contained cells, instead they can simply be answered with the count and offset values of the first and last CellBlock contained. To find these first and last contained points we extract the first and last child of the query cell at our specified granularity level. We then locate the first child in the GeoBlock Header using an upper bound binary search. Once we found this first child we use its position as a search start for the last child, which is again located using binary search. Once we have located the aggregates of the first and last contained child, we can simply calculate the resulting count as

\[
\text{child}_{\text{last,offset}} + \text{child}_{\text{last,count}} - \text{child}_{\text{first,offset}}
\]

**SELECT Queries.** SELECT queries differ from COUNT queries as they have to look at all CellBlocks contained in the query cells, not just the first and the last. After a query cell has passed the pre-query check, we try to further limit the search space to the overlapping area. The first remaining CellBlock is located using an upper-bound binary search. For all following cells, we can use the fact that the header cells are stored contiguously in ascending order. This allows us to scan the following CellBlock Headers until we reach a CellBlock not contained in the query cell, combining all CellBlock aggregates along the way into the query result.

3.4 Query-Driven Adaption

While our intermediate aggregates already have a lot of potential in speeding up queries, we noticed further potential in keeping track of frequently queried areas. A lot of times queries are run on the same area multiple times, extracting different aggregates. Other times the query polygon is only resized or reshaped around the borders, keeping an area on the inside of the polygon untouched. Furthermore, these analytic queries often focus on a geographic subset of the whole data. For the analysis of the NYC taxi data [34] e.g., focus lies mostly on Manhattan, Brooklyn, and the airport regions, ignoring most suburbs. In all of these cases it makes sense to pre-aggregate lower-level grid cells covering bigger areas in those frequently queried regions to avoid costly scans and aggregate combinations on lots of individual grid cells.

**Collecting Statistics.** We do not want to make assumptions on the expected query workloads or the semantics of the indexed data. This means we cannot know which cells will be queried often or even which CellBlocks compose popular regions, e.g., Manhattan and surrounding areas. Therefore we need to keep track of all previously seen queries to determine those areas that are most relevant and thus worth being additionally aggregated. We only track statistics for queried areas, not which aggregates where queried, but extending this principle to select certain column aggregates is possible. To store those query statistics for all possible query cells, we propose a new index structure, the StatsTrie.

In the StatsTrie, we use the property of the S2 mapping that children of the same parent share the same level-dependent prefix. This way we only need to encode which of the four children of the direct parent we selected at each level, without loosing information about the current key. As we expect the input data to cover only parts of the possible Earth-wide input space, we prune the tree to start at a cell level where a single cell is capable of covering the whole GeoBlock. This saves space and index traversal times and further has no negative impact on the quality of the collected information. We are still able to collect all queried cells that overlap with the GeoBlock, only losing information on those who do not. Since queries on non-overlapping cells can be answered in constant time using the pre-query checks anyways, we can safely ignore this information loss.

At the trie root, we store the offset level and pruned prefix to later reconstruct all encoded cells. For each node, we store an array of four integers keeping track of how often each of the four children cells was queried, as well as four pointers to their trie nodes. When handling an arriving query cell, we insert the cell into our StatsTrie. At first we prune the common prefix levels and then use each child id as an offset into the next node until we reach the level of the query cell parent. At that point we update the corresponding score and perform the query as described in Section 3.3. If a missing node is encountered, it is created on the fly.

**Determining Relevant Aggregates.** After collecting information on the query workload, we can determine the regions worth aggregating. There are two main points to consider when deciding if a
cell should be aggregated. The first point is the number of times a region was queried. For each query of the cell, the contained CellBlocks have to be traversed and combined in order to obtain the corresponding result. The second point to consider is the level of the cell. Results for coarser-grained cells have to be combined out of more CellBlocks. This amount increases by a factor of four per level in the worst case, i.e., when there are no empty children. While both of these points are easy to determine using our collected statistics, we have to consider the relations between the cells as well. Child cells can be used to speed up queries for parent cells by reducing the number of grid cells to query. Each available child cell reduces the number of grid cells by a quarter.

