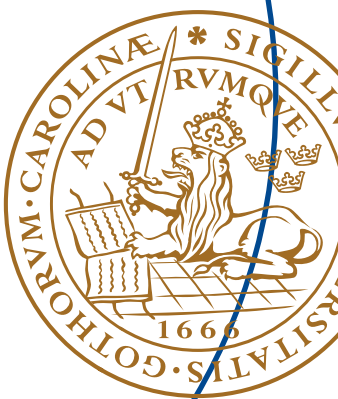
Master's Thesis

# Improving an open source geocoding server

Víctor García

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# Improving an open source geocoding server

By


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# Abstract

A common problem in geocoding is that the postal addresses as requested by the user differ from the addresses as described in the database. The online, open source geocoder called Nominatim is one of the most used geocoders nowadays. However, this geocoder lacks the interactivity that most of the online geocoders already offer. The Nominatim geocoder provides no feedback to the user while typing addresses. Also, the geocoder cannot deal with any misspelling errors introduced by the user in the requested address.

This thesis is about extending the functionality of the Nominatim geocoder to provide fuzzy search and autocomplete features. In this work I propose a new index and search strategy for the OpenStreetMap reference dataset. Also, I extend the search algorithm to geocode new address types such as street intersections. Both the original Nominatim geocoder and the proposed solution are compared using metrics such as the precision of the results, match rate and keystrokes saved by the autocomplete feature. The test addresses used in this work are a subset selected among the Swedish addresses available in the OpenStreetMap data set.

The results show that the proposed geocoder performs better when compared to the original Nominatim geocoder. In the proposed geocoder, the users get address suggestions as they type, adding interactivity to the original geocoder. Also, the proposed geocoder is able to find the right address in the presence of errors in the user query with a match rate of 98%.

# Popular science article

The demand of geospatial information is increasing during the last years. There are more and more mobile applications and services that require from the users to enter some information about where they are, or the address of the place they want to find for example. The systems that convert postal addresses or place descriptions into coordinates are called geocoders. How good or bad a geocoder is not only depends on the information the geocoder contains, but also on how easy is for the users to find the desired addresses.

There are many well-known web sites that we use in our everyday life to find the location of an address. For example sites like Google Maps, Bing Maps or Yahoo Maps are accessed by millions of users every day to use such services. Among the main features of the mentioned geocoders are the ability to predict the address the user is writing in the search box, and sometimes even to correct any misspellings introduced by the user. To make it more complicated, the predictions and error corrections these systems perform are done in real time. The owners of these address search engines usually impose some restrictions on the number of addresses a user is allowed to search monthly, above which the user needs to pay a fee in order to keep using the system. This limit is usually high enough for the end user, but it might not be enough for the software developers that want to use geospatial data in their products.

There is a free alternative to the address search engines mentioned above called Nominatim. Nominatim is an open source project whose purpose is to search addresses among the OpenStreetMap dataset. OpenStreetMap is a collaborative project that tries to map places in the real world into coordinates. The main drawback of Nominatim is that the usability is not as good as the competitors. Nominatim is unable to find addresses that are not correctly spelled, neither predicts the user needs. In order for this address search engine to be among the most used the prediction and error correction features need to be added.

In this thesis work I extend the search algorithms of Nominatim to add the functionality mentioned above. The address search engine proposed in this thesis offers a free and open source alternative to users and systems that require access to geospatial data without restrictions.

Resumen:

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Título: Mejora de un sistema de geolocalización de código libre
Tutor: Maria Kihl
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La demanda de información geoespacial está aumentando en los últimos años. Cada vez existen más aplicaciones y servicios móviles que requieren de los usuarios introducir información acerca de dónde están, o la dirección del lugar que quieren encontrar por ejemplo. Los sistemas que convierten las direcciones postales a coordenadas y viceversa se llaman geocodificadores. Cómo de bueno o malo es un geocodificador no sólo depende de la información que el geocodificador contiene, sino también en lo fácil que es para los usuarios encontrar las direcciones deseadas.

Existen muchos sitios web conocidos que utilizamos en nuestra vida cotidiana para encontrar la ubicación de una dirección. Por ejemplo, sitios como Google Maps, Bing Maps o Yahoo Maps son accedidos por millones de usuarios cada día. Entre las principales características de los geocodificadores se encuentran la capacidad de predecir la dirección que el usuario está escribiendo en el campo de búsqueda y, a veces incluso de corregir los errores ortográficos introducidos por el usuario. Para hacerlo más complicado, las predicciones y las correcciones de errores en estos sistemas se realizan en tiempo real. Los propietarios de estos motores de búsqueda de direcciones generalmente imponen restricciones en la cantidad de direcciones que se permite buscar a un usuario en un plazo de tiempo, generalmente un mes, por encima del cual el usuario tiene que pagar una cuota para poder seguir usando el sistema. Este límite suele ser lo suficientemente alto para el usuario final, pero tal vez no sea suficiente para desarrolladores de software que quieran utilizar datos geoespaciales en sus productos.

Hay una alternativa de código libre a los motores de búsqueda de direcciones mencionadas anteriormente llamado Nominatim. Nominatim es un proyecto de código libre cuyo propósito es buscar direcciones entre el conjunto de datos de OpenStreetMap. OpenStreetMap es un proyecto colaborativo que intenta asignar lugares en el mundo real a coordenadas. El principal inconveniente de Nominatim es que la usabilidad del sistema no es tan buena

como la de los competidores. Nominatim no puede encontrar las direcciones que no están escritas correctamente, ni predice las búsquedas de los usuarios. Para que este motor de búsqueda de direcciones pueda estar entre los más utilizados se deben agregar las funciones de corrección de errores y de predicción.

En este proyecto mejoro los algoritmos de búsqueda de Nominatim para añadir la funcionalidad mencionada anteriormente. El principal objetivo del proyecto consiste en estudiar técnicas de corrección de errores y predicción de búsquedas. Posteriormente diseñar un sistema de indexado para realizar estas funciones de forma eficiente y en tiempo real. Por último, implementar el sistema y testearlo para ser comparado con el sistema original llamado Nominatim. El motor de búsqueda de direcciones propuesto en esta tesis ofrece una alternativa de código libre a usuarios y sistemas que requieren acceso a datos geoespaciales sin restricciones.

## Acknowledgements

This Master's thesis would not exist without the invaluable support and guidance of my supervisor and examiner Dr. Maria kihl. Also, I would like to thank to my family for the not to be underestimated mental support.

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# CHAPTER 1

# 1 Introduction

## *1.1 Introduction*

Geocoding is the activity of assigning geospatial codes to text based postal addresses [26]. Addresses can be seen as textual descriptions of real world places, in such a way that they are easy to understand for human beings. However, geospatial information given in textual form is not easy to analyze by computers or humans. That is why addresses are usually converted to geographic references. Figure 1 represents the activity of geocoding performed by an online geocoder server.

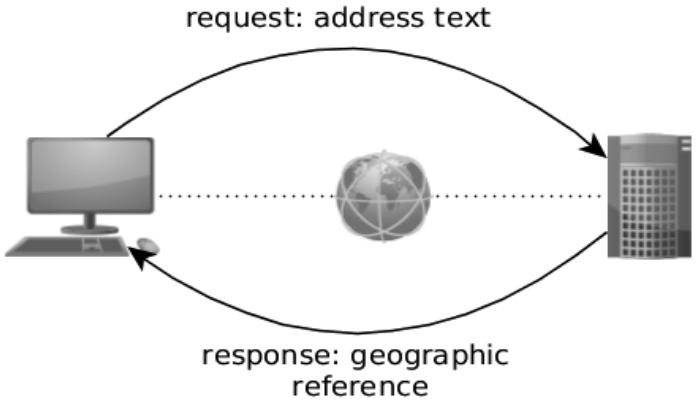


**Figure 1: Geocoding**

The use of information containing geospatial references is widespread among many disciplines such as criminology, medicine and public health, epidemiology, geography, history or general information retrieval among others. The geospatial information used by these or other disciplines can be of many and heterogeneous forms. Geocoding tools are commonly utilized to provide initial data processing so these data can be used to their fullest potential in the process of scientific inquiry by associating a much-needed spatial footprint to otherwise seemingly spatial data [26].

Imagine a Taxi company that wants to make some predictions about the workload at a specific future time in different areas of a city, based on the workload history of the company. Taxi dispatchers and users usually provide the pickup location by giving the textual based postal address representation of a real world place. The way the user or dispatcher writes the address is not standardized, and nothing ensures the validity of the address. These addresses are not suitable to be analyzed for example in terms of density of jobs in different areas. To do so, the text addresses have to be converted to geographical coordinates first. And then the resulting coordinates need to be processed in order to obtain the desired predictions.

Systems which translate textual based postal addresses to geospatial coordinates are called Geocoders. The inverse operation is called reverse geocoding, i.e. given some geospatial code, assigning an address to it that is understandable by human beings. Whether or not a system performs one or both operations, it is commonly called Geocoder. Nowadays, there are many commercial geocoders. Some geocoders are offered in the form of software packages, in which the user is in charge of providing the reference geospatial data, maintaining the database that will hold the data, and adjusting the parameters of the geocoding process, as is the case of ArcView and Automatch [4]. There are also online geocoding services, accessible through the network, like Google Maps geocoding service, Bing maps offered by Microsoft or Yahoo! Maps geocoding service among others [4]. The geocoders in the latter category have the advantage of making the geocoding process easier to the end user, since the only thing the user needs to do is to feed the geocoding service with a user query.

In principle, the basic operation a geocoder performs is to return a geocode for the input text address provided by the user. To do so, the geocoder matches the user query with the addresses available in a reference dataset, rank the reference addresses depending on how similar they are to the user query and return a sorted list of addresses in descending similarity. However, this is not as simple as it seems. A multitude of problems can make the geocoder fail while trying to match the user query against the addresses available in the reference dataset. Some of these possible scenarios include: typing errors, lack of knowledge about the right spelling of the address, or even database errors and inconsistencies [27]. For all these reasons geocoders need to support fuzzy search.

Fuzzy search is the activity of matching text strings approximately. A geocoder user trying to find the address "Professorsgatan" in Lund, might enter a query such as "profesorgatan" or "professor gatan", and it is the task of the geocoder to find relevant addresses to the query in the reference dataset and provide the associated geocodes. Fuzzy string matching is part of a broader discipline called Information retrieval (IR). IR is the activity of extracting information relevant to a user query from a reference dataset. It relies in a set of theories and techniques for string matching and document ranking given a user query. Among others, these techniques include, prefix search, different approaches for string approximation, word and phrase string matching, and metrics to sort the matching documents by relevance given a user query, like edit distance, and cosine similarity [1, 2, 9, 11, 22].

Traditionally geocoders, and more generally, information retrieval systems return answers after a user submits a complete query. Users often feel "left in the dark" when they have limited knowledge about the underlying data, and have to use a try-and-see approach for finding information. Many systems are introducing various features to solve this problem. One of the commonly used methods is autocomplete, which predicts a word or phrase that the user may type based on the partial query the user has entered. As an example, almost all the major search engines nowadays automatically suggest possible keyword queries as a user types in partial keywords [28].

This is not the case of Nominatim [29], an open source geocoder that has become the reference geocoder for OpenStreetMap (OSM) data [6]. It powers the search feature of the online geocoding service offered by OpenStreetMap. However, the current search capabilities provided by Nominatim are getting obsolete compared to the ones offered by other online geocoders mentioned before. The two main lacking features in Nominatim are, first, the lack of support for fuzzy search, and second, the real time autocomplete feature. The main objective of this thesis is to add this missing functionality to the Nominatim geocoder.

## *1.2* Research questions

This thesis tries to answer the following questions:

1. How to add support for autocomplete to Nominatim geocoder?
2. How to add support for fuzzy search to Nominatim geocoder?
3. Can fuzzy search and autocomplete be done in real time, so that the user experiences an "instant" response?

4. How can the search algorithm in the existent solution be improved? Can the algorithm be extended to find intersections? Or suggest addresses under a postcode?
5. Nominatim computes postal addresses by simply concatenating all the names of the parents of a place. Can this be improved so only relevant parent names appear in the suggested addresses?

## *1.3* Methodology

The thesis is divided in two parts. The first part explores the paradigm of geocoding, geocoding process, address models, and geocoding errors. It also provides a background in fuzzy and prefix search and document scoring within the paradigm of Information retrieval.

In the second part a new address index strategy to provide support for prefix and fuzzy search to the Nominatim geocoder is proposed. A new geocoder is implemented using Elasticsearch, a text search engine written in JAVA, and Jersey, a JAVA library for building web services on top of the web service container Tomcat. And finally the added functionality of this geocoder is tested and evaluated using some predefined metrics, commonly used to assess geocoders.

