Lab 4. Analytics with Elasticsearch

In this lab, we will look at how Elasticsearch can serve as our analytics engine. We will cover the following topics:

- Preparing data for analysis
- Metric aggregations
- Bucket aggregations
- Pipeline aggregations

We will learn about all of this by using a real-world dataset.

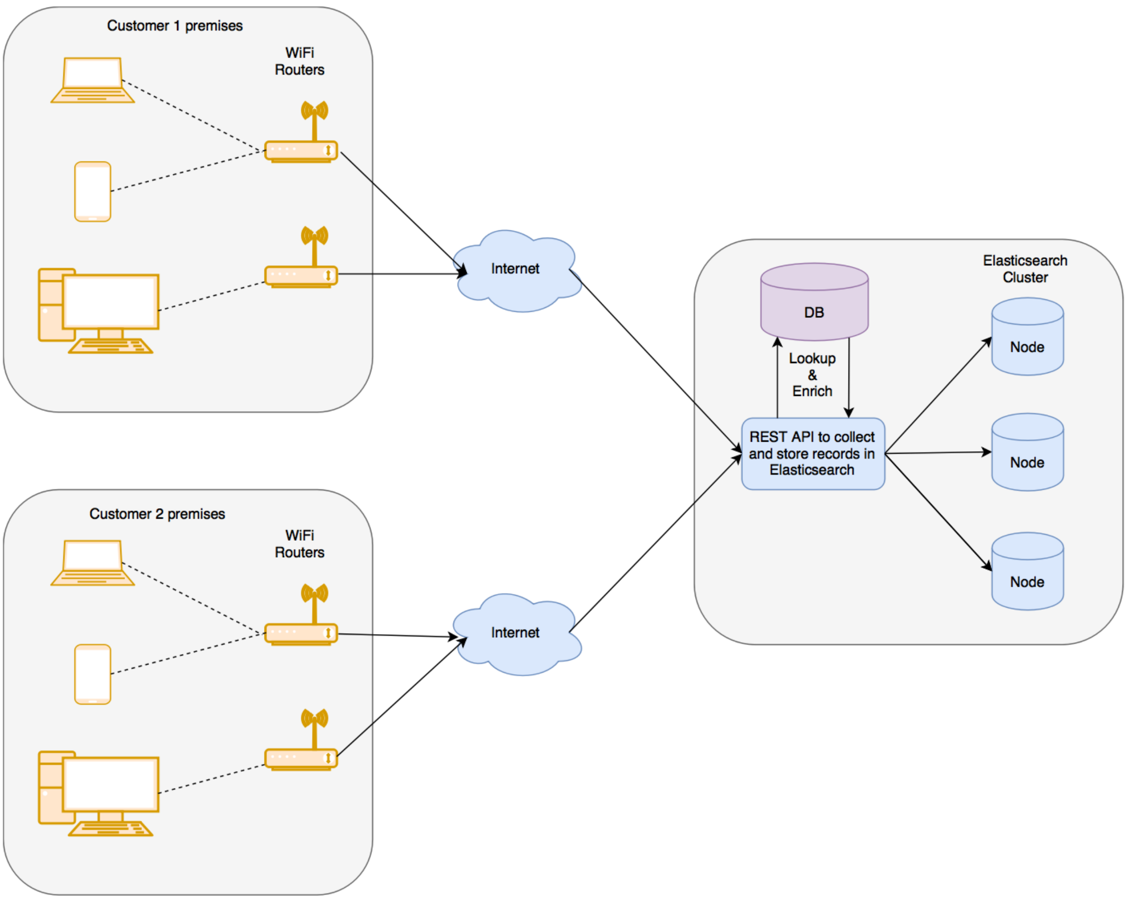
Preparing data for analysis

We will cover the following topics while we prepare and load the data into the local Elasticsearch instance:

- Understanding the structure of the data
- Loading the data using Logstash

Understanding the structure of the data

The following diagram depicts the design of the system, in order to help you gain a better understanding of the problem and the structure of the data that's collected:



The enriched records are stored in Elasticsearch in a flat data structure. One record looks as follows:

```
"_source": {
  "customer": "Google"         // Customer to which the WiFi router and device belongs
to
  "accessPointId": "AP-59484", // Identifier of the WiFi router or Access Point
  "time": 1506148631061,       // Time of the record in milliseconds since Epoch Jan
1, 1970
  "mac": "c6:ec:7d:c6:3d:8d",  // MAC address of the client device

  "username": "Pedro Harrison", // Name of the user to whom the device is assigned
  "department": "Operations",   // Department of the user to which the device belongs
to

  "application": "CNBC",        // Application name or domain name for which traffic
is reported
  "category": "News",           // Category of the application

  "networkId": "Internal",      // SSID of the network
  "band": "5 GHz", // Band 5 GHz or 2.4 GHz

  "location": "23.102789,72.595381", // latitude & longitude separated by comma

  "uploadTotal": 1340,      // Bytes uploaded since the last report
  "downloadTotal": 2129,    // Bytes downloaded since the last report
  "usage": 3469,            // Total bytes downloaded and uploaded in current period

  "uploadCurrent": 22.33,   // Upload speed in bytes/sec in current period
  "downloadCurrent": 35.48, // Download speed in bytes/sec in current period
  "bandwidth": 57.82,       // Total speed in bytes/sec (Upload speed + download
speed)

  "signalStrength": -25,    // Signal strength between WiFi router and device
  ...
}
```

One record contains various metrics for the given end client device at the given time.