For this paper we used a very rudimentary metric: At first we extract all ids with corresponding scores. The score is calculated using a sum of the cell hits and the direct parents hits. We then sort all these cells by descending score. When the score is identical, we sort by ascending level (coarser-grained cells come first), and as a last criterion to guarantee reproducibility, we sort by spatial key.

We chose this metric as it is sufficient to properly and repeatably represent the skew in the experiments of the evaluation while being easy to understand and implement. But it has weaknesses that we do not want to hide: For one it is possible for smaller cells to overshadow bigger cells that were only slightly less often queried, even when aggregating the bigger cell would lead to bigger improvements. Furthermore, it does not completely represent the complexity of parent-child relationships as children only provide a part of the needed aggregates for parents. More advanced metrics taking all these points into account properly are left to future work.

**Aggregate Storage.** Now that we have established which of the cells we want to aggregate, we have to discuss how we want to store and access those aggregates. The first decision we made is where to store them. While we could store them out-of-place like the StatsTrie we decided to give the user control over the induced storage overhead. To achieve this, we store our trie-like structure, the AggregateTrie, in-place between our GeoBlock Header and the raw data. The size of the available storage can be specified by the user as a percentage of the size of the GeoBlock Header. Having a strict order of cells, we can simply insert the most relevant unaggregated cell until the reserved area is filled.

The storage for the additional aggregates is split in two. The first part contains the index on these aggregates, the AggregateTrie, while the second part stores the aggregates themselves. The AggregateTrie uses the same level-wise encoding as the StatsTrie and is pruned to the same height. As we store the AggregateTrie in-place, we chose a compact encoding storing all nodes contiguously. Each node consists of only two 32-bit integers. The first one denotes the offset of the corresponding aggregate in the aggregate storage. The second one is the offset of the first child in the AggregateTrie storage. Storing only the offset to the first child forces us to allocate all children for a node every time, even when only one is needed. While this seems wasteful at first, the alternative would be to store four individual child offsets per node in addition to the aggregate offset. Because children are only created and stored if they are needed our encoding never occupies more storage than this individual encoding. In fact, this design is more space-efficient in all cases except for the worst case, when exactly one child is required.

**Adapted Query Algorithm.** To utilize the additional aggregates, they have to be integrated into the GeoBlock query algorithm described in Section 3.3. We do not expect noticeable speedups of COUNT queries as their runtime is mostly independent of the cell level, only the first and last grid cell are relevant. Therefore, the following adapted process is only used for SELECT queries.

Once the pre-query checks are completed, we first try to answer the query using the AggregateTrie and resort to the old algorithm only when necessary. For each arriving query cell, we traverse the trie to the position where we expect an aggregate. If there is no node for this cell, we abort probing and answer the query with the old algorithm. Once the node corresponding to the cell is reached, there are two possible ways forward. If the cell is aggregated, i.e., if it has a valid aggregate offset, the aggregate is extracted as a result. As nodes are only created on demand, there has to be at least one child at any level that has an aggregate if the current node has none. While theoretically all children could be used to reduce the number of grid-level cells to query, the number drops with each level while keeping track of the missing children gets increasingly expensive. Therefore, we only consider direct children for this optimization. We combine the aggregates of the aggregated direct children with the results of the old algorithm for the non-aggregated ones to obtain the final result. An overview of this adapted query process is shown in Figure 5.

![Figure 5: Overview of adapted query algorithm](image)

4 EXPERIMENTAL EVALUATION

We compare GeoBlocks against on-the-fly aggregation approaches on real-world data. We do not consider alternative pre-aggregation approaches such as the aR-tree [23, 24] for all experiments, as those either only support rectangular queries (no query polygons) or cannot guarantee bounded precision. However, we still include similar baselines in form of the RTree baseline. To show that our advantage is not dependent on the indexing strategy, we use different strategies to index the base data of the on-the-fly approaches. At first we describe the setup used, the data set, and the baselines. Afterwards,
we show that GeoBlocks outperform the baselines independent of overall selectivity and configuration. Further, we show the influence that the configuration has on the runtime and overhead of GeoBlocks.