## *1.4* Goals

The goals of this thesis are described in Figure 2. They are divided in four groups, each one addressing one or more research questions listed in section 1.2. Text matching strategies tries to answer questions 1 and 2, realistic match rate values are in between 70 and 90 percent. The search time constraint of 100ms system response relates to question 3. Extended search capabilities refer to question 4 and last, address computation refers to question 5.

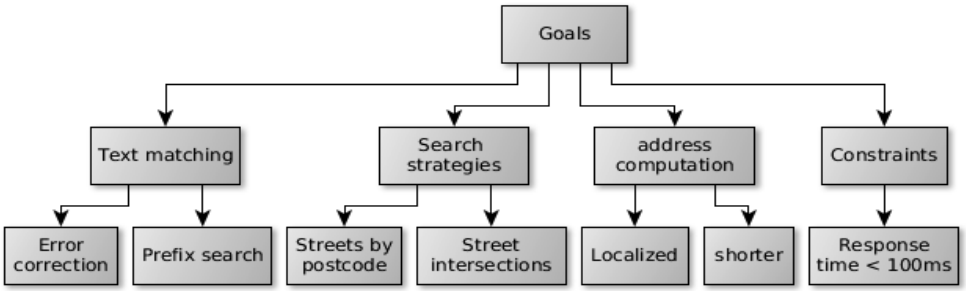


**Figure 2: Goals**

## *1.5* Limitations

The proposed solution is based on the following limitations:

1. Only Swedish addresses are indexed and searchable.
2. Addresses are not searchable by their type, for example, “bus stop in Lund”, only by name.
3. Addresses without a name are not searchable.
4. Non adaptive algorithms. The machines do not learn about previous searches.
5. The system response is invariant respect to the geographical position of the user.
6. It is assumed that geospatial data attached to the OSM elements is right, and thus, never considered a source of error in our study.
7. The accuracy of the derived geospatial information, is not considered a source of error (i.e. house numbers geocoded by interpolation or street intersections).
8. The only possible source of error is the one caused by a miss match between the address requested by the user and the suggestions offered by the geocoder.

## *1.6* Outline of the thesis

The remainder of the thesis is structured as follows. The next section gives a brief background on geocoding concepts, fuzzy search within the paradigm of Information retrieval and lists a set of metrics to evaluate geocoders and search engines in general. Chapter 3 gives an overview of how the current geocoder, Nominatim, works. Chapter 4 explains in detail the proposed and implemented geocoding solution, i.e. software architecture, index structure and search algorithms. Chapter 5 shows the results of the tests performed against the proposed solution. And the last chapter shows the conclusions and future work.

# CHAPTER 2

# 2 Relevant work

## *2.1* Geocoding

Literally, geocoding means "to assign a geographic code." This definition stems from the two root words: geo, from the Latin for earth, and coding, defined as "applying a rule for converting a piece of information into another". A more technical description is: the activity of assigning a geographic code (e.g., coordinates) to a given place name by comparing its description to the descriptions of location-specific elements in the reference database [4]. Notice that these definitions do not imply nor constrain in any way the input to the geocoding system, the processing of the input data, the data sources used to assign the geographic code, or even what the geographic code returned as output must be [13]. Figure 3 is a more detailed graphical description of the process of geocoding.

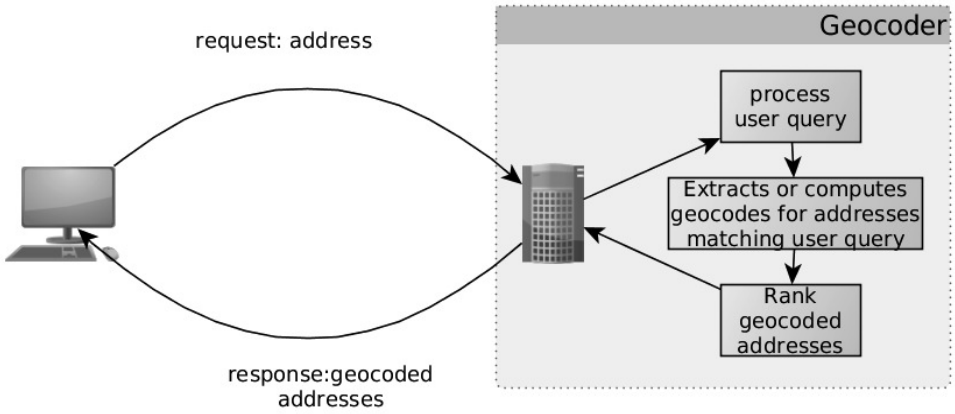


**Figure 3: Geocoding process overview**

Jones and Purves [11], give a detailed explanation of the geospatial information retrieval system (GIR) search process. First, the geographic

references have to be recognized and extracted from the user's query or a document. Second, place names are not unique and the GIR system has to decide which interpretation is intended by the user. Third, geographic references are often vague; typical examples are vernacular names like *"historic center"* and fuzzy geographic footprints. Fourth, and in contrast to classical text based search, documents also have to be indexed according to particular geographic regions. Finally, geographic relevance rankings extend existing relevance measures with a spatial component. I.e., the relevance of a place given a user query might be affected by the geographical position of that place. For example, if a user wants to find *"restaurants near the historic center of Stockholm"*, the geocoder would rank the places not only based on thematic aspects, e.g., the restaurants, but it would also give higher ranks to the restaurants closer to the historic center.

Goldberg et al. [13], characterize the geocoding system in terms of its fundamental components: the input, output, processing algorithm and reference dataset. The input is the locational reference the user wishes to have geographically referenced that contains attributes capable of being matched to some datum that has been previously geographically coded.

The output is the geographically referenced code determined by the processing algorithm to represent the input. In most situations, the output is a simple geographic point, but nothing forbids it from being any valid type of geographic object, like polygons, lines or combinations of them. The proposed solution offers a 2D representation of the output besides the centroid (lat/lon geocode), when available.

The processing algorithm determines the appropriate geographic code to return for a particular input based on the values of its attributes and the values of attributes in the reference dataset.

The reference database contains geographical reference elements used by the geocoding algorithm to derive the output. Several address models exist for building the reference database, such as the street network data model, the geographic unit model or the parcel boundaries data model (e.g., postal codes, counties, cities, census enumeration areas), and the address point data model [4, 16].

In the last decade online geocoding services have gained popularity. An online geocoding service is a network-accessible component, sometimes a

module of a GIS, which automatically performs the geocoding process. It is usually available on the Internet by utilizing a Web service interface. The data entry, such as a place name, street address, or zip code, is passed over the Internet using a communication protocol to the geocoding service. The overall process usually takes less than a few seconds per data entry. The geocoding service converts an entry into coordinates and then delivers the result, which includes the coordinates, the address used in geocoding, and the level of accuracy back to the user over the Internet. The underlying algorithm and reference database used by the service are transparent to the user [4].

### *2.1.1* Sources of error in the geocoding process

During the process of geocoding, it is important to identify the error sources and quantify the error, if possible. Even simply defining what the error of the geocoding process is presents an arduous task. For example, when speaking of geocoding error, do we refer to the positional accuracy of the returned geographic object, the probability that the feature returned is the one that was desired, or the validity of one or more assumptions used by the geocoding algorithm? Goldberg et al. [13], give a classification of the error causes and the possible effects on the output. The classification is shown in Table 1. Matching errors refer to the errors that might happen while matching the search terms to the index terms. The cause of these errors are usually caused by the relaxation of the conditions imposed to determine if two terms match or not. Derivation errors are those the geocoder introduces while calculating geocodes based on assumptions. For example, the house numbers of a street that are given as a range (even house numbers 2 to 20 along the street line) instead of providing the coordinates of each house number in the reference dataset. The geocoder might assume that the house numbers are equally spaced along the street, but this is not necessarily true. Reference data errors are those introduced in the reference data itself. I.e. Data which does not described the features in the real world accurately.

| **Stage** | **Cause of error** | **Effect of error** |
|---|---|---|
| Matching | | |
| | Attribute relaxation | Incorrect feature |
| | Probabilistic confidence level | Incorrect feature |
| Derivation | | |

| | | |
|---|---|---|
| | | |
| | Parcel homogeneity assumption | Wrong distribution |
| | Address range existence assumption | Wrong number |
| Reference data | | |
| | Spatial accuracy | Results inaccurate |
| | Temporal accuracy | Results inaccurate |

**Table 1: Common causes and effects of errors of the geocoding process**

In the case of our study, we only take into account those errors caused by attribute relaxation, i.e. approximate string matching. We do not study the accuracy of the underlying dataset used as reference (original OSM reference data), neither what error Nominatim introduces while creating the derived dataset when it calculates house numbers of a street by interpolation given a house number range (derivation).

The simplest way a geocoder works is by matching the description of a place or address given in the user query, with the addresses available in the reference dataset. The reference addresses are composed by:

1. Text based address
2. A geocode

The geocoder finds matches between the user query and the reference addresses, and score the reference addresses as a function of the user query. The activities of text matching and scoring are part of a broader discipline called Information retrieval.

## *2.2* Information retrieval

Information retrieval (IR) is a broad and interdisciplinary research field including information indexing, relevance rankings, search engines, evaluation measures such as recall and precision, as well as robust information carriers and efficient storage [10].

The meaning of information retrieval can be very broad, a good and general definition can be found in [1], in which Information retrieval is defined as:

the activity of finding relevant information (usually documents) of an unstructured nature (usually text) that satisfies an information need, formally described in the user query, from within large collections (usually stored on computers).

Although Information retrieval has traditionally referred to unstructured data, in reality almost no data is unstructured, since often documents have title, headings, paragraphs and footnotes [1]. Ed Greengrass [5] sort the target documents of an Information retrieval system in three groups, based on the degree of order into the information they contain. He states that documents can be structured, unstructured, semi structured or a mix of these types. A document is structured if it consists of named components, and organized according to some well defined syntax (e.g. all rows in a table of a relational database will have the same columns). By contrast, in a collection of unstructured natural language documents, there is no well-defined syntactic position where a search engine could find data with a given semantics. In between there is the case of semi structured documents, in which documents share some common structure and semantics. The set of documents subject of an information retrieval system is called collection, corpus or reference dataset interchangeably.

Hai Dong [2] categorized the traditional Information retrieval models into set theoretic models, algebraic models and probabilistic models. Further, he presents a subdivision for each one of these three models. This subdivision is shown in Figure 4.

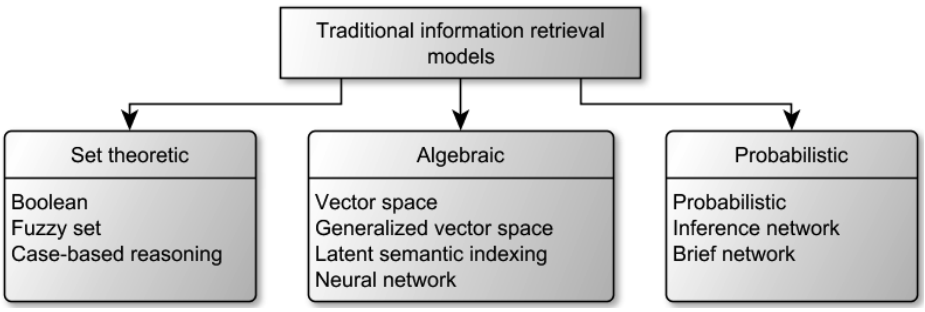


**Figure 4: Information retrieval models classification**

The general idea of these models is to represent the documents in the reference dataset by a set of identifiers, called index terms. The same idea is

applied to the user query, which is represented by identifiers called search terms. During the search (information retrieval phase), the index terms are compared to the user query search terms, and those documents with more terms in common with the user query, are said to be relevant to that query. The index terms for each document are precomputed and stored in the index, a data structure that organizes the index terms in such a way that it is easy to perform the search later on. The set of index terms is called (index) dictionary. Nothing is said about the nature of the documents, the user query or the index/search terms. They could be text documents, images, audio files, or any other type of information.

Set-theoretic models

Set-theoretic models represent documents as sets of words or phrases. Similarities are usually derived from set-theoretic operations on those sets.

The Boolean model is based on Set theory and Boolean algebra. A set is a collection of abstract objects, where each object is the member of this set. Boolean algebra is a set of logical operations between two sets, such as conjunction, disjunction and complement.

In the Boolean model, whether an index term appears in a document or not determines the value of the weight between the index term and the document, which is a binary value. A query normally consists of several index terms connected by a set of logical operations, and it can be translated to a conjunctive form which is composed of a number of conjunctive components [8].