Now that we know what our data represents and what each record represents, let's load the data in our local instance.

Loading the data using Logstash

To import the data, please follow these instructions:

Import network traffic data to learn Analytics capabilities of Elasticsearch

1. Switch user from terminal: `su elasticsearch`
2. Logstash has been already downloaded at following path: `/elasticstack/logstash-7.12.1`.
3. Files have been already copied at path `/elasticstack/logstash-7.12.1/files_lab4` . The structure of files should look like -

```
/elasticstack/logstash-7.12.1/files_lab4/network_traffic_data.json
/elasticstack/logstash-7.12.1/files_lab4/logstash_network_traffic_data.conf
```

6. Create the following index by executing the command in the your Kibana - Dev Tools.

```
PUT /bigginsight
{
  "settings": {
    "index": {
      "number_of_replicas": "1",
      "number_of_shards": "5"
    }
  },
  "mappings": {
    "properties": {
      "accessPointId": {
        "type": "keyword",
        "fields": {
          "analyzed": {
            "type": "text"
          }
        }
      },
      "application": {
        "type": "keyword",
        "fields": {
          "analyzed": {
            "type": "text"
          }
        }
      },
      "band": {
        "type": "keyword",
        "fields": {
          "analyzed": {
            "type": "text"
          }
        }
      },
      "bandwidth": {
        "type": "double"
      },
      "category": {
        "type": "keyword",
        "fields": {
          "analyzed": {
            "type": "text"
          }
        }
      },
      "customer": {
        "type": "keyword",
        "fields": {
          "analyzed": {
            "type": "text"
```

```
          }
        }
      },
      "department": {
        "type": "keyword",
        "fields": {
          "analyzed": {
            "type": "text"
          }
        }
      },
      "downloadCurrent": {
        "type": "double"
      },
      "downloadTotal": {
        "type": "integer"
      },
      "inactiveMs": {
        "type": "integer"
      },
      "location": {
        "type": "geo_point"
      },
      "mac": {
        "type": "keyword",
        "fields": {
          "analyzed": {
            "type": "text"
          }
        }
      },
      "networkId": {
        "type": "keyword",
        "fields": {
          "analyzed": {
            "type": "text"
          }
        }
      },
      "signalStrength": {
        "type": "integer"
      },
      "time": {
        "type": "date",
        "format": "strict_date_optional_time||epoch_millis"
      },
      "uploadCurrent": {
        "type": "double"
      },
      "uploadTotal": {
        "type": "integer"
      },
```

```
      "usage": {
        "type": "double"
      },
      "username": {
        "type": "keyword",
        "fields": {
          "analyzed": {
            "type": "text"
          }
        }
      }
    }
  }
}
```

7. Run logstash from command line, using the following commands

```
cd /elasticstack/logstash-7.12.1
logstash -f files_lab4/logstash_network_traffic_data.conf
```

Note: Logstash will take few minutes to import the data. Please wait for import to complete

Verify Data Import

Once you have imported the data, verify that your data has been imported with the following query:

```
GET /bigginsight/_search
{
  "query": {
    "match_all": {}
   },
  "size": 1
}
```

You should see a response similar to the following:

```
{
  ...
  "hits":
    {
    "total" : {
      "value" : 10000,
      "relation" : "gte"
    },
    "max_score": 1,
    "hits": [
            {
        "_index": "bigginsight",
        "_type": "_doc",
        "_id": "AV7Sy4FofN33RKOLlVH0",
        "_score": 1,
        "_source": {
          "inactiveMs": 1316,
```

```
          "bandwidth": 51.03333333333333,
          "signalStrength": -58,
          "accessPointId": "AP-1D7F0",
          "usage": 3062,
          "downloadCurrent": 39.93333333333333,
          "uploadCurrent": 11.1,
          "mac": "d2:a1:74:28:c0:5a",
          "tags": [],
          "@timestamp": "2017-09-30T12:38:25.867Z",
          "application": "Dropbox",
          "downloadTotal": 2396,
          "@version": "1",
          "networkId": "Guest",
          "location": "23.102900,72.595611",
          "time": 1506164775655,
          "band": "2.4 GHz",
          "department": "HR",
          "category": "File Sharing",
          "uploadTotal": 666,
          "username": "Cheryl Stokes",
          "customer": "Microsoft"
        }
      }
    ]
  }
}
```


Now that we have the data that we want, we can get started and learn about different types of aggregations from the data that we just loaded. You can find all the queries that are used in this lab in following directory:

```
/root/Desktop/elasticsearch/Lab04/queries.txt
```

Metric aggregations

In this section, we will go over the following metric aggregations:

- Sum, average, min, and max aggregations
- Stats and extended stats aggregations
- Cardinality aggregations

Let's learn about them, one by one.

Sum, average, min, and max aggregations

Finding the sum of a field, the minimum value for a field, the maximum value for a field, or an average, are very common operations. For people who are familiar with SQL, the query to find the sum is as follows:

```
SELECT sum(downloadTotal) FROM usageReport;
```

The preceding query will calculate the sum of the `downloadTotal` field across all the records in the table. This requires going through all the records of the table or all the records in the given context and adding the values of the given fields.