4.1 Experimental Setup

**Baselines.** To keep the experiments as fair as possible, we used the mapping from geospatial space to linear space for the baselines as an index key unless specified otherwise. This allows us to use the same cell-based queries and thereby produce identical results. Furthermore, we keep all data in columnar layout. For our experiments, we chose three strategies for indexing the raw data as well as one simulating aggregation:

- **BinarySearch:** This is the simplest baseline. Instead of indexing the data we use the same binary search as for locating the CellBlock Header to locate the first and last contained raw tuple in the data. Afterwards, we loop over all tuples in between and aggregate them.
- **BTree:** For the BTree baseline, we used Google’s implementation [7] and indexed the raw data with the BTree as a secondary index. We probe the tree for the first child and scan the sorted raw data until no further tuple qualifies.¹
- **PHTree:** Our last non-aggregating baseline is a multi-dimensional point index structure, the PH-tree [46]. Instead of the one-dimensional spatial S2 key, we used the latitude and longitude of the points to index the data. As the PH-tree only supports range queries on rectangular query objects, we used S2 to get the interior rectangle of the query polygon. This way we hope to keep the comparison fair, if not biased for the PHTree, as this interior rectangle covers fewer points than our approach. As a consequence, the PHTree’s query results differ from the results of the other baselines and the GeoBlock. For the measurements, we used an open-source C++ implementation [28].
- **RTree:** With the RTree baseline, we tried to simulate the aR-tree [23, 24] using the boost R-tree [5] (configuration: quadratic creation algorithm, max. 16 elements per node), as we did not have an efficient implementation for the aR-tree available. For this, we skip aggregating the results and only report the result count, which can be done using the inner nodes, similar to the query process of the aR-tree which uses aggregates at these nodes. The adaption only aims at runtime, therefore we omit it from all non-runtime related experiments and where the aggregate count can influence the outcome. We use the same query mapping as for the PHTree baseline.

**Implementation.** We implemented the GeoBlocks in C++ as described in Section 3. Our implementation, as well as that of all baselines, is single-threaded. All implementations were compiled using g++ 5.4.0. Throughout this section, especially in all figures, we will refer to the GeoBlocks as Blocks. Furthermore, we will differentiate between V1 and V2. V1 denotes a GeoBlock without StatsTrie and AggregateTrie using the basic query algorithm. V2 is a GeoBlock using the AggregateTrie and adapted query process.

**Hardware.** All experiments were run on an Ubuntu 16.04.1 LTS server with two Intel Xeon E5-2680 v4 processors clocked at a frequency of 2.4 GHz. The machine is equipped with 256 GiB of DDR4-2400 RAM. All experiments run in the evaluation fit entirely into this main memory.

**Dataset.** The primary dataset used in the experiments is composed of trip records from 12 million NYC yellow cab rides in the time between January and March 2015. It is made openly available for download by the NYC Taxi and Limousine Commission (TLC) [41]. Consisting of data from individual rides like pickup and drop-off location and time, passenger count as well as trip distance. We cleared the dataset of obvious spatial outliers and extracted the drop-off location as our spatial dimension, as well as the drop-off time, the passenger count and trip distance. To speed up repeated benchmarking runs, we materialized the mapped S2 spatial key as an additional column.

Unless specified otherwise, the queries consist of polygons representing NYC neighborhoods taken from [20]. As a base workload, we query each polygon once, as a skewed workload, we select 10% of neighborhoods uniformly at random and query them multiple times. We select a set of 7 aggregates, requesting each column at least once, as query output.

4.2 Baseline Comparison

**Influence of Number of Aggregates.** We first want to show how the number of aggregates influences the performance of the baselines and the blocks. Therefore we built a combined workload of once the base and four times the skewed workload. We ran this combined workload for 1, 2, 4 and 8 aggregates and report the results in Figure 1. The y-axis depicts the total runtime on a logarithmic scale.

As one can see easily the GeoBlocks outperform both the BTree and BinarySearch baseline for all number of aggregates. We omitted the PHTree from these experiments as it had problems representing the biased workload. Even for the base workload part it was slower than the other baselines by a factor of about 3× while covering fewer tuples. The runtime slightly increases for all algorithms with increasing number, but it is obvious that it the number of aggregates is not a highly influential factor.