For example, we have a reference dataset with the documents shown in Table 2:

| Doc id | Document | Index terms |
|---|---|---|
| 1 | "Central station, Lund" | [central, station, lund] |
| 2 | "Gunnesbo station, Lund" | [gunnesbo, station, lund] |
| 3 | "Central station, Malmö" | [central, station, malmö] |

**Table 2: Document collection example and the associated index terms**

A query like this: *"central station" → (conjunctive form) → "central AND station"* will give the results shown in Table 3.

| Doc id | Match query? |
|---|---|
| 1 | Yes |
| 2 | No |
| 3 | Yes |

**Table 3: Example of document matching using Boolean model**

Since documents 1 and 3 are the only ones that contain both terms, *central* and *station*.

If instead the query is *"central station lund"*, combining the terms with the AND operator, we would only get document number 1, since it is the only one that matches the query. Boolean model do not rank the results in any way, just spot the documents that fulfills the requirements given in the query.

Algebraic models

Algebraic models represent documents and queries usually as vectors, matrices, or tuples. The similarity of the query vector and document vector is represented as a scalar value. These models let us rank the documents by similarity. An example of algebraic model is the Vector space model [31, 32], in which each document is represented as a vector, and each dimension of the vector corresponds to a term of the indexed terms as in Figure 5.

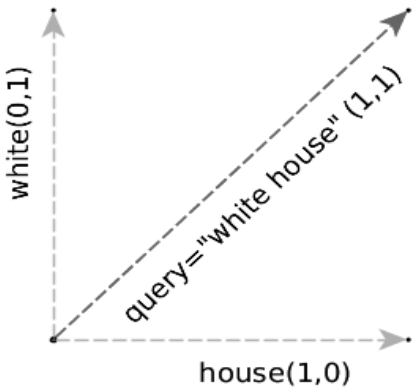


**Figure 5: Vector space model example**

If a term appears in a document, a weight is assigned to the corresponding dimension in the vector. Similarly the user query can also be represented as a vector with corresponding search terms. The relevance of a document given a query can be calculated as the cosine of the angle between the two vectors [8]. Depending on how the index terms are assigned, the documents in the collection will be more or less similar to each other. Good index terms are those that occur unevenly among the documents in the reference dataset. The extreme case is an index term that appears only in one document, because a query containing that term can only refer to one document. The reverse is true for the bad index terms [33]. For instance, the word "the" is one of the most commonly words found in English documents, therefore, the election of "the" as vector dimension to represent documents, does not seem a good choice to find individual documents among a collection. Figure 6 shows graphically what happens after assigning an unevenly distributed index term. After the assignment, the documents represented as vectors in the vector space model are further from each other. Thus it is easier to identify them.

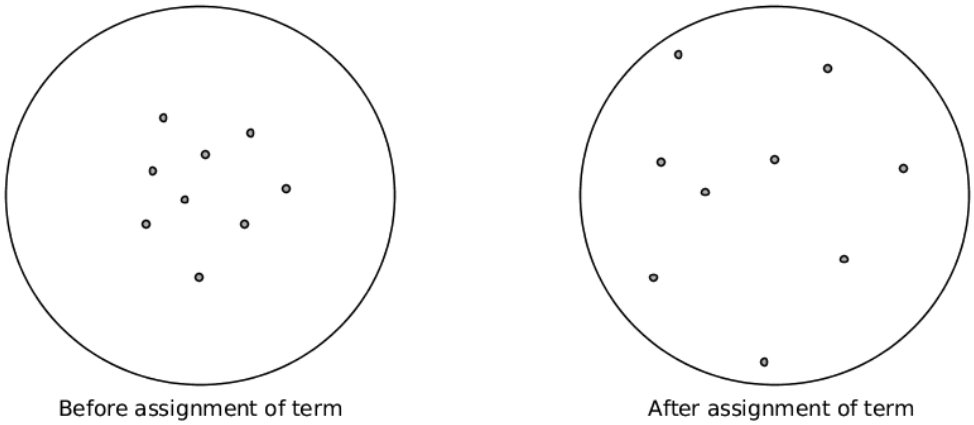


**Figure 6: Vector space model, effect of assigning index terms**

Using the document collection in Table 2, for the user query *"central station"*, and assuming the algorithm assigns a constant weight of 1 to the search and index terms, we would get these results shown in Table 4. In this example, the dimensions of the vector space are {central, station, lund, gunnesbo, malmö}. The query vector representation is (1,1,0,0,0). The ranking is calculated using the cosine similarity between each document and the query vector. Cosine similarity is explained later in section 2.2.2.

| Doc id | Doc. vector | Ranking |
|---|---|---|
| 1 | (1,1,1,0,0) | $\frac{(1,1,1,0,0)\cdot(1,1,0,0,0)}{\lvert(1,1,1,0,0)\rvert\cdot\lvert(1,1,0,0,0)\rvert} = 0.816$ |
| 2 | (0,1,1,1,0) | 0.577 |
| 3 | (1,1,0,0,1) | 0.816 |

**Table 4: Example of document ranking using the Vector model and the cosine similarity**

The Extended Boolean model extends the Boolean model with the function of term weighting, which is a hybrid model to combine the Boolean model and the vector space model [19]. By weighting the association between a document and a query term, the similarity between a conjunctive query, a disjunctive query and a document can be calculated [9].

The query *"central station",* would give the results shown in Table 5 for the document collection in Table 2. The rankings are calculated using the cosine similarity as in the previous example, but only for those documents which fulfill the conditions imposed by the Boolean model. In this case the document number 2 does not match the query, so it is discarded as a relevant result for the query used in this example.

| Doc id | Match query? | Ranking |
|---|---|---|
| 1 | Yes | 0.816 |
| 2 | No | - |
| 3 | Yes | 0.816 |

**Table 5: Example of document ranking using the Extended Boolean model**

Probabilistic model

Last, the fundamental of Probabilistic models is that they try to improve the probabilistic description of the ideal answer set of documents relating to a query by a series of iterations [8]. Given a user query and a document in a collection, the probabilistic model tries to estimate the probability that the user will find the interesting document. The model assumes that this probability of relevance depends on the query and the document representations only. Furthermore, the model assumes that there is a subset of the documents which the user prefers as the answer set for the query. Such

an ideal answer set should maximize the overall probability of relevance to the user. Documents in the ideal set are predicted to be relevant to the query, and documents out of this set are predicted to be non-relevant [9].

### *2.2.1* Fundamentals of prefix and fuzzy search

The problem of devising algorithms and techniques for automatically word prediction and correction in texts has been a main research challenge since the early 1960s [21]. Traditional systems have used word frequency lists to correct or complete words that the user has already started spelling out. Some of the most extended techniques to predict and correct words are minimum edit distance, n-grams and phonetic representations of words.

Minimum edit distance

By far the most studied spelling correction algorithms are those that compute a minimum edit distance between a misspelled string and a dictionary entry. The term minimum edit distance or Levenshtein distance was defined by Vladimir Levenshtein [1965] as the minimum number of editing operations (i.e., insertions, deletions, and substitutions) required to transform one string into another [30].

Mathematically, the distance between two strings $a$ and $b$ is given by $lev_{a,b}(|a|,|b|)$ where:

$$lev_{a,b}(i,j) = \begin{cases} max(i,j) & if\ min(i,j) = 0, \\ min\begin{cases} lev_{a,b}(i-1,j)+1 \\ lev_{a,b}(i,j-1)+1 \\ lev_{a,b}(i-1,j-1)+1_{(a_i \neq b_j)} \end{cases} & otherwise. \end{cases}$$

$1_{(a_i \neq b_j)}$ is the indicator function, which is equal to 0 when $a_i = b_j$ and equal to 1 otherwise.

In general, minimum edit distance algorithms require $m$ comparisons between the misspelled string and the dictionary, where $m$ is the number of the dictionary entries [21].

N-grams

Given a string *s*, i.e. a sequence of characters, and n-gram is any substring of *s* of some fixed length *n*. A simple similarity measure between two strings is to choose *n* and count the number of n-grams the two strings have in common [22]. Given the strings *"abc"* and *"bcd"* with *n=2*, then the strings' 2-grams are:

| **String** | **2-grams** |
|---|---|
| "abc" | {"ab", "bc"} |
| "bcd" | {"bc", "cd"} |

A problem with this approach is that some information about the string is lost. As we see in the example above, both strings have one 2-gram in common, even though they are clearly not the same string.

A variation of the basic n-gram scheme allows efficient word prediction or prefix search. The idea is to represent a word by its variable length n-grams, always computed from the first character of the word. For instance, the word "Sweden" can be represented by its variable length edge-gram set:

| **word** | **Edge-grams** |
|---|---|
| sweden | [s, sw, swe, swed, swede, sweden] |

Phonetic techniques

Phonetic models are a subtype of similarity key techniques. The notion behind similarity key techniques is to map every string into a key such that similarly spelled strings will have identical or similar keys. Thus, when a key is computed for a misspelled string it will provide a pointer to all similarly spelled words (candidates) in the lexicon [21]. Probably the best-known phonetic algorithm is SOUNDEX [22], invented in 1918. SOUNDEX uses codes based on the sound of each letter to translate a string into a canonical form of at most four characters, preserving the first letter [22]. With time some other models appeared that improve the phonetic accuracy of this algorithm, such as METAPHONE and later DOUBLE METAPHONE, which take into account other languages than English, and generates at most two codes for each input, being the second an alternative code. There is more information about how METAPHONE and DOUBLE METAPHONE work in the original paper written by Lawrence Phillips [23].

### *2.2.2* Document Similarity and TF-IDF

In vector space model, documents and queries are represented as vectors, where each component of the vector is the weight assigned to a term of the document. The terms of the documents could be, depending on the type of search the system is intended to support, phrases (ordered list of words), single words (being a document represented by the words in that document), or any other term resulting from the processing of the document words (for instance, n-grams or metaphone code of a word) as described in the previous section, 2.2.1.

"Term frequency–inverse document frequency" (tf–idf) is one of the most commonly used term weighting schemes in today's information retrieval systems [20]. Tf-idf is a numerical statistic that is intended to reflect how important a word is to a document in a collection or corpus.

The tf-idf weighting scheme assigns a weight to term $t$ in document $d$ given by the product of term frequency in the document and the inverse document frequency:

$$tf\text{-}idf_{t,d} = tf_{t,d} \cdot idf_t$$

Tf provides a direct estimation of the occurrence probability of a term in the document. The more occurrences of a term in a document the more relevant that term is for the given document. Term frequency can be defined as:

$$tf_{t,d} = \text{Number of ocurrences of term } t \text{ in document } d$$

Or the normalized form:

$$tf_{t,d} = \frac{\text{Number of ocurrences of term } t \text{ in document } d}{\text{Total number of terms in document } d}$$

Raw term frequency suffers from a critical problem: it does not take into account the frequency of the term among the documents in the collection. Terms that occur to often in the collection have very little or none discriminating power.

Idf is a mechanism for attenuating the effect of terms that occur too often in the collection. An immediate idea is to scale down the term weights of terms with high collection frequency ($cf_t$), defined to be the total number of

occurrences of a term in the collection. The idea would be to reduce the tf weight of a term by a factor that grows with its collection frequency. It is more commonplace to use for this purpose the document frequency ($df_t$), defined to be the number of documents in the collection that contain a term. Idf is usually defined as:

$$idf_t = \log\left(\frac{N}{df_t}\right)$$

$N$ is the size of the collection. $Idf_t$ can be interpreted as 'the amount of information' in conventional information theory, given as the log of the inverse probability [20].

For example, imagine a document collection of $N=10$, in which every document of the collection contains the word *"the"*. No matter what the term frequency is, the $idf_t$ will be zero, $idf_t = log(1) = 0$. Therefore, the weight assigned to the vector component that represents the term *"the"* will be zero for all the vectors representing the documents. Intuitively, since the term *"the"* appears in all the documents in the collection, this term is not good for searching criteria. Let's say now that the term *"geocoding"* appears only in one document once, the term frequency for *"geocoding",* in that document will be 1, while it will be 0 in the rest documents. The $idf_t$ will be in this case equal to $log(10/1)=1$. Tf-idf assigns a high weight to that term since *"geocoding"* appears only in one document of the collection.

In other words, tf-idf assigns a weight $w$ to the term $t$ in document $d$ that is:

1. higher when $t$ occurs many times within a small number of documents (thus lending high discriminating power to those documents)
2. lower when the term occurs fewer times in a document, or occurs in many documents (thus offering a less pronounced relevance signal)
3. lowest when the term occurs in virtually all documents.

Cosine similarity

Vector space model represents each document as a vector in which each vector dimension corresponds to a term in the index dictionary, together with a weight for each component that is given by the *tf-idf* value. For dictionary terms that do not occur in a document, this weight is zero.