In Elasticsearch, a similar query can be written using the sum aggregation. Let's look at the sum aggregation first.

Sum aggregation

Here is how to write a simple sum aggregation:

```
GET bigginsight/_search?track_total_hits=true
{
 "aggregations": {
    "download_sum": {
      "sum": {
        "field": "downloadTotal"
      }
    }
  },
  "size": 0
}
```

The response should look like the following:

```
{
  "took": 92,
  ...
  "hits": {
    "total" : {
      "value" : 242836,          1
      "relation" : "eq"
    },            1
    "max_score": 0,
    "hits": []
  },
  "aggregations": {              2
    "download_sum": {            3
      "value": 2197438700        4
    }
  }
}
```

Let's go over the key aspects of the response. The key parts are numbered 1, 2, 3, and so on, and are explained in the following points:

- The `hits.total` element shows the number of documents that were considered or were in the context of the query. If there was no additional query or filter specified, it will include all of the documents in the type or index. We passed `?track_total_hits=true` in the request, and hence, you will see the exact count of total hits in the index.
- Just like the request, this response is wrapped inside `aggregations` to indicate them.
- The response of the aggregation we requested was named `download_sum`; hence, we get our response from the sum aggregation inside an element with the same name.
- This is the actual value after applying the sum aggregation.

The average, min, and max aggregations are very similar. Let's look at them briefly.

Average aggregation

The average aggregation finds an average across all the documents in the querying context:

```
GET bigginsight/_search
{
 "aggregations": {
    "download_average": {
      "avg": {
        "field": "downloadTotal"
      }
    }
  },
  "size": 0
}
```

The only notable differences from the sum aggregation are as follows:

- We chose a different name, `download_average`, to make it apparent that the aggregation is trying to compute the average.
- The type of aggregation that we are doing is `avg`, instead of the `sum` aggregation that we were doing earlier.

The response structure is identical, but the value field will now represent the average of the requested field.

The min and max aggregations are exactly the same.

Min aggregation

The min aggregation is how we will find the minimum value of the `downloadTotal` field in the entire index/type:

```
GET bigginsight/_search
{
 "aggregations": {
    "download_min": {
      "min": {
        "field": "downloadTotal"
      }
    }
  },
  "size": 0
}
```

Now, let's take a look at max aggregation.

Max aggregation

Here's how we will find the maximum value of the `downloadTotal` field in the entire index/type:

```
GET bigginsight/_search
{
 "aggregations": {
    "download_max": {
      "max": {
        "field": "downloadTotal"
      }
    }
  },
```

```
  "size": 0
}
```

These aggregations were really simple. Now, let's look at some more advanced stats and extended stats aggregations.

Stats aggregation

Stats aggregation computes the sum, average, min, max, and count of documents in a single pass:

```
GET bigginsight/_search
{
 "aggregations": {
    "download_stats": {
      "stats": {
        "field": "downloadTotal"
      }
    }
  },
  "size": 0
}
```

The structure of the stats request is the same as the other metric aggregations we have looked at so far, so nothing special is going on here.

The response should look like the following:

```
{
  "took": 4,
  ...,
  "hits": {
    "total" : {
      "value" : 10000,
      "relation" : "gte"
    },
    "max_score": 0,
    "hits": []
  },
  "aggregations": {
    "download_stats": {
      "count": 242835,
      "min": 0,
      "max": 241213,
      "avg": 9049.102065188297,
      "sum": 2197438700
    }
  }
}
```

Let's look at the extended stats aggregation.

Extended stats aggregation

The `extended stats` aggregation returns a few more statistics in addition to the ones returned by the `stats` aggregation:

```
GET bigginsight/_search
{
 "aggregations": {
    "download_estats": {
      "extended_stats": {
        "field": "downloadTotal"
      }
    }
  },
  "size": 0
}
```

The response looks like the following:

```
{
  "took": 15,
  "timed_out": false,
  ...,
  "hits": {
    "total" : {
      "value" : 10000,
      "relation" : "gte"
    },
    "max_score": 0,
    "hits": []
  },
  "aggregations": {
    "download_estats": {
      "count": 242835,
      "min": 0,
      "max": 241213,
      "avg": 9049.102065188297,
      "sum": 2197438700,
      "sum_of_squares": 133545882701698,
      "variance": 468058704.9782911,
      "std_deviation": 21634.664429528162,
      "std_deviation_bounds": {
        "upper": 52318.43092424462,
        "lower": -34220.22679386803
      }
    }
  }
}
```

It also returns the sum of `squares`, `variance`, `standard deviation`, and `standard deviation bounds`.

Cardinality aggregation

Finding the count of unique elements can be done with the cardinality aggregation. It is similar to finding the result of a query such as the following:

```
select count(*) from (select distinct username from usageReport) u;
```

Finding the cardinality, or the number of unique values, for a specific field is a very common requirement. If you have a click stream from the different visitors on your website, you may want to find out how many unique visitors you had in a given day, week, or month.