**Indexing Overhead.** Having shown that GeoBlocks are able to outperform non-aggregating baselines, we took a look at the size and time required to do so, the indexing overhead. We compare the build time, the time required by each algorithm until being able to run the first query, in Figure 6a with the Block level set to 17 (~100m diagonal). The reported times for sorting are measured once for the optimized out-of-place sorting for the Blocks and reported for each baseline as this step is completely identical in all sorting baselines. There is a noticeable drop-off in the sorting phase between the BTree/BinarySearch and the Block. This gap is caused by the collection of grid cell ids to aggregate that we piggybacked on the sorting process to save an additional pass on the data. Overall, the Block is faster built than the BTree and PHTree, only slightly beaten by the BinarySearch which only needs to sort the input data. Most notably, the majority of the block preparation is spent on sorting, indicating that once the data was sorted building additional blocks with different filter sets would be rather cheap.

¹Instead of the BTree we first used the PointIndex contained in the S2 library [32] that uses the same R-tree as point storage. Initial measurements showed that an optimized version implemented by us outperformed the PointIndex by 3× so we opted for our version.
The relative space overhead of each algorithm is depicted in Figure 6b. BinarySearch was omitted as it does not require any additional storage. One could argue that this is not a fair comparison as the other baselines index individual points, but as our goal is to provide approximate results we wanted to show that storing intermediate results is less space-consuming than one would assume for such fine-grained aggregates.

Influence of Selectivity. Another point we want to work out is the influence of selectivity on the runtime. Selectivity is usually defined on the basis of a single query, but in our context it is hard to specify what a single query is. We break down query polygons to different-sized cells covering the polygon, which in turn are broken down into equally sized cells to query. While the intermediate cells of the query-polygon covering are the best representation of individual queries, each index is probed once for them, they are artificial concepts introduced by our algorithm. Furthermore, these are hard to map to the PHTree and RTree. Therefore, we decided to define selectivity on the basis of query polygons. For this experiment, we artificially selected polygons covering a part of NYC which contain a certain percentage of the total rides. Figure 7 reports the runtime of the base workload at different selectivities using a logarithmic scale. PHTree’s and RTree’s measured selectivities are lower than the reported ones due to the different covering described above.

While runtime rises quickly for all baselines for selectivities above 1%, the increase is much softer for both Block versions. Even though the workload is not skewed and we only use 2% of additional storage for the AggregateTrie, the Block using the adapted query algorithm still outperforms the non-adapting one across all selectivities. This is likely explained by the simple shape of the polygons representing the selectivity, often simple quadrilaterals or pentagons. These can be covered using few cells and therefore most of these cells can be pre-aggregated. BinarySearch can keep up with the BTree, reporting similar runtimes independent of selectivity while the PHTree drops behind quickly. Even if the relative runtime gap narrows for higher selectivity, the absolute gap still favors GeoBlocks. The RTree, our emulation of the aR-tree outperforms the on-the-fly aggregating benchmarks easily while staying behind GeoBlocks for lower selectivities. However, it is almost able to catch up for higher selectivities, which makes sense as the queries can then be answered more often using inner nodes higher up in the RTree. Overall, GeoBlocks outperform the non-aggregating baselines by at least two and up to four orders of magnitude while staying ahead of the RTree consistently.

4.3 Configuration Influence

After showing that GeoBlocks easily outperform all baselines, we want to show the influence the configuration of the GeoBlocks can have on throughput, as well as the influence of data skew on the adaptive Block version. The Block configuration can be specified by three parameters. The first setting we study is the level of the Block, the resolution of the grid overlying the spatial domain. Afterwards, we take a look at the influence of skew on the adaptive and non-adaptive Block. Finally, we examine how the size of the AggregateTrie can influence the runtime of unskewed and skewed workloads.