In the same way, queries can also be represented as vectors. The advantage of this strategy is that, since both queries and documents are seen as vectors, we can use some measure of similarity between vectors to score documents given a user query. One possible solution is to use the cosine similarity of their vector representations [1]. Given the query vector *v(q)* and a document vector representation *v(d)*, the cosine similarity is calculated as [31]:

$$similarity(q,d) = cosine(v(q),v(d)) = \frac{\vec{v}(d) \cdot \vec{v}(q)}{|\vec{v}(d)| \cdot |\vec{v}(q)|}$$

### *2.2.3* Text indexing

The previous section introduced the paradigm of information retrieval, as well as techniques for fuzzy and prefix search. The documents of the collection and user query are represented by a set of identifiers, called index/search terms. These terms can be anything from phrases, words, to n-grams or metaphone codes. The way these terms are computed and stored affects the search speed as well as the way the user can search for documents.

In order to make the search efficient, index terms are usually stored in data structures called inverted indexes. An inverted index maps index terms to documents, or document ids. That way, when a user wants to find the documents relevant to a user query, the IR system does not need to read through all the documents in the collection, it only needs to extract the document id:s from the index whose documents contain the search terms of the query.

If we use the document collection in Table 2, the inverted index for such a collection would look like Table 6.

| Index term | Document ids | Term freq | Document freq |
|---|---|---|---|
| Central | [1,3] | [1: 1, 3: 1] | 2 |
| Station | [1,2,3] | [1: 1, 2:1, 3: 1] | 3 |
| Lund | [1,2] | [1: 1, 2: 1] | 2 |
| Gunnesbo | [2] | [2: 1] | 1 |
| Malmö | [3] | [3: 1] | 1 |

**Table 6: Inverted index for a document collection**

Table 6 represents the inverted index, together with the term frequencies and document frequencies of each term, used to assign weights to the document terms as described in section 2.2.2.

This index strategy is efficient for searches such as “central station lund”. However, a search like “centrl station” will return no results, since there is no mechanism for correcting errors. The same applies for a prefix search like “centr”, in this case the system would need to find index terms among the dictionary following the pattern given by “centr*”, an expensive operation. We could instead, create a reverse index in which the index terms are n-grams of the document words, or metaphone codes to approximate the words by their sound. In this case a match would be found if the metaphone codes match or the number of n-grams in common is over a certain limit for instance.

A more detailed description of text indexing, and inverted index tables can be found in [1, 31, 32].

## *2.3* Evaluation metrics

The two elementary metrics to evaluate correctness in Information Retrieval are [9, 18]:

*Precision (positive predictive value): Percentage of retrieved documents that is relevant to the user.*

$$precision = \frac{|relevant\ documents \cap retrieved\ documents|}{|retrieved\ documents|}$$

*Recall (sensitivity): Percentage of the documents relevant to the user query that are successfully retrieved.*

$$recall = \frac{|relevant\ documents \cap retrieved\ documents|}{|relevant\ documents|}$$

Besides these measures, geocoding systems can be evaluated taking into account the geospatial properties of the documents. Common metrics for evaluating the quality of geocoding results are completeness (or match rate), positional accuracy, and repeatability [16]. In general, the geocoding quality

depends on several factors such as geographic areas of addresses, quality of the reference databases, match scores, and geocoding algorithms [4].

The match rate is a statistical metric commonly used to measure the geocoder's ability to successfully determine a geocode for a given set of text addresses. High match rates (above 90%) are possible, however there are always street addresses that are difficult to geocode. Match rates typically vary from 70% to over 90%. Match rates can be a good metric, but can be misleading [14].

If we assume that for each query, the user expects to get one and only one relevant result, being the result the geocode of the place the user is trying to find, then the match rate can be defined as the average recall over a number of *n* geocoding requests.

*Match rate: Percentage of correctly geocoded places by the geocoding system.*

$$match\ rate = \frac{Number\ of\ \ geocoded\ \ places}{Total\ geocoding\ requests}$$

For systems with auto-complete features, keystroke saving can be a good measure (percentage of keystrokes eliminated by integrating the prediction method) [22]. However, keystroke saving highly depends on the format and length of the addresses being tested.

*Absolute keystroke saving: Difference between the original address length, and the query length when the address is found by the geocoder.*

$$keystroke\ saving = address_{length} - query_{length}$$

*Relative keystroke saving (or keystroke saving percentage): Absolute keystroke saving divided by the original address length.*

$$relative\ keystroke\ saving = \frac{address_{length} - query_{length}}{address_{length}}$$

Last, it is important to know how much time it takes a system to perform an action. In the case of a geocoder, that would be the time it takes to execute the geocoding algorithm. This times does not take into account the round trip time or the client side code intended to present the results of the geocoding request, for example the JavaScript code.

# CHAPTER 3

# 3 OpenStreetMap and Nominatim

This chapter describes the geospatial reference dataset used in the project, OpenStreetMap, and the open source geocoder in which this project is based, Nominatim.

## *3.1* OpenStreetMap

OpenStreetMap [6] is an editable map of the world, released with an open content license, and created by volunteers. Everyone is free to contribute by adding new geographical data to the map, and it is the origin of many projects in different fields, such as geocoding, semantic analysis, map browsers and map renderers, map editing tools.

The map data and map images are free to use for everyone, released with OpenStreetMap license, and supported by the OpenStreetMap foundation, which is an organization that performs fund raising in order to provide servers to host the OpenStreetMap project, but it does not control the project or own the data. It is dedicated to encouraging the growth, development and distribution of free geospatial data and to providing geospatial data for anybody to use and share [6].

### *3.1.1* OSM data model

The OSM data model consists of three different element types or data primitives, plus a type to store metadata about the three data primitives:

- Nodes: points with a geographic position, they represent features without a size.
- Ways: ordered list of nodes representing polylines or polygons if closed. Used to represent features with linear shapes like rivers, and areas like forests, parks, Etc.
- Relations: they are an ordered list of nodes, ways and other relations, they represent relations between the elements they contain.

- Tags: they are key/value pairs used to store metadata about the map features like names, type, physical properties. Tags are not free-standing, but attached to one of the previous features.

OSM data elements represent physical features on the ground (e.g., roads or buildings) using tags attached to its basic data structures (nodes, ways, and relations). Each tag describes a geographic attribute of the feature being shown by that specific node, way or relation.

OpenStreetMap's free tagging system allows the map to include an unlimited number of attributes describing each feature. The community agrees on certain key and value combinations for the most commonly used tags, which act as informal standards. However, users can create new tags to improve the style of the map or to support analyses that rely on previously unmapped attributes of the features.

Most features can be described using only a small number of tags, such as a path with a classification tag such as *highway=footway*, and perhaps also a name using *name=[name identifying the path]*. But, since this is a worldwide, inclusive map, there can be many different feature types in OpenStreetMap [34].

OpenStreetMap data is usually distributed in XML format, and each feature is described with an XML element (<node>, <way> and <relation>) [7]. Text 1 is a small portion of the OSM data file for Sweden. The relation in this code snippet corresponds to the definition of the *Electronic building (E-huset), in Lunds Tekniska Högskola*:

```
<?xml version='1.0' encoding='UTF-8'?>
<osm version='0.6' upload='true' generator='JOSM'>
  <bounds minlat='55.7101169' minlon='13.2088387'
maxlat='55.7119181' maxlon='13.2123256' />
  …
  <way id='89001056' timestamp='2010-12-11T08:29:00Z'
uid='31450' user='sanna' visible='true' version='1'
changeset='6619970'>
    <nd ref='1032852252' />
      …
  </way>
  <relation id='1315684' timestamp='2013-10-07T08:46:15Z'
uid='13957'        user='Grillo' visible='true' version='5'
changeset='18225042'>
    <member type='way' ref='89001056' role='inner' />
    <member type='way' ref='89001057' role='outer' />
    <member type='way' ref='89001059' role='inner' />
    <member type='way' ref='89001058' role='inner' />
    <tag k='addr:city' v='Lund' />
    <tag k='addr:country' v='SE' />
    <tag k='addr:housenumber' v='3' />
    <tag k='addr:street' v='Ole Römers väg' />
    <tag k='building' v='yes' />
    <tag k='name' v='E-Huset' />
    <tag k='operator' v='Lunds Tekniska Högskola' />
    <tag k='type' v='multipolygon' />
  </relation>
  …
</osm>
```

**Text 1: Example of OSM data in XML format**

Table 7 lists the common attributes in each OSM element.

| name | value | description |
|---|---|---|
| id | integer | Used for identifying the element. Element types have their own ID space, so there could be a node with id=100 and a way with id=100, which are unlikely to be related or geographically near to each other. |
| user | string | The display name of the user who last modified the object. A user can change their display name |
| uid | integer | The numeric user id of the user who last modified the object. The user id number will remain constant. |

| | | |
|---|---|---|
| timestamp | W3C Date and Time Formats | time of the last modification |
| visible | "true" "false" | whether the object is deleted or not in the database, if visible="false" then the object should only be returned by history calls. |
| version | integer | The edit version of the object. Newly created objects start at version 1 and the value is incremented by the server when a client uploads a new version of the object. The server will reject a new version of an object if the version sent by the client does not match the current version of the object in the database. |
| changeset | integer | The changeset in which the object was created or updated. |

**Table 7: OSM element, common attributes**

In addition, tags, and also a full editing history of every element is stored [6].

## *3.2* Nominatim

This project is based on an open source geocoding solution called Nominatim. Nominatim is an online geocoder written in PHP and it uses OSM data as reference dataset.

Nominatim stores the OSM elements into postgreSQL, a relational database, with PostGIS extension, a library of geospatial tools and types. The tool to read and import OSM data in XML format into the database is called Osm2pgsql.There is very little or no documentation on the implementation and algorithms Nominatim uses, all the information have to be obtained from the source code.

We could have chosen to create our index from the raw OSM data instead of relying on Nominatim to make a first data processing. These are the advantages and disadvantages of using Nominatim index over raw OSM data.

Disadvantages:

- Nominatim index process takes several days, using the hardware that runs the Nominatim project. The index time is around 250 hours, plus 2 days of the initial import process [6].

- Nominatim import process is lossy, meaning that some features are not imported into the database. For example, Nominatim drops coastlines and manipulates the data in a way that routing relationships are lost [6].

Advantages:

- Nominatim calculates the parents of a place.
- Nominatim provides a database with geospatial indexes.
- Nominatim calculates information like country code, street and postcode of OSM postal addresses if the information is missing.
- Nominatim assigns an address rank to each place.
- Nominatim (optionally) calculates a search rank to each place at index time, based on the number of entries in Wikipedia that refers to that place. This can be used to sort suggestions.
- Nominatim classifies the map features by class and type based on the set of tags that identifies a feature.
- Nominatim provides tools to maintain the database.

### *3.2.1* Usage and statistics

The most recent Nominatim usage statistics were presented in the annual conference, "OpenStreetMap. State of the map" in September 2013, in Birmingham [17]. By that time, the server was handling 100 requests per second, where 10% of the requests were search queries and 90% reverse queries.

They also provided some numbers on the state of the database (Table 8).

| **Address type** | **Number of entries in the database ($x10^6$)** |
|---|---|
| House number | 60 |
| Streets | 47 |
| POIs | 12 |
| Administrative areas | 5 |
| Water bodies | 1.5 |
| Total | 130 |

**Table 8: Database entries by type**

### *3.2.2* Database overview

This section is meant to be an overview of the main database relations involved in the geocoding process in Nominatim. This chapter is not a detailed view of the entire database structure. It focuses mainly on those tables that contain the reverse index and/or are used to compute the address. Figure 7 shows the tables used during the search process in Nominatim.

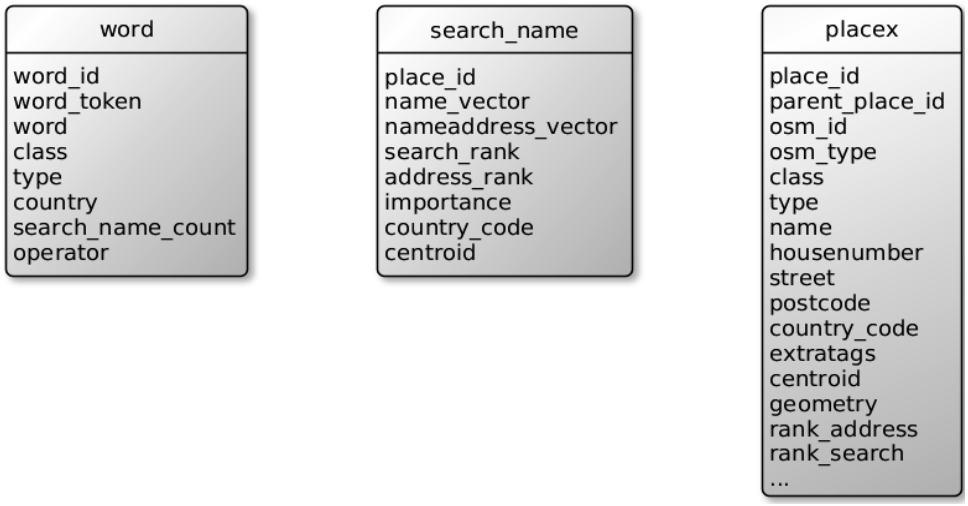


**Figure 7: Tables involved in the address search and computation process**

The dictionary of the inverted index is stored in the relation *word* (the term word here is misleading, since what is stored in the word table can be actually several words per entry. We will show an example later). During the import process, for each new term to be indexed, a new entry is inserted. The *word* column contains the original string, *word_token* contains the normalized string, and *search_name_count* is the frequency of that word in the data set. Each word gets assigned a word id *word_id*. The rest of the columns in this table are used for filtering, like finding places by country code or Nominatim class and type.