Let's look at how we can find out the count of unique users for which we have network traffic data:

```
GET bigginsight/_search
{
 "aggregations": {
    "unique_visitors": {
      "cardinality": {
        "field": "username"
      }
    }
  },
  "size": 0
}
```

The cardinality aggregation response is just like the other metric aggregations:

```
{
  "took": 110,
  ...,
  "hits": {
    "total" : {
      "value" : 10000,
      "relation" : "gte"
    },
    "max_score": 0,
    "hits": []
  },
  "aggregations": {
    "unique_visitors": {
      "value": 79
    }
  }
}
```

Now that we have covered the simplest forms of aggregations, we can look at some of the bucket aggregations.

Terms aggregation

We are interested in the most surfed categories -- not in terms of the bandwidth used, but just in terms of counts (record counts). In a relational database, we could write a query like the following:

```
SELECT category, count(*) FROM usageReport GROUP BY category ORDER BY count(*) DESC;
```

The Elasticsearch aggregation query, which would do a similar job, can be written as follows:

```
GET /bigginsight/_search
{
  "aggs": {
    "byCategory": {
      "terms": {
        "field": "category"
      }
    }
  },
  "size": 0
}
```

Let's look at the terms of the aggregation query here. Notice the numbers that refer to different parts of the query:

- The `aggs` or `aggregations` element at the top level should wrap any aggregation.
- Give a name to the aggregation. Here, we are doing `terms` aggregation by the category field, and hence, the name we chose is `byCategory`.
- We are doing a `terms` aggregation, and hence, we have the `terms` element.
- We want to do a `terms` aggregation on the `category` field.
- Specify `size = 0` to prevent raw search results from being returned. We just want aggregation results, and not the search results, in this case. Since we haven't specified any top-level `query` element, it matches all documents. We do not want any raw documents (or search hits) in the result.

The response looks like the following:

```
{
  "took": 11,
  "timed_out": false,
  "_shards": {
    "total": 5,
    "successful": 5,
    "failed": 0
  },
  "hits": {
    "total" : {
      "value" : 10000,                      1
      "relation" : "gte"
    },
    "max_score": 0,
    "hits": []                              2
  },
  "aggregations": {                         3
    "byCategory": {                         4
      "doc_count_error_upper_bound": 0,     5
      "sum_other_doc_count": 0,             6
      "buckets": [                          8
        {
          "key": "Chat",                    9
          "doc_count": 52277                10
        },
        {
          "key": "File Sharing",
```

```
          "doc_count": 46912
        },
        {
          "key": "Other HTTP",
          "doc_count": 38535
        },
        {
          "key": "News",
          "doc_count": 25784
        },
        {
          "key": "Email",
          "doc_count": 21003
        },
        {
          "key": "Gaming",
          "doc_count": 19578
        },
        {
          "key": "Jobs",
          "doc_count": 19429
        },
        {
          "key": "Blogging",
          "doc_count": 19317
        }
      ]
    }
  }
}
```

As you can see, there are only eight distinct buckets in the results of the query.

Next, we want to find out the top applications in terms of the maximum number of records for each application:

```
GET /bigginsight/_search?size=0
{
  "aggs": {
    "byApplication": {
      "terms": {
        "field": "application"
      }
    }
  }
}
```

Note that we have added `size=0` as a request parameter in the URL itself.

This returns a response like the following:

```
{
  ...,
  "aggregations": {
```

```
    "byApplication": {
      "doc_count_error_upper_bound": 6339,
      "sum_other_doc_count": 129191,
      "buckets": [
        {
          "key": "Skype",
          "doc_count": 26115
        },
        ...
}
```

To get the top *n* buckets instead of the default 10, we can use the `size` parameter inside the `terms` aggregation:

```
GET /bigginsight/_search?size=0
{
  "aggs": {
    "byApplication": {
      "terms": {
        "field": "application",
        "size": 15
      }
    }
  }
}
```

Notice that this `size` (specified inside the `terms` aggregation) is different from the `size` specified at the top level. At the top level, the `size` parameter is used to prevent any search hits, whereas the `size` parameter being used inside the `terms` aggregation denotes the maximum number of term buckets to be returned.

Terms aggregation is very useful for generating data for pie charts or bar charts, where we may want to analyze the relative counts of string typed fields in a set of documents. In Lab 7, you will learn that Kibana terms aggregation is useful for generating pie and bar charts.

Next, we will look at how to do bucketing on `numerical` types of fields.

Histogram aggregation

Here, we have some records of network traffic usage data. The `usage` field tells us about the number of bytes that are used for uploading or downloading data. Let's try to divide or slice all the data based on the usage:

```
POST /bigginsight/_search?size=0
{
 "aggs": {
 "by_usage": {
 "histogram": {
 "field": "usage",
 "interval": 1000
 }
 }
 }
}
```

The preceding aggregation query will slice all the data into the following buckets:

- **0 to 999**: All records that have usage >= 0 and < 1,000 will fall into this bucket
- **1,000 to 1,999**: All records that have usage >= 1,000 and < 2,000 will fall into this bucket
- **2,000 to 2,999**: All records that have usage >= 2,000 and < 3,000 will fall into this bucket

The response should look like the following (truncated for brevity):

```
{
  ...,
  "aggregations": {
    "by_usage": {
      "buckets": [
        {
          "key": 0.0,
          "doc_count": 30060
        },
        {
          "key": 1000.0,
          "doc_count": 42880
        },
        {
          "key": 2000.0,
          "doc_count": 42041
        },
...
}
```

Let's look at another aggregation, range aggregation, which can be used on numerical data.