Block Level Influence. We now take a look at the influence of the Block level. Therefore, we varied the Block levels from 13 to 21 (between ~1.5km and ~6m diagonal) while keeping the other configuration parameters fixed. From a runtime-only point of view, lower-level (coarser-grained) Blocks will always win as they have fewer intermediate cells to take into account. But this comes at the price of precision loss. Figure 8 illustrates the connection between Block level, runtime, and the relative error between the measured result and the exact one. As we chose an exterior covering for the polygon, the error is always of positive nature (false positives),
reporting more results than actually qualify. The relative error is defined as $\frac{|\text{# tuples in query result} - \text{# tuples in polygon}|}{\text{# tuples in polygon}}$.

The expected correlations between level and runtime, as well as runtime and error can be seen very clearly with one exception, the runtime of level 13. But this correlation seems to be less linear as we first expected. There seems to be a “sweet spot” around levels 17 and 18 after which the error hardly decreases while the runtime grows almost exponentially. At level 18, the cell diagonal, and thereby the maximum error, is roughly 50 meters long, at level 19 it reduces to 27 meters. Compared to the area of a neighborhood, and thereby a query polygon, this is already relatively small. Further decreasing this error margin from there on makes sense when exact results are required, which is seldom the case in exploratory scenarios. But not only the query error and runtime are influenced by the Block level, the influence already begins in the building of GeoBlocks. Figure 6c depicts the build time and size overhead for GeoBlocks from level 13 to 21. The build time seems to be only lightly affected by the level rising slowly with it (a split into sorting and building parts can be found in Table 1). There is a noticeable increase in sorting along the Block level, in addition to the expected increase in building. This sorting rise can be explained through our grid cell extraction that we piggybacked to the sorting process, which has to extract more cells with higher levels (finer-grained cells). The size overhead, however, grows exponentially. This is easily explained with the also exponential growth of children along the level.

Skew Influence. To show the influence data skew can have on the different Block query algorithms, we ran the NYC base workload along different numbers of the skewed workload. The AggregateTrie was built after running the base workload once and skew workload as often as mentioned for each experiment. We fixed the Block level to 17 (~100m diagonal) and the aggregate threshold to 5%, which roughly corresponds to aggregating all cells of the skewed workload. Figure 9 displays the absolute runtime for both the base and skewed part of the workloads. One can see that even at very limited skew both are almost on par, with the basic query algorithm winning slightly. As expected, the runtime for the basic workload stays nearly constant throughout all runs, always slightly faster for V1. This is easily explained by the overhead of probing the AggregateTrie for each cell, regardless of whether it is aggregated or not. But after four skewed runs, the additional aggregates start to pay off. With even more skew in the total workload, our query-driven storage V2 quickly starts to outperform V1.

Aggregate Threshold Influence. Having examined the influence of skew, we want to show how the aggregate threshold, and thereby the size of the AggregateTrie (V2), has on the runtime of the base and the skewed workload. The aggregate threshold denotes the relative size overhead the AggregateTrie introduces compared to the size of the GeoBlock Header. We again fixed the Block level to 17 and the number of skewed runs to four. Figure 10 depicts the measured runtimes. The runtime of V1 stays unaffected of the changed threshold and only acts as a baseline to highlight the
influence on V2. Up until a threshold of around 5% only queries from the skewed workload can be answered using the AggregateTrie. The small speedup of the base workload can be explained through the containment of the skewed workload in the base workload. After all cells in the skewed workload were aggregated, other query cells of the base workload start to get pre-aggregated as well. While this, of course, leads to further runtime improvements this is undesirable especially when memory is scarce. In our experiments at around 50% all cells of the workload have been aggregated so there is no further speedup, even when the available memory is doubled.

5 DISCUSSION
In this section, we discuss the takeaways of the evaluation as well as properties not mentioned until now.

Evaluation Summary. The first point we showed is that pre-aggregation in a spatial context pays off when limited error is acceptable, independent of the number of aggregates queried and the selectivity of the queried polygons. Furthermore we showed that, while index creation is more expensive than for rudimentary baselines like the BinarySearch, there is no huge overhead that would make them unprofitable for seldom queried workloads. Even when ignoring the build time for our baselines, GeoBlocks’s build time of around 7 seconds can be amortized by fewer than 30 polygon queries with a selectivity of 10% as can be seen from the runtime numbers of Figures 6a and 7.