*Search_name* maps place id:s to word id:s. Nominatim classifies the index terms for each place into two different lists, *name_vector* and *nameaddress_vector* (the reason for this is to assign higher weight to the tokens that are present in the name than the ones in the address). *name_vector*

contains the word id:s of the words that appear in the name of the place. In the same way, *nameaddress_vector* contain the id:s of the words that appear in the place parents. So, in the case of "E-Huset, Lund, Sweden", *name_vector* contains the word id corresponding to token "e huset" and *nameaddress_vector* the word id:s of tokens "lund", and "sweden".

*Placex* stores the OSM elements, together with their tags, rank, parent id, and class and type. It contains all the information needed to compute the address string for a place given the place id and the preferred language. *Placex.name* contains a map of key/value pairs, each value being a different name or a name in a different language. Keys for names in a specific language looks like *name:*,* where the wildcard corresponds to a two-letter language code defined in the standard ISO-639 [38]. So the translation of Göteborg in English would be mapped in OSM and Nominatim like *name:en=>Gothemburg* (if the translation exists). Nominatim also stores the geometry and centroid of the element into this table. We will use this table to compute the address of a place and retrieve the geometry and other information as a response to a geocoding request.

During the import of new OSM data, Nominatim uses three intermediate tables, *osm_nodes*, *osm_ways* and *osm_relations*. These tables contain raw OSM nodes, ways and relations.

### *3.2.3* Processing OSM data

This section explains how Nominatim processes OSM data, which element tags are processed, and how the index is built.

As explained before, OSM elements have associated tags with information about the element, a subset of these tags contain information about the name and address of the element. Nominatim processes the values of these tags to compute the index terms associated to each OSM feature.

#### *3.2.3.1* Processing feature names

For each OSM element, Nominatim processes the values of the tags in the list as possible names for that element. It also processes the language variants of the tags following the pattern [tag_name]:[language code in ISO 639-1].

For example, the OSM element corresponding to the city of *Lund, Skåne län, Sweden*, has an associated tag *name=>Lund,* and an additional tag *name:ru=>Лунд* which corresponds to the translation of Lund into Russian.

- name
- name:[lang]
- int_name
- common_name
- loc_name
- nat_name
- alt_name
- place_name
- official_name
- reg_name
- short_name
- old_name
- ref
- iata*
- icao*
- operator

**iata and icao are two especial tags to uniquely identify most major airports across the globe*

Nominatim also processes the address tags associated with the element, i.e. tags of the form *addr:**. This is used to provide postal information for a building or facility. Some possible tags are:

- housenumber
- housename
- street
- place
- postcode
- city
- province
- country
- ...

*A complete list of these tags can be found in the OSM wiki [6] in the subsection map feature.*

Before being indexed, each of the tags' values listed above is normalized and tokenized. The normalization process is as follows:

1. The tag value is lowercase
2. Diacritics are removed
3. The text is transliterated, text converted to Latin letters
4. Text words are transformed to common abbreviations

Once the tag value is normalized, Nominatim calculates the index terms by which the element will be identified.

1. The normalized tag value is split using space character
2. The result of splitting the tag value is a list of tokens, some of these tokens are too common to add any information to the index, consequently are removed (for example the word "the" in English texts)
3. The result is the index terms for that element

Figure 8 represents the different steps taken to process the tags.

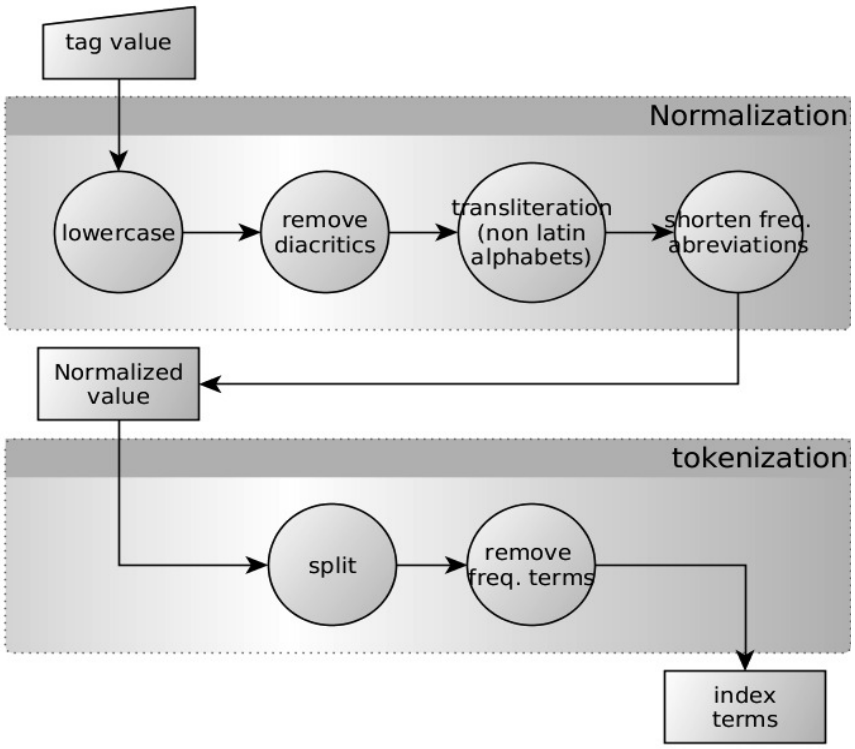


**Figure 8: Nominatim import: normalization and tokenization**

#### *3.2.3.2* OSM Administrative boundaries

Administrative boundaries [15] are subdivisions of areas, territories, or jurisdictions recognized by governments or other organizations for administrative purposes. Administrative boundaries range from large groups of nation states right down to small administrative districts and suburbs. OSM allows to specify the administrative level of the map features by adding the tag *boundary=administrative* and *admin_level* = [1 to 10].

For example, the map feature representing the Swedish national borders is assigned admin level 2. The Swedish administrative regions, like *Skåne Län* or *Örebro Län*, are assigned admin level 4. Last, the city areas, like Stockholm or Malmö, are tagged as admin level 9. The admin levels are used differently from country to country, the complete list can be found in the OSM admin levels site [15].

#### *3.2.3.3* OSM features hierarchy

All indexed features are converted to a simple hierarchy (rank) of importance with points scored between 0 and 30 (where 0 is most important). Rank takes account of differences in interpretation between different countries but is generally calculated as:

| **Address type** | **rank** |
|---|---|
| Administrative boundaries: admin_level * 2 | 4–22 |
| Continent, sea | 2 |
| Country | 4 |
| State | 8 |
| Region | 10 |
| County | 12 |
| City | 16 |
| Island, town, moor, waterways | 17 |
| Village, hamlet, municipality, district, borough, airport, national park | 18 |
| Suburb, croft, subdivision, farm, locality, islet | 20 |
| Hall of residence, neighborhood, housing estate, landuse (polygon only) | 22 |
| Airport, street, road | 26 |
| Paths, cycleways, service roads, etc. | 27 |
| House, building | 28 |
| Postcode | 11–25 (depends on country) |
| Other | 30 |

**Table 9: Address rank**

For each feature down to level 26 (street level) a list of parents is calculated using the following algorithm:

1. All polygon/multi-polygon areas which contain this feature (in order of size).
2. All items by name listed in the *is_in* are searched for within the current country (in no particular order).

3. The nearest feature for each higher rank, and all others within 1.5 times the distance to the nearest (in order of distance).

The tags of each parent of the element are also indexed and consequently, used to find that element.

Buildings, houses and other lower than street level features (i.e., bus stops, phone boxes, etc.) are indexed by relating them to their most appropriate nearby street.

The street is calculated as:

1. The street member of an *associatedStreet* relation
2. If the node is part of a way:
   2.1. If this way is street level, then that street
   2.2. The street member of an *associatedStreet* relation that this way is in
   2.3. A street way with 50/100 meters and parallel with the way we are in
   2.4. A nearby street with the name given in addr:street of the feature we are in or the feature we are part of
   2.5. The nearest street (up to three miles)
   2.6. Not linked

All address information is then obtained from the street. As a result addr:* tags on low level features are not processed [24].

For interpolated ways simple numerical sequences are extrapolated (alpha numerical sequences are not currently handled) and additional building nodes are inserted into the way by duplicating the first (lowest) house number in the sequence [6].

#### *3.2.3.4* Index example

For each index term, i.e., a term which does not appear in the dictionary, Nominatim creates a new entry into the *word* table. Table 10 shows a partial view of the *word* table, with some of the indexed terms for *"E-Huset, Lunds Tekniska Högskola, Lund, Sweden"*.

| word_id | word_token | search_name_count |
|---|---|---|
| 2069 | huset | 206 |
| 17303 | lunds | 157 |
| 85819 | tekniska | 115 |
| 18403 | hogskola | 0 |
| 115540 | lunds tekniska hogskola | 0 |
| 312900 | e huset | 0 |

**Table 10: Example of index terms in word table**

The index terms in Nominatim are the normalized address words. These index terms are later matched against the user query by Nominatim. The consequences are:

- User can only search for full words, i.e., if a user query contains the term *lund*, this will not be matched to the word id 17303, which corresponds in the example to the term *lunds.*
- The geocoder cannot correct any misspelling.
- There is no information about the language this index term corresponds to, meaning that Nominatim does not split the index by language, having to look up the whole index when trying to find a match.

The same strategy is applied to the address tags of every OSM named element, the tags *addr:[housenumber/street/postcode/...]* and so on. This table forms the dictionary of the retrieval system, but it contains no reference to the actual OSM places.

Nominatim maintains a map of index terms to place ids in *search_name.* Table 11 is a partial view of *search_name* for the entry mapping E-huset building in LTH

| place_id | name_vector | nameaddress_vector |
|---|---|---|
| 1513474 | [2069,312900] | [17303, 85819, 18403, 115540, place_id(Lund), place_id(Sweden)] |

**Table 11: Search name relation in Nominatim database**

Finally, all the information about the element with id 1513474, E-Huset, can be found in the relation *placex,* the geocoder uses this table to build the localized address of that place. Table 12 is a partial view of the *placex* table showing some of the information about the feature *"E-Huset"*.

| place_id | parent_place_id | class | type | name | ... |
|---|---|---|---|---|---|
| 1513474 | place_id(LTH) | place | house | name=>'E-Huset', name:en=>'Electronics department' | ... |

**Table 12: Placex relation in Nominatim database**

### *3.2.4* Search algorithm

The search algorithm in Nominatim is written in PHP, and its extension is around one thousand lines of code, plus some SQL functions. Nominatim search algorithm finds matches between the user query search terms and index terms obtained from the name and address tags of map elements and its parents. The search algorithm can be described as follows.

1. The user query is normalized and split into tokens, commas help finding address parts (This is the same process as the one described in Figure 4)
2. Remove tokens, or token combinations that are not into the dictionary (The dictionary is stored in the table word in the database).
3. Each valid token (or combination of tokens) is given a meaning, either name, address or special term like OSM class, type, house number, Etc.
4. A new search is executed for each token combination/meaning. i.e., guessing the token is part of the place name, or place address, or the token is a house number etc.
5. After all searches are done, Nominatim has a collection of places, these places are sorted by a) how many the terms from the search query appear in the place name. Nominatim does not use any of the mathematical models described in section 2.2, b) rank based on place coordinates (if the user uses the web site, Nominatim assigns a slightly higher relevance to the places located in the region of the map the user is looking at) and c) importance assigned by Nominatim at index time.
6. Addresses for each found place is computed, this includes address translation to the requested language. See next section: Address computation

7. Response is sent to the client.

### *3.2.5* Address computation

An address can be defined as a description of a real world place. Addresses in Nominatim are not calculated and stored in the database beforehand, but computed when a map feature is requested. Since each map feature has a reference (*parent_place_id*) to its parent element, Nominatim simply concatenates the place name of each parent in descending rank order.

Nominatim does not have any criteria to discern the representative parts of an address, therefore, it often computes long address strings. The address string returned by Nominatim for E-Huset in LTH is:
*"E-Huset, 3, Ole Römers väg, Olshög, Tuna, Lund, Lund Municipality, Skåne län, Götaland, 224 64, Sweden"*

The relevant parts of an address vary from country to country. In the example above the address parts: Olshög, Tuna, Lund Municipality and Götaland can be removed and the address text would identify the E-Huset map feature uniquely.