Range aggregation

The following `range` aggregation slices the data into three buckets: up to 1 KB, 1 KB to 100 KB, and 100 KB or more. Notice that we can specify `from` and `to` in the ranges. Both `from` and `to` are optional in the range. If only `to` is specified, that bucket includes all the documents up to the specified value in that bucket. The `to` value is exclusive, and is not included in the current bucket's range:

```
POST /bigginsight/_search?size=0
{
  "aggs": {
    "by_usage": {
      "range": {
        "field": "usage",
        "ranges": [
          { "to": 1024 },
          { "from": 1024, "to": 102400 },
          { "from": 102400 }
        ]
      }
    }
  }
}
```

The response of this request will look similar to the following:

```
{
  ...,
  "aggregations": {
    "by_usage": {
      "buckets": [
        {
          "key": "*-1024.0",
          "to": 1024,
          "doc_count": 31324
        },
        {
          "key": "1024.0-102400.0",
          "from": 1024,
          "to": 102400,
          "doc_count": 207498
        },
        {
          "key": "102400.0-*",
          "from": 102400,
          "doc_count": 4013
        }
      ]
    }
  }
}
```

It is possible to specify custom `key` labels for the range buckets, as follows:

```
POST /bigginsight/_search?size=0
{
  "aggs": {
    "by_usage": {
      "range": {
        "field": "usage",
        "ranges": [
          { "key": "Upto 1 kb", "to": 1024 },
          { "key": "1 kb to 100 kb","from": 1024, "to": 102400 },
          { "key": "100 kb and more", "from": 102400 }
        ]
      }
    }
  }
}
```

The resulting buckets will have the keys set with each bucket. This is helpful for looking up the relevant bucket from the response without iterating through all the buckets.

Next, we will look at a couple of important concepts related to bucket aggregation and aggregations in general.

Aggregations on filtered data

Let's revisit the example that we looked at in the *Terms aggregation* section. We found out the top categories in the whole index and type. Now, what we want to do is find the top category for a specific customer, not for all of the customers:

```
GET /bigginsight/_search?size=0&track_total_hits=true
{
  "query": {
    "term": {
      "customer": "Linkedin"
    }
  },
  "aggs": {
    "byCategory": {
      "terms": {
        "field": "category"
      }
    }
  }
}
```

This type of query, when used with any type of aggregation, changes the context of the data on which aggregations are calculated. The query/filter decides the data that the aggregations will be run on.

Let's look at the response of this query to understand this better:

```
{
  "took": 18,
  ...,
  "hits": {
"total" : {
      "value" : 76607,
      "relation" : "eq"
    },
    "max_score": 0,
    "hits": []
  },
  ...
}
```

The `hits.total` element in the response is now much smaller than the earlier aggregation query, which was run on the whole index and type. We may also want to apply more filters to limit the query to a smaller time window.

The following query applies multiple filters and makes the scope of the aggregation more specific. It does this for a customer, and within some subset of the time interval:

```
GET /bigginsight/_search?size=0
{
  "query": {
    "bool": {
      "must": [
        {"term": {"customer": "Linkedin"}},
        {"range": {"time": {"gte": 1506277800000, "lte": 1506294200000}}}
      ]
    }
  },
```

```
  "aggs": {
    "byCategory": {
      "terms": {
        "field": "category"
      }
    }
  }
}
```

This is how the scope of aggregation can be modified using filters. Now, we will continue on our detour of learning about different bucket aggregations and look at how to nest metric aggregations inside bucket aggregations.

Nesting aggregations

We have to take the following steps:

1. First, filter the overall data for the given customer and for the given day. This can be done using a global query element of the `bool` type.
2. Once we have the filtered data, we will want to create some buckets per user.
3. Once we have one bucket for each user, we will want to compute the sum metric aggregation on the total usage field (which includes upload and download).

The following query does exactly this. Please refer to the annotated numbers, which correspond to the three main objectives of the the following query:

```
GET /bigginsight/_search?size=0
{
  "query": {
    "bool": {
      "must": [
        {"term": {"customer": "Linkedin"}},
        {"range": {"time": {"gte": 1506257800000, "lte": 1506314200000}}}
      ]
    }
  },
  "aggs": {
    "by_users": {
      "terms": {
        "field": "username"
      },
      "aggs": {
        "total_usage": {
          "sum": { "field": "usage" }
        }
      }
    }
  }
}
```

The thing to notice here is that the top level `by_users` aggregation, which is a `terms` aggregation, contains another `aggs` element with the `total_usage` metric aggregation inside it.

The response should look like the following:

```
{
  ...,
  "aggregations": {
    "by_users": {
      "doc_count_error_upper_bound": 0,
      "sum_other_doc_count": 453,
      "buckets": [
        {
          "key": "Jay May",
          "doc_count": 2170,
          "total_usage": {
            "value": 6516943
          }
        },
        {
          "key": "Guadalupe Rice",
          "doc_count": 2157,
          "total_usage": {
            "value": 6492653
          }
        },
   ...
}
```

As you can see, each of the `terms` aggregation buckets contains a `total_usage` child, which has the metric aggregation value. The buckets are sorted by the number of documents in each bucket, in descending order. It is possible to change the order of buckets by specifying the order parameter within the bucket aggregation.