Additionally, building multiple GeoBlocks once the data is sorted is possible within one second for our dataset, cf. Figure 6a. This means that building new blocks for a changed filter set is amortized even faster. However, not all configurations are optimal for GeoBlocks, but there seems to be acceptable trade-offs in regards to error and runtime, in our case around levels 17 and 18. While the level does not play a huge role in the index build time, the size overhead growth is almost exponential, cf. Figure 6b, indicating that it is wise to think about which error is acceptable for the given query workload when memory is scarce.

Updates. Up until now we considered GeoBlocks to be read only as they are designed for historical point data. However, the layout of the GeoBlock allows us to integrate updates easily very similar to query processing, as long as the CellBlock Header for the region of the newly arriving tuple already exists. For the non-adaptive version all we have to do is locate the CellBlock Header where the tuple is located, and update all stored aggregates. Analogous to the non-adaptive version, the adaptive one needs to update the CellBlock aggregate as well. Furthermore, we need to traverse the AggregateTrie and see if any of the tuple’s CellBlock parents are aggregated. Thanks to the prefix-based indexing property of the trie, we can do this in a single depth-first search and update all existing aggregates along the path. Only if tuples arrive for a new, previously unaggregated, region we have to recalculate the header as we rely on the CellBlock Headers to be sorted. But as we showed recalculating the headers is possible often within a second, so this would not induce too much delay when updates are implemented in batches instead of single tuples. Other indexing approaches on the CellBlock Headers (e.g., a clustered B-tree) could eliminate the need to rebuild if we keep storage for newly required aggregates at hand.

Future Work. For now, we resort to a simple binary search when searching for aggregates. While this is the most space-efficient option, other index structures on the CellBlock Headers could promise faster lookup times. As we discussed before, this could enable full update functionality. Another promising space-efficient approach would be a learned index, capable of learning the distribution of a sorted array, like proposed by Kraska et al. [15]. Ideally this allows for lookups in constant time with negligible size overhead, but in our case it introduces the same update restrictions the binary search does. Another thing worth considering is splitting a single GeoBlock into multiple ones, for example splitting along a temporal domain for (append-only) time-series data, and querying these blocks individually. While this would likely lead to a slight performance decrease when querying all blocks, it would speed up the build phase and make results available even sooner in addition to the mentioned possibility to filter the temporal domain.

Another use for multiple GeoBlocks could be building the header for multiple column and filter combinations while storing the underlying data only once. As we showed in Section 4.2 and already discussed above, the most time-consuming part of building a GeoBlock is sorting, meaning once we have the sorted data we can build new aggregates from this data without much delay. Possible future improvements on the adapted query process include using a Bloom filter [4] to reduce the overhead of probing a query cell in the AggregateTrie. This would benefit the adapted approach, especially for unbiased workloads. Finally, we could invert the parent-child optimizations used in the adapted query process and subtract child results from the parent result, for example when three of the four child cells are required but only an aggregate for the parent is stored in addition to using child results for queried parents.

6 CONCLUSIONS
We have introduced GeoBlocks, a novel storage layout for geospatial data. GeoBlocks use pre-aggregation of intermediate results while still supporting arbitrary shaped query polygons. Using these aggregates, GeoBlocks can provide fast query results with a user-controllable spatial error. Comparing our approach with on-the-fly aggregating indexing baselines, we have shown that we can outperform these competitors for any number of aggregates, in parts by two orders of magnitude.

Furthermore, we have described how GeoBlocks can speed up aggregating queries for commonly queried regions by dynamically adapting to any given workload using limited additional storage. The introduced overhead on the raw data is comparable, and often even lower, to those of traditional indexing structures while GeoBlocks can be built equally fast. Looking at the configuration options for GeoBlocks, we have shown how they can be adapted to the given dataset and workload and how the configuration influences runtime, overhead, and error in the result. Finally, we have described how GeoBlocks can support updates, essentially making GeoBlocks query-adapting materialized views optimized for geospatial point data.