# CHAPTER 4

## 4 Proposed geocoder

This chapter proposes an extension to the Nominatim geocoder. The main problem with the Nominatim geocoder is that, due to the indexing strategy, there is very little flexibility in the way users can access the data. The geocoder does not allow any spelling errors, neither get any feedback while the user is typing the address. The reason for this is that addresses are represented in the index by the address words, therefore, the search fails each time one or more words are misspelled.

The proposed solution adds autocomplete and error correction functionality to the Nominatim search module. It does not modify the way OSM map features are imported into the Nominatim database, how these features are later updated or how Nominatim classify them by class and type.

A naive approach would be for example to use the Levenshtein distance to find addresses in the database similar to a user query, and rank the addresses according to this distance. However, this approach is completely inefficient since the Levenshtein distance needs to be calculated for each entry in the database. We need a more scientific approach like the one described in section 2.2.

In order to make autocomplete and error correction efficient, i.e. interactive from the user perspective, a new index is designed. The proposed index represents the addresses using n-grams and phonetic codes instead of words (See section 2.2.1). This new approach of representing the addresses needs a smarter way to evaluate the similarity with the user queries. The proposed solution uses the Extended Boolean model for this purpose.

I build the proposed solution over a general-purpose search engine called Elasticsearch [35]. As a general purpose search engine, Elasticsearch can be setup to index documents in a variety of ways, for example using n-grams. Also, Elasticsearch uses Extended Boolean model and Tf-idf to compute the

similarity between the user query and the indexed addresses. Elasticsearch relies internally in Lucene [36]. Lucene is a general-purpose java library for information retrieval which contains the implementation of the Extended Boolean model, vector component weighting schemes like the Tf-idf approach and functionality to calculate similarity between documents.

I used Elasticsearch to move from the original ad-hoc solution implemented in Nominatim, to a more mathematical and scientific approach for indexing, and searching addresses.

## *4.1* Elasticsearch

Elasticsearch is an open source search engine first release in 2010. It is available under the Apache 2 license, one of the most flexible open source licenses [35]. The main features of Elasticsearch are:

- Full text search: Elasticsearch uses Java Lucene, a Java library for Information retrieval. Lucene uses the Extended Boolean model to build indexes and search for documents.
- Distributed: designed to grow horizontally as the size of reference dataset grows. The index is distributed among several servers, increasing the performance and robustness of the system.
- API driven: Elasticsearch is accessible from an API using JSON data over HTTP protocol.
- Schema free: Elasticsearch allows to index JSON documents without following any predefined schema. Later you can apply your domain specific knowledge of your data to configure how the data is indexed.

## *4.2* Proposed system software stack

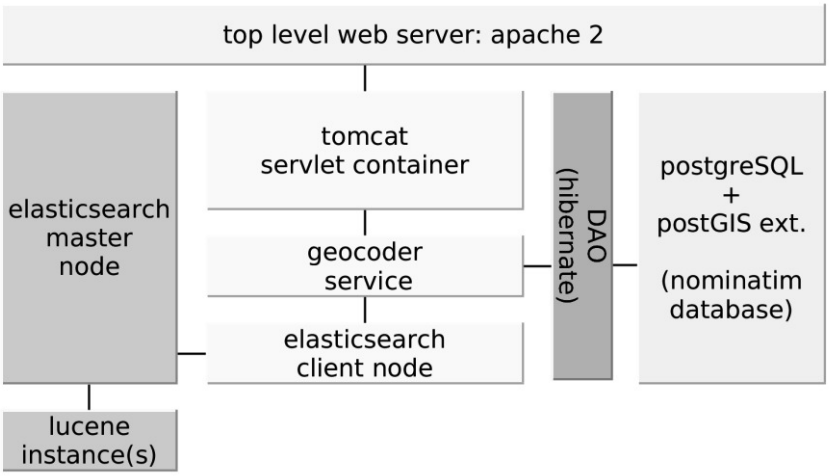


**Figure 9: Proposed geocoder software stack**

The proposed geocoder service architecture is described in Figure 9. The top level is Apache 2 web server which serves static user web pages, and acts as a security layer in the system. This way, the rest of the components are not exposed to the outside but Apache (reverse) proxies the requests to them when needed.

In the second layer there are three different modules:

1. Tomcat: This is the web service container that runs the proposed geocoder system. The geocoder communicates with:
   1.1. The Elasticsearch master node(s), which manages the address index and do the actual search on it.
   1.2. The database through the data access object (DAO). Hibernate [37] is a library that maps relations in a database to Java objects. It is used to access the relational database. The DAO layer isolates the internals of the persistence layer, in this case the database used to store the OSM/Nominatim data from the geocoder logic. All it does is, given a place id or set of places ids, it returns information about that place id stored in the database. The way it does it, it is transparent to the geocoding logic.

2. Elasticsearch: Contains the index that gives support for fuzzy and prefix search.

3. SQL database: PostgreSQL database with PostGIS extension. This is the original Nominatim database, without any change. The database contains the reference dataset, i.e. the map features indexed by Nominatim. It is accessed to retrieve the geospatial information of the requested address and compute the address string.

## *4.3* Online geocoding service

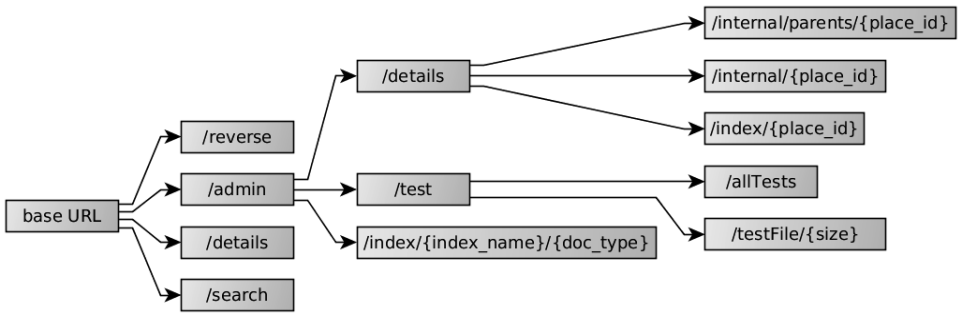


**Figure 10: Online service: URL pattern**

The proposed solution is meant to work as an extension to the original Nominatim geocoder. This means that the URL's pattern for the resources and the request parameters and response formats are the same as in the original Nominatim service. The URL's structure is shown in Figure 10.

The web service offers 3 public resources: search, details and reverse, to request a geocode operation (search), request a reverse geocode operation (reverse), or get the details of an address. There is also a set of sub-resources under the main resource "admin". This set of sub-resources is useful for indexing addresses, debugging and testing the system.

## *4.4* Address indexing

In order to support fuzzy and prefix search, Elasticsearch is setup to analyze and compute more advance index terms than the ones used in the original Nominatim geocoder.

During the index process, the proposed geocoder extracts one by one all the Nominatim entries stored in the original database, and performs the next operations on each one of them:

1. The geocoder calculates the index values of the *index_name*, i.e. individual words from the *name:** tags assigned to that OSM map feature.
2. It computes and stores the Double metaphone values of these words into *values_dm*.
3. It extracts the parents of the Nominatim entry from the database (Nominatim offers a SQL function to obtain the parent id:s given a place id). Each parent is assigned an address type depending on the Nominatim class, type and admin_level OSM tag if it was assigned to that entry. The possible address types that the proposed geocoder uses are *{housenumber, street, city, postcode, state, country, unknown}*. If a parent matches an address type, its id is added to the list of parent id:s used to build the address at search time. Otherwise the address type is set to unknown. This is explained in more detail in section 4.4.1.
4. The geocoder calculates the individual words of the names of the parents that have been assigned an address type and their Double metaphone codes.
5. Finally, the JAVA object containing the data calculated in the previous steps is serialized in JSON format and sent to Elasticsearch.

The JSON object in Text 2 corresponds to the address *"E-Huset, Lund Tekniska Högskola, Lund"*.

```
{
        "place_id":1513474,
        "osm_type":"R",
        "osm_id":1315684,
        "class":"place",
        "type":"house",
        "indexed_parent_ids":[515119,1513602,1517827],
        "importance":0.0,
        "address":{
                "index_name":{
                        "short_terms":["E"],
                        "values":[" E Huset Lunds Tekniska Högskola"],
                        "values_dm":["LNTS","HST","KSKL","TKNS"]
                },
                "index_road":{
                        "values":["Ole Römers väg"],
                        "values_dm":["FK","RMRS","AL"]
                },
                "index_city":{
                        "translation_map":{"ru":"Лунд"},
                        "values":["Lund"],
                        "values_dm":["LNT"]
                },
                "index_state":{
                        "translation_map":{"ru":"Сконе"},
                        "values":["Skåne Län"],
                        "values_dm":["SKN", "LN"]
                },
                "index_postcode":"22464",
                "index_country_code":"se"
        },
        "centroid":[13.211050073039036,55.7110348],
        "calculated_address_type":"PLACE"
}
```


**Text 2: Example of serialized address into JSON**

Elasticsearch is setup to process each JSON field as explained in Table 13. For instance, the address names are represented in the index by their n-grams of minimum length 3, and also by the metaphone codes. The postal code field is represented in the index by its edge-grams.

| Document field | Index strategy |
|---|---|
| *place_id* | Unique id, the same as in Nominatim database. |
| *indexed_parent_ids* | Stored in Elasticsearch but not indexed (they are not searchable). |

| | |
|---|---|
| *index_[name/road/city/state].values* | Analyzed using n-grams of minimum size equals to 3. Any word shorter that 3 chars is ignored. |
| *index_[name/road/city/state].values_dm* | This property contains the double metaphone values of the tokens in [*name/road/city].values.* The length of these tokens varies between 2 and 4.<br>They are analyzed using edge-grams (n-grams starting always from the first character). |
| *index_[name/road/city/state].short_terms* | For short address tokens which will be ignored (length <3 characters). Indexed as it is. |
| *index_postcode* | Analyzed using edge-grams. |
| *index_country_code* | Not analyzed, indexed as it is, for filtering by country code. |
| *centroid* | Indexed as a geo-point type, for spatial filtering. |

**Table 13: Document field index strategy**

### *4.4.1* Address type computation

The address type of the Nominatim entries is computed using the class and type attributes of the entry and the OSM administrative level if assigned (*admin_level* attribute, see section 3.2.3.2). Table 14 shows the criteria to assign the address type to a Nominatim entry.

| **Address type** | **Condition(s)** |
|---|---|
| House number | class = *place* **AND** type = *house* |
| Street | class = *highway* **OR** *bridge* **OR** *tunnel* |
| City | class = *place* **AND** (type = *city* **OR** *town* **OR** *village* **OR** *hamlet*)<br>**OR** admin_level = *city admin level* |
| Postal code | (class = *place* **AND** type = *postcode*) **OR** (class = *boundary* **AND** type = *postal_code*) |

| | |
|---|---|
| State | admin_level = *state admin level* |
| Country | class = *place* **AND** type = *country_code*<br>**OR** admin_level = *country admin level* |
| Unknown | otherwise |

**Table 14: Criteria to assign the address type to the Nominatim entries**

## *4.5* Searching addresses

The proposed geocoder relies on Elasticsearch to perform the search of relevant addresses given a user query. Elasticsearch makes use of the Boolean model to extract relevant documents given a user query. And then, it ranks the relevant documents by representing documents and query as vectors, and computes the similarity among the query and each document.

Elasticsearch provides a full query domain specific language (query DSL) based on JSON to define queries. Elasticsearch queries specify what must be searched and in which document fields must be found. However, the user provides only a text query, and probably some extra information to apply filters on the results. For this reason the user query needs to be processed and translated to Elasticsearch queries.

### *4.5.1* Query processing

The query processor purpose is to assign some meaning to some parts of the user query and to translate the user query into one or more Elasticsearch queries (Figure 11). The input of the query processor is a formal query in text format, expressing the user needs, for example if the user need is "to know where the Electronics building in LTH is", the associated query would be something like "E-Huset, LTH, Lund". The output of the processor is one or more Elasticsearch queries, in which some of the words of each query might have been given some meaning.

For instance, to find street intersections, the geocoder needs to find first the streets to intersect. The query processor splits the user query in two subqueries. The proposed geocoder split the queries at *"?"* character. Then, the geocoder assigns a meaning to each subquery. In this case each subquery is interpreted as the name of a street. The user query *"Bytaregatan ? Knut den stores gatan, Lund"* will be interpreted by the proposed geocoder in the following way: a request for finding the intersection of the streets *"Bytaregatan"* and *"Knut den stores gatan"* in *"Lund"*.