Please see the following partial query, which has been modified to sort the buckets in descending order of the `total_usage` metric:

```
GET /bigginsight/usageReport/_search
{
  ...,
  "aggs": {
    "by_users": {
      "terms": {
        "field": "username",
"order": { "total_usage": "desc"}
      },
      "aggs": {
        ...
...
}
```

The highlighted order clause sorts the buckets using the `total_usage` nested aggregation, in descending order.

Bucket aggregations can be nested inside other bucket aggregations. Let's considering this by getting an answer to the following question:

[*Who are the top two users in each department, given the total bandwidth consumed by each user?*]

The following query will help us get that answer:

```
GET /bigginsight/_search?size=0
{
  "query": {
    "bool": {
      "must": [
        {"term": {"customer": "Linkedin"}},
        {"range": {"time": {"gte": 1506257800000, "lte": 1506314200000}}}
      ]
    }
  },
  "aggs": {
    "by_departments": {
      "terms": { "field": "department" },
      "aggs": {
        "by_users": {
          "terms": {
            "field": "username",
            "size": 2,
            "order": { "total_usage": "desc"}
          },
          "aggs": {
            "total_usage": {"sum": { "field": "usage" }}
          }
        }
      }
    }
  }
}
```

This is how we can nest bucket and metric aggregations to answer complex questions in a very fast and efficient way, regarding big data stored in Elasticsearch.

Bucketing on custom conditions

The following aggregations allow us to create one or more buckets, based on the queries/filters that we choose:

- Filter aggregation
- Filters aggregation

Let's look at them, one by one.

Filter aggregation

Why would you want to use filter aggregation[*?*] Filter aggregation allows you to create a single bucket using any arbitrary filter and computes the metrics within that bucket.

For example, if we wanted to create a bucket of all the records for the `Chat` category, we could use a term filter. Here, we want to create a bucket of all records that have `category = Chat`:

```
POST /bigginsight/_search?size=0
{
 "aggs": {
   "chat": {
     "filter": {
```

```
        "term": {
          "category": "Chat"
        }
      }
    }
  }
}
```

The response should look like the following:

```
{
  "took": 4,
  ...,
  "hits": {
    "total" : {
      "value" : 10000,
      "relation" : "gte"
    },
    "max_score": 0,
    "hits": []
  },
  "aggregations": {
    "chat": {
      "doc_count": 52277
    }
  }
}
```

As you can see, the `aggregations` element contains just one item, corresponding to the `Chat` category. It has `52277` documents. This response can be seen as a subset of the `terms` aggregation response, which contained all the categories, apart from `Chat`.

Let's look at filters aggregation next, which allows you to bucket on more than one custom filter.

Filters aggregation

Suppose that we want to create multiple buckets to understand how much of the network traffic was caused by the `Chat` category. At the same time, we want to understand how much of it was caused by the Skype application, versus other applications in the `Chat` category. This can be achieved by using filters aggregation, as it allows us to write arbitrary filters to create buckets:

```
GET bigginsight/_search?size=0
{
  "aggs": {
    "messages": {
      "filters": {
        "filters": {
          "chat": { "match": { "category": "Chat" }},
          "skype": { "match": { "application": "Skype" }},
          "other_than_skype": {
            "bool": {
              "must": {"match": {"category": "Chat"}},
              "must_not": {"match": {"application": "Skype"}}
```

```
            }
          }
        }
      }
    }
  }
}
```

Next, we will look at how to slice data on a `date` type column, so that we can slice it into different time intervals.

Creating buckets across time periods

The following query will slice the data into intervals of one day. Just like how we were able to create buckets on different values of strings, the following query will create buckets on different values of time, grouped by one-day intervals:

```
GET /bigginsight/_search?size=0                    1
{
  "aggs": {
    "counts_over_time": {
      "date_histogram": {                          2
        "field": "time",
        "interval": "1d"                           3
      }
    }
  }
}
```

The key points from the preceding code are explained as follows:

- We have specified `size=0` as a request parameter, instead of specifying it in the request body.
- We are using the `date_histogram` aggregation.
- We want to slice the data by day; that's why we specify the `interval` for slicing the data as `1d` (for one day). Intervals can take values like `1d` (one day), `1h` (one hour), `4h` (four hours), `30m` (30 minutes), and so on. This gives tremendous flexibility when specifying a dynamic criteria.

The response to the request should look like the following:

```
{
  ...,
  "aggregations": {
    "counts_over_time": {
      "buckets": [
        {
          "key_as_string": "2017-09-23T00:00:00.000Z",
          "key": 1506124800000,
          "doc_count": 62493
        },
        {
          "key_as_string": "2017-09-24T00:00:00.000Z",
          "key": 1506211200000,
          "doc_count": 5312
        },
        {
```

```
          "key_as_string": "2017-09-25T00:00:00.000Z",
          "key": 1506297600000,
          "doc_count": 175030
        }
      ]
    }
  }
}
```

As you can see, the simulated data that we have in our index is only for a three-day period. The returned buckets contain keys in two forms, `key` and `key_as_string`. The `key` field is in milliseconds since the epoch (January 1st 1970), and `key_as_string` is the beginning of the time interval in UTC. In our case, we have chosen the interval of one day. The first bucket with the `2017-09-23T00:00:00.000Z` key is the bucket that has documents between September 23, 2017 UTC, and September 24, 2017 UTC.