**Figure 11: Query processor input and output**

The query processing is as follows:

1. The query is converted to lowercase.
2. Split the query in punctuation and space letter.
3. For each token which does not contain numeric characters, it computes the double metaphone code.
4. Tokens whose length is 2 or lower are marked as short tokens.
5. Tokens containing numeric characters, these tokens might have a special address meaning, like house number or postcode. These tokens are analyzed as follows
   5.1. If the query contains only one token, it is considered a postcode.
   5.2. If the query contains more than one token, then tokens with numeric characters have three possible interpretations, since they can be part of the name, house number or postcode.

Last, after processing the query, the geocoder decides which type of search it needs to perform. The search types are divided in four categories, basic search, intersections, house numbers and addresses by postcode. The system decides the search type following the next rules:

1. If the query contains the intersection character, the search type is set to intersection, and then the geocoder search for addresses of type street and derive the intersection geocode by finding the intersection of the street line geometries.
2. If the query does not contain the intersection character, then the system will behave as follows:
   2.1. The geocoder search for addresses matching the words in the user query.
   2.2. If any of the search terms was marked as possible house number, the system will try to find children of the addresses in the previous step, matching such house number(s)
   2.3. In the special case of having only one search term, that could be a postcode, the geocoder find streets whose parent is the given postcode.

### *4.5.2* Basic search

The diagram in Figure 12 shows the geocoding process, from the user query to the final geocoded places response. First, the user query is processed and translated into Elasticsearch queries. Second, the system searches into Elasticsearch/Lucene index, and optionally apply filters, like spatial filter if the user provided a search area. The output is a sorted list of place ids and parent ids for each place. Last, the geocoder extracts the geocodes corresponding to each place id and builds the address strings using the OSM data stored in the Nominatim database.

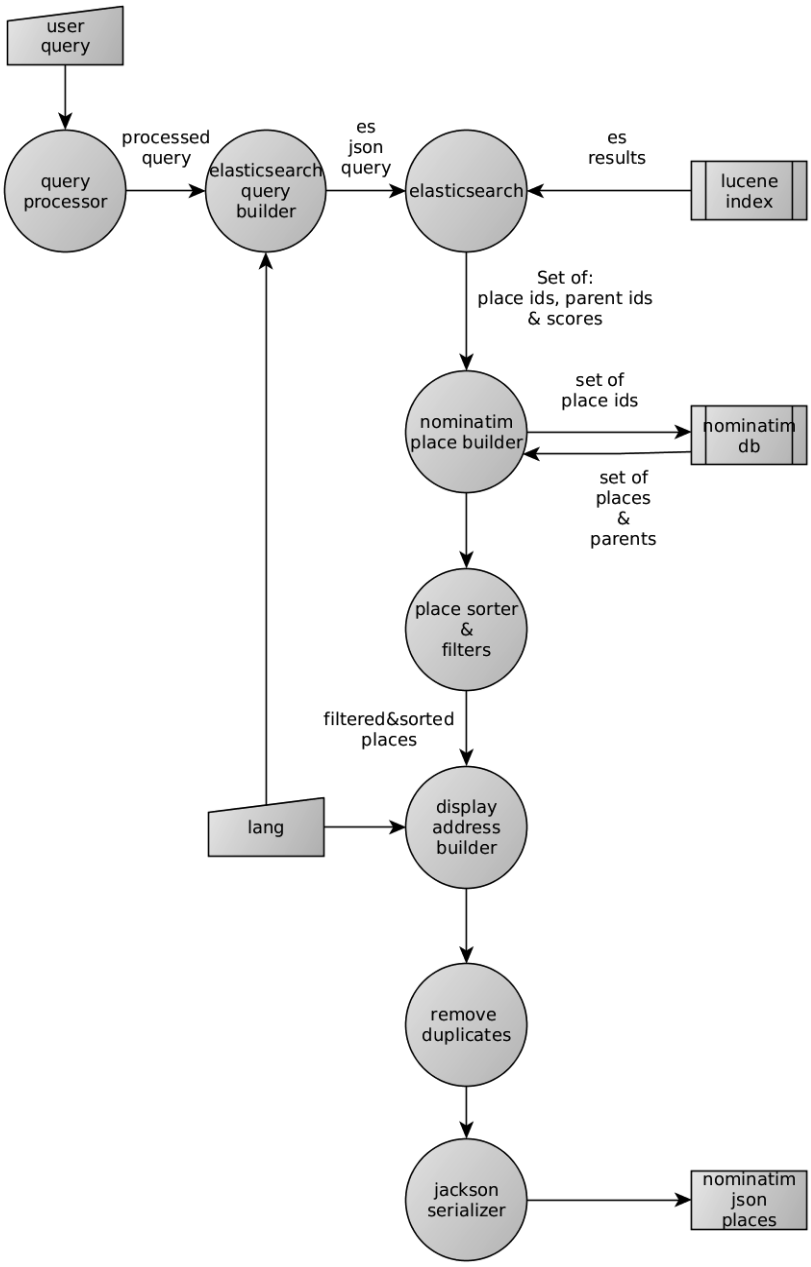


**Figure 12: Search algorithm**

### *4.5.3* House number

House number search (Figure 13) is executed if any of the query terms was identified as possible house number by the query processor. After the basic search against Elasticsearch/Lucene index, if the system found any place of type street, it will try to find children of those streets whose house number is the one in the query.

This house number search is done against the Nominatim SQL database using scanning, since as mentioned before, house numbers are not indexed into Elasticsearch. After searching for streets, the system does not return more than a few tens of places, so the scanning does not affect the response time.

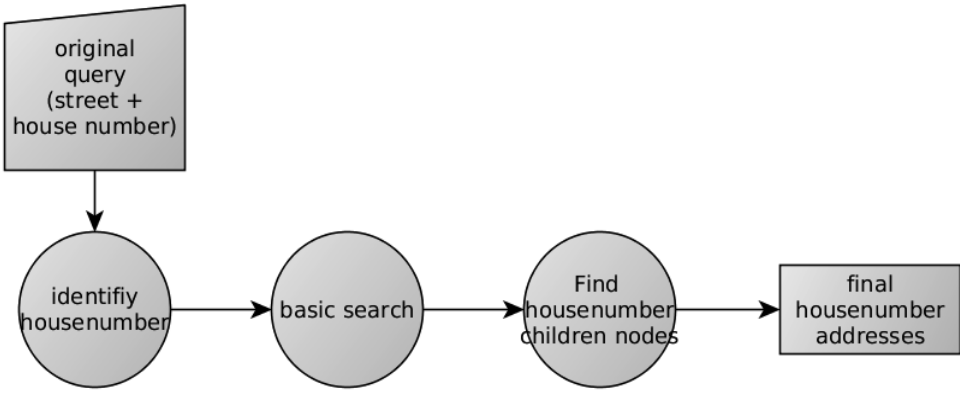


**Figure 13: House number search**

### *4.5.4* Street intersections

Street intersections are the only case of derived place returns. By derived we mean that intersections are not precomputed at indexing time.

Street intersections are calculated in the following way (Figure 14). First, the user query is divided into two subqueries, one per street. Next the geocoder makes two independent searches against Elasticsearch, meaning that the result of the first subquery will not affect the second search. On each search Elasticsearch tries to find indexed places of type *street* by the name, and maybe additional information like city, provided in the subquery. After this, the geocoder has two lists of streets, or better, the place ids of these streets. So next is to retrieve the geospatial information and name/address

information from the Nominatim SQL database. Once the geospatial information is available, the system computes the intersections among the streets in results #1 and results #2. Most of the intersection operations will return an invalid intersection, meaning that there is no real intersection between those street geometries, but some will return a point of intersection. These are the relevant places the user is interested in. Next the geocoder removes the invalid intersections and reevaluate the scores of the valid intersections as the sum of the scores of intersected streets. Last it calculates the address of each intersection as:

*intersection address = [street 1 address] [intersection char '?'] [street 2 address]*

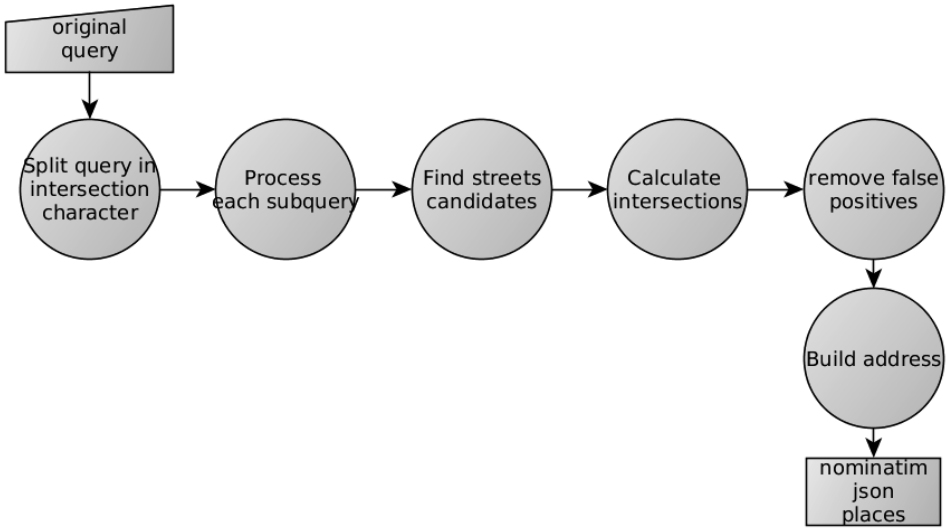


**Figure 14: Street intersections**

For example, if a user wants to find the corner of *"Bytaregatan"* with *"Knut den stores gatan"* in *"Lund"*, the geocoder finds first streets by these names located in *"Lund"* using Elasticsearch. Then it retrieves the geometries of the found streets from the Nominatim database. Last it computes the intersection of the geometries. If the intersection is not null, it's a valid intersection, and the final score is the sum of the individual scores assigned by Elasticsearch for each street search. Otherwise it is removed from the results.

### *4.5.5* Searching streets by postal code

This section introduces a new search type, addresses under a postcode. Postal codes are used in some countries to divide geographical areas, stablish billing strategies or as a way to narrow down the search of a postal address under a postcode.

For example in the UK, taxi dispatchers usually search streets by typing first the postcode they belong to. The goal of this search type is to find addresses that are under a postcode. The original Nominatim geocoder returns instead the centroid coordinates of the area a postcode refers to, being this information of little value for the users.

Another example. The taxi business in UK, and especially in London, charges their customers depending on their pickup and drop off postcode addresses, which means that the postcode is the most used type of geocoding. By presenting the user the addresses under that postcode, which in turn correspond to a specific area of the city, we improve the user experience.

Due to the structure of the original Nominatim database, in which each of the OSM map features indexed is assigned a parent id, the implementation of this type of search is rather simple. Nominatim entries indexed in Elasticsearch contains a postcode field, the geocoder just search for places whose postcodes match or prefix match the (partial) postcode given in the search query. The geocoder does not try to correct any possible mistake in the postcode given by the user.

### *4.5.6* Building the addresses

The proposed geocoder follows the same strategy as Nominatim when computing the address of a place. It calculates addresses by concatenating the names of the place parents, but instead of taking one parent from each address rank, and concatenate its name to the address, it concatenates the names following a pattern defined for each country.

During the index process, the geocoder calculated a list of parent ids that is now used to compute the address (see section 4.4). The geocoder uses this list now to retrieve only the needed parents to build the address. This reduces the amount of information the geocoder needs to extract from the database. In addition, since a user will frequently search for places in a delimited geographical region, the suggestions returned by the geocoder will have

common parents, reducing even more the information needed to compute the addresses for all the suggestions. Imagine the query *q* gives as a result a set of suggested places $\{s_1, s_2, s_3\}$. Together with these suggestions, Elasticsearch gives a list of parent id:s needed to compute the address of each place (previously computed and stored), like the ones shown in Table 15.

| Place id | Parent id:s |
|---|---|
| $s_1$ | $p_1, p_2, p_3, p_5$ |
| $s_2$ | $p_1, p_2, p_4, p_5$ |
| $s_3$ | $p_2, p_3, p_5$ |

**Table 15: Example of parent id lists used to compute the place addresses**

Next, the geocoder computes the union of parent id:s:

$$p_1, p_2, p_3, p_5 \cup p_1, p_2, p_4, p_5 \cup p_2, p_3, p_5 = p_1, p_2, p_3, p_4, p_5$$

These are all the Nominatim entries the geocoder needs to retrieve from the Nominatim database in order to build the addresses for the response to the query *q*.

We can define one address pattern for each country(i.e. the order in which the different parts of the address are concatenated), since every Nominatim entry has an associated country code with it, the geocoder will concatenate the address parts following the pattern that matches the country code, or a fallback if none is found. Table 16 shows the address pattern I defined for Swedish addresses.

| Country code | Address pattern |
|---|---|
| fallback | name, housenumber, street, city, postcode, country |
| SE | name, housenumber, street, postcode, city, state, country |

**Table 16: Address pattern used for Sweden (SE)**

Last the geocoder computes the addresses of each suggestion by concatenating the names of the Nominatim entry and the parents, following

the pattern. Each address part is translated to the preferred language *l* indicated by the user, if a translation for that language exists.

$$address(r_1, l) = name(p_1, l), name(p_2, l), name(p_3, l)$$

The address computation process of the proposed geocoder is described in the diagram in Figure 15.

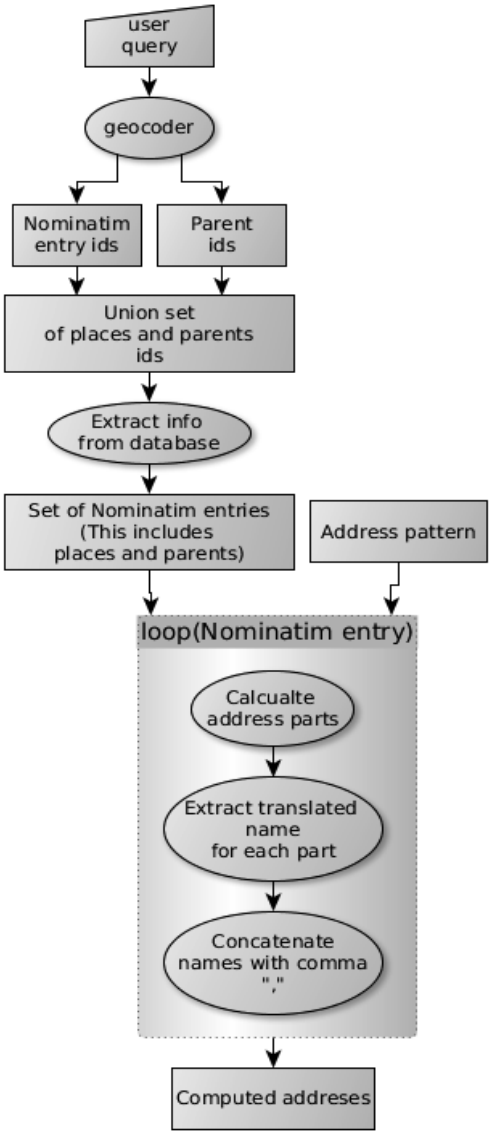


**Figure 15: Address computation of a set of places**

This way of building the addresses is the answer offered to the research question number 5 in section 1.2. I.e. how to improve the address computation algorithm so the final address is shorter and contains only relevant parent names.

We get two improvements compared to the original implementation in Nominatim:

1. The geocoder computes shorter addresses. The addresses contain only the names of the parents whose address type appear in the address pattern (patterns like the ones defined in Table 16).
2. The order of the address parts is defined in the pattern.

The motivation to assign an address pattern per country code is that address formats usually differ from country to country. In some countries the house number is written before the street name or vice versa. Also, in some countries the state might be an important part of the address, while in others it might be redundant information bloating the map feature.

Table 17 shows an example of the address calculated by the original Nominatim geocoder and the proposed geocoder for the "E-huset" building in LTH.

| Geocoder | Computed Address |
|---|---|
| Nominatim | *E-Huset, 3, Ole Römers väg, Norra universitetsområdet, Norr, Lund, Lund municipality, Skåne län, Götaland, 22464, Sverige* |
| Proposed geocoder | *E-Huset, 3, Ole Römers väg, 22464, Lund, Skåne län, Sverige* |

**Table 17: Example of computed addresses by the Nominatim and proposed geocoder**

The address given by the Nominatim geocoder contains address parts that provide little information to the user, like *"Norra universitetsområdet, Norr, Lund, Lund municipality"*, since the place can be identified uniquely even without these address parts. On the contrary, the address computed by the proposed solution is more clear and concise.

### *4.5.7* Scoring the addresses

Each address returned by the geocoder gets a score calculated in several steps. First, Elasticsearch, using the concepts of Vector space model and cosine similarity, calculates a score which is basically a function of the index terms and query terms. The more query terms matching the index terms of an address, the higher the score.

Then, the score is boosted by adding the importance which Nominatim computes for each place at index time. This importance (a value between 0 and 1) is a function of:

1. Number of links in Wikipedia that relates to this place.

2. If no entry is found in Wikipedia about this place, a weighted value of the inverse of the *rank_address* property of each map feature.

$$importance = 0.75 - \left( \frac{rank\ address}{40} \right)$$

Finally the score is optionally boosted depending on the search type.

1. For intersections, the final score is calculated as the sum of the scores of each street.
2. Since house numbers are not indexed in Elasticsearch, but the geocoder performs a second lookup in the Nominatim database, house number matches are not boosted in the original score. The geocoder boosts the score of the found children matching the requested house number.

$$score_{final} = score_{elasticsearch} + importance_{Nominatim} + (optional\ boost)$$

### *4.5.8* Filtering out addresses by relative score

The proposed geocoder filters out addresses whose score is lower than a fraction of the highest score of the suggested addresses. In the proposed geocoder I use 0.8 as threshold. I.e. given a list of suggested addresses, all the addresses whose score is lower than 0.8 times the highest score are removed from the suggestions.

For example, if we have a list of suggestions calculated by the proposed geocoder in which the highest score is 100 and another result has been scored with 10, since $10/100 = 0.1 < 0.8$ that result is removed from the returned suggestions.

The reason to impose this condition in the results list is that even if the user query and an arbitrary address are "very different", they might have an n-gram (section 2.2.1) in common. Therefore Elasticsearch assigns a score greater than zero, but that score might be too low compared to the highest score found in the results offered by the proposed geocoder. As a consequence, the precision (See section 2.3 for a definition of precision) of the proposed geocoder increases, since it returns fewer results.

## *4.6* Proposed solution of a distributed geocoder service

The number of addresses indexed in Sweden is around 400K. If we were to index the whole world, the number of Nominatim entries to index would amount to several millions. For such a big collection, Elasticsearch allows to split the index in different chunks also called shards. Each shard can be maintained by one or more Elasticsearch nodes (for redundancy). This is a convenient approach for a geocoder to offer global results, since each data node needs to manage a small part of the index and the searches are computed in parallel by the different data nodes. In the proposed solution, described graphically in Figure 16, the top level Elasticsearch node works as a load balancer, it knows the state of the master nodes and routes the query to the less loaded. The master nodes coordinate the data nodes to perform a distributed search, and aggregate the results returned by each data node. Also, this solution offers reliability and a better performance, since the search can be done in any of the shard replicas (Figure 16 shows an index with two replicas, each replica assigned to a different node, for robustness)

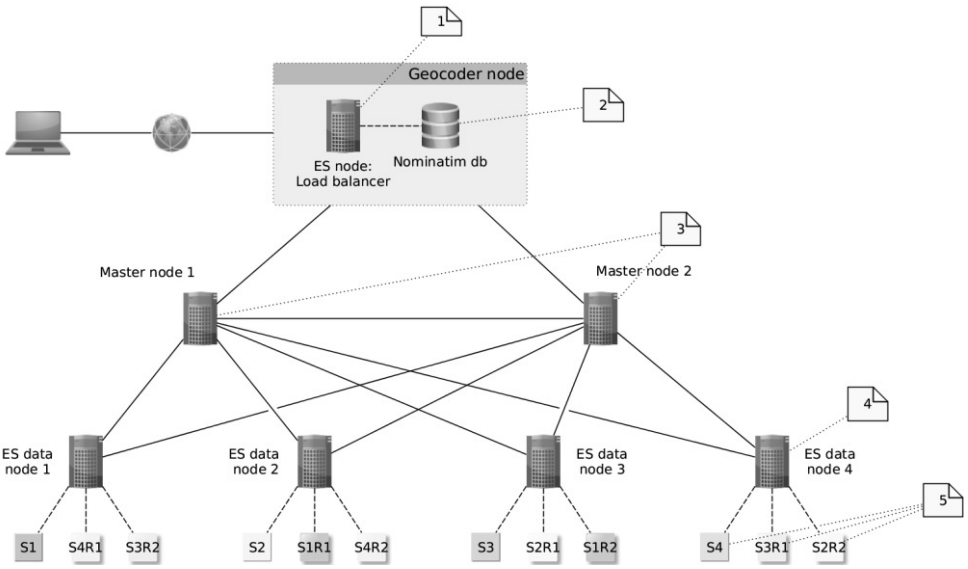


**Figure 16: Distributed geocoder, proposed solution**

Notes in the Figure 16:

1. Top level Elasticsearch node: This node acts as a "search load balancer". It routes the search requests that arrive to the geocoder to the less loaded master node.

2. PostgreSQL database: It hosts the Nominatim data stored. The geocoder accesses this database to index Nominatim places and to compute the place addresses.
3. Elasticsearch master nodes: their task is to coordinate the distributed search among the Elasticsearch data nodes and aggregate the results return by each data node.
4. Elasticsearch data nodes: These are the nodes hosting the data. The index is spread among 5 primary shards, hosted in one of the data nodes. Each primary shard (in the picture represented as shards S1 to S5) is copied into a replica hosted in a different data node (represented as S1R1 and S1R2 for replicas 1 and 2 of shard S1 and so on).
5. Index shards: They are small parts of the index maintained by the data nodes. Each one of the 5 shards in which the index is divided is replicated twice among the data nodes. If a data node is down, the master node knows about it and it routes the search to another data node hosting a replica.

# CHAPTER 5

# 5 Test results

## *5.1* Evaluation methodology and tools

In order to evaluate the proposed geocoder, a set of tools and test resources was implemented. These include a random address generator, a random text error generator to simulate misspelled addresses, a set of tests written in Java to evaluate the system and a web to adjust the test parameters and show the test results.

### *5.1.1* Server specifications and configuration

The geocoding server was tested in a machine with the next specifications:

| | |
|---|---|
| Processor | Intel Core I7 – 2.2Ghz (x4 cores) |
| Memory | 8GB RAM |
| Hard disk | SSD 80 GB |

**Table 18: Server specifications**

### *5.1.2* Random address generator

The addresses used to test the system are selected randomly among the reference dataset, i.e. the OSM places stored in the Nominatim database. The sub-resource *.../admin/test/testFile/{size}/{lang}* builds files containing lists of size *"size"* of addresses which are used later as user queries to geocode. The addresses can be translated optionally to the language defined by the path parameter *"lang"*.

A file with 100 addresses was generated to test the system. The addresses were computed without any translation, resulting in addresses written in Swedish. Each Nominatim entry, identified by its Nominatim *place_id*, contains the text address computed by the Nominatim geocoder and the proposed geocoder (Text 3).

```
...
"518439" : {
      "elasticsearch" : "Hotel Scandic Triangeln, Föreningsgatan, 21145, Malmö, Skåne län,
                        Sverige",
     "nominatim" : "Hotel Scandic Triangeln, Föreningsgatan, Rådmansvången, Norr,
                        Malmö, Skåne län, Götaland, 21145, Sverige"
},
...
```

**Text 3: Extract of the test addresses file**

Since we aim to evaluate the fuzzy and prefix search in the proposed solution, map features whose only name is of type reference (*"ref:*"* tags) in the Nominatim database are not included in this file. The reason for this is that references are in most cases a single letter or a letter and a number such as *"E 4"*, the highway between Malmö and Stockholm.

### *5.1.3* Random text error generator

The goal of the error generator is to simulate a user which, while typing an address, makes a mistake and misspells the address. The error generator takes as input a text string. This is the address the user sends to the geocoder to find the location of the address. The error generator alters the input address by applying one of these operations on a single character: change, delete or insert a character. The number of alterations can be defined in the test settings. As a result, the output of the error generator is a modified text string whose difference with the original text string can be measured using the edit distance (See section 2.2.1).

For example, a user might be trying to geo locate *"Bytaregatan 4c, Lund, Skåne län, Sweden"*. The user expects to see suggestions in a dropdown box offered by the geocoder while the user types in new characters. But it might happen that he makes a mistake while typing in and he sends a query like *"Bytaregtan"* to the geocoder. In this example, the user is missing an *"a"* character. The mission of the error generator is to model the user errors.

### *5.1.4* Test setup

I designed the test algorithm in a way that it simulates the behavior of a user that tries to find the location of an address. The behavior is modeled by these rules:

1. The user knows more or less accurately how to spell the names of the address.

2. The user types in one character after another. Sometimes, either because the user don't know exactly the spelling of the address, or because he or she makes a mistake typing the character, the user introduces an error in the address text.
3. With each new character added to the user query, the geocoder returns a list of places that prefix match the user query. The user keeps typing characters until the desired address appears in the suggestions of the geocoder response.
4. Once the desired address is among the suggestions, the user needs no longer to keep typing new characters