Using a different time zone

We actually want to slice the data by the IST time zone, rather than slicing it according to the UTC time zone. This is possible by specifying the `time_zone` parameter. We need to separate the offset of the required time zone from the UTC time zone. In this case, we need to provide `+05:30` as the offset, since IST is 5 hours and 30 minutes ahead of UTC:

```
GET /bigginsight/_search?size=0
{
  "aggs": {
    "counts_over_time": {
      "date_histogram": {
        "field": "time",
        "interval": "1d",
        "time_zone": "+05:30"
      }
    }
  }
}
```

The response now looks like the following:

```
{
  ...,
  "aggregations": {
    "counts_over_time": {
      "buckets": [
        {
          "key_as_string": "2017-09-23T00:00:00.000+05:30",
          "key": 1506105000000,
          "doc_count": 62493
        },
        {
          "key_as_string": "2017-09-24T00:00:00.000+05:30",
          "key": 1506191400000,
          "doc_count": 0
        },
        {
```

```
          "key_as_string": "2017-09-25T00:00:00.000+05:30",
          "key": 1506277800000,
          "doc_count": 180342
        }
      ]
    }
  }
}
```

As you can see, the `key` and `key_as_string` for all the buckets have changed. The keys are now at the beginning of the day, in the IST time zone. There are no documents for September 24, 2017, now, since it is a Sunday.

Computing other metrics within sliced time intervals

So far, we have just sliced the data across time by using the Date Histogram to create the buckets on the time field. This gave us the document counts in each bucket. Next, we will try to answer the following question:

[*What is the day-wise total bandwidth usage for a given customer?*]

The following query will provide us with an answer for this:

```
GET /bigginsight/_search?size=0
{
  "query": { "term": {"customer": "Linkedin"} },
  "aggs": {
    "counts_over_time": {
      "date_histogram": {
        "field": "time",
        "interval": "1d",
        "time_zone": "+05:30"
      },
      "aggs": {
        "total_bandwidth": {
          "sum": { "field": "usage" }
        }
      }
    }
  }
}
```

We added a term filter to consider only one customer's data. Within the `date_histogram` aggregation, we nested another metric aggregation, that is, sum aggregation, to count the sum of the usage field within each bucket. This is how we will get the total data consumed each day. The following is the shortened response to the query:

```
{
  ..,
  "aggregations": {
    "counts_over_time": {
      "buckets": [
        {
          "key_as_string": "2017-09-23T00:00:00.000+05:30",
          "key": 1506105000000,
          "doc_count": 18892,
```

```
          "total_bandwidth": {
            "value": 265574303
          }
        },
        ...
      ]
    }
  }
}
```

Focusing on a specific day and changing intervals

What we are doing is also called drilling down in the data. Often, the result of the previous query is displayed as a line chart, with time on the [*x*] axis and data used on the [*y*] axis. If we want to zoom in on a specific day from that line chart, the following query can be useful:

```
GET /bigginsight/_search?size=0
{
  "query": {
    "bool": {
      "must": [
        {"term": {"customer": "Linkedin"}},
        {"range": {"time": {"gte": 1506277800000}}}
      ]
    }
  },
  "aggs": {
    "counts_over_time": {
      "date_histogram": {
        "field": "time",
        "interval": "1h",
        "time_zone": "+05:30"
      },
      "aggs": {
        "hourly_usage": {
          "sum": { "field": "usage" }
        }
      }
    }
  }
}
```

The shortened response would look like the following:

```
{
  ...,
  "aggregations": {
    "counts_over_time": {
      "buckets": [
        {
          "key_as_string": "2017-09-25T00:00:00.000+05:30",
          "key": 1506277800000,
          "doc_count": 465,
```

```
          "hourly_usage": {
            "value": 1385524
          }
        },
        {
          "key_as_string": "2017-09-25T01:00:00.000+05:30",
          "key": 1506281400000,
          "doc_count": 478,
          "hourly_usage": {
            "value": 1432123
          }
        },
    ...
}
```

As you can see, we have buckets for one-hour intervals, with data for those hours aggregated within each bucket.

Geodistance aggregation

The following aggregation will form a bucket with all the documents within the given distance from the given geo-point. This corresponds to the first (left) circle in the preceding diagram. The shaded area is from the center up to the given radius, forming a circle:

```
GET bigginsight/_search?size=0
{
  "aggs": {
    "within_radius": {
      "geo_distance": {
        "field": "location",
        "origin": {"lat": 23.102869,"lon": 72.595692},
        "ranges": [{"to": 5}]
      }
    }
  }
}
```

As you can see, the `ranges` parameter is similar to the `range` aggregation that we saw earlier. It includes all the points up to 5 meters away from the given `origin` specified. This is helpful in aggregations like getting the counts of things that are within 2 kilometers from a given location, and is often used on many websites. This is a good way to find all businesses within a given distance of your location (such as all coffee shops or hospitals within 2 km).

Now, let's look at what happens if you specify both `from` and `to` in the geodistance aggregation. This will correspond to the right circle in the preceding diagram:

```
GET bigginsight/_search?size=0
{
  "aggs": {
    "within_radius": {
      "geo_distance": {
        "field": "location",
        "origin": {"lat": 23.102869,"lon": 72.595692},
        "ranges": [{"from": 5, "to": 10}]
      }
```

```
    }
  }
}
```

Here, we are bucketing the points that are at least 5 meters away, but less than 10 meters away, from the given point. Similarly, it is possible to form a bucket of a point which is at least [*x*] units away from the given origin, by only specifying the `from` parameter.

Now, let's look at GeoHash grid aggregation.

GeoHash grid aggregation

GeoHash grid aggregation uses the GeoHash mechanism to divide the map into smaller units. The GeoHash system divides the world map into a grid of rectangular regions of different precisions. Lower values of precision represent larger geographical areas, while higher values represent smaller, more precise geographical areas:

```
GET bigginsight/_search?size=0
{
  "aggs": {
    "geo_hash": {
      "geohash_grid": {
        "field": "location",
        "precision": 7
      }
    }
  }
}
```

The data that we have in our network traffic example is spread over a very small geographical area, so we have used a `precision` of `7`. The supported values for precision are from 1 to 12. Let's look at the response to this request:

```
{
  ...,
  "aggregations": {
    "geo_hash": {
      "buckets": [
        {
          "key": "ts5e7vy",
          "doc_count": 161893
        },
        {
          "key": "ts5e7vw",
          "doc_count": 80942
        }
      ]
    }
  }
}
```

After aggregating the data onto GeoHash blocks of `"precision": 7`, all the documents fell into two GeoHash regions, with the respective document counts seen in the response. We can zoom in on this map or request the data to be aggregated on smaller hashes, by increasing the value of the precision.

When you try a `precision` value of `9`, you will see the following response:

```
{
  ...,
  "aggregations": {
    "geo_hash": {
      "buckets": [
        {
          "key": "ts5e7vy80k",
          "doc_count": 131034
        },
        {
          "key": "ts5e7vwrdb",
          "doc_count": 60953
        },
        {
          "key": "ts5e7vy84c",
          "doc_count": 30859
        },
        {
          "key": "ts5e7vwxfn",
          "doc_count": 19989
        }
      ]
    }
  }
}
```

As you can see, the GeoHash grid aggregation allows you to slice or aggregate the data over geographical regions of different sizes/precisions, which is quite powerful. This data can be visualized in Kibana, or it can be used in your application with a library that can render the data on a map.

Calculating the cumulative sum of usage over time

While discussing Date Histogram aggregation, we looked at the aggregation that's used to compute hourly bandwidth usage for one particular day. After completing that exercise, we had data for September 24, with hourly consumption between 12:00 am to 1:00 am, 1:00 am to 2:00 am, and so on. Using cumulative sum aggregation, we can also compute the cumulative bandwidth usage at the end of every hour of the day. Let's look at the query and try to understand it:

```
GET /bigginsight/_search?size=0
{
  "query": {
    "bool": {
      "must": [
        {"term": {"customer": "Linkedin"}},
        {"range": {"time": {"gte": 1506277800000}}}
      ]
    }
  },
  "aggs": {
    "counts_over_time": {
      "date_histogram": {
        "field": "time",
        "interval": "1h",
```

```
        "time_zone": "+05:30"
      },
      "aggs": {
        "hourly_usage": {
          "sum": { "field": "usage" }
        },
        "cumulative_hourly_usage": {
          "cumulative_sum": {
              "buckets_path": "hourly_usage"
          }
        }
      }
    }
  }
}
```

The response should look as follows. It has been truncated for brevity:

```
{
  ...,
  "aggregations": {
    "counts_over_time": {
      "buckets": [
        {
          "key_as_string": "2017-09-25T00:00:00.000+05:30",
          "key": 1506277800000,
          "doc_count": 465,
          "hourly_usage": {
            "value": 1385524
          },
          "cumulative_hourly_usage": {
            "value": 1385524
          }
        },
        {
          "key_as_string": "2017-09-25T01:00:00.000+05:30",
          "key": 1506281400000,
          "doc_count": 478,
          "hourly_usage": {
            "value": 1432123
          },
          "cumulative_hourly_usage":
           {
            "value": 2817647
           }
}
```

As you can see, `cumulative_hourly_usage` contains the sum of `hourly_usage`, so far. In the first bucket, the hourly usage and the cumulative hourly usage are the same. From the second bucket onward, the cumulative hourly usage has the sum of all the hourly buckets we've seen so far.

Summary

In this lab, you learned how to use Elasticsearch to build powerful analytics applications. We covered how to slice and dice the data to get powerful insight. We started with metric aggregation and dealt with numerical datatypes. We then covered bucket aggregation in order to find out how to slice the data into buckets or segments, in order to drill down into specific segments.

We also went over how pipeline aggregations work. We did all of this while dealing with a real-world-like dataset of network traffic data. We illustrated how flexible Elasticsearch is as an analytics engine. Without much additional data modeling and extra effort, we can analyze any field, even when the data is on a big data scale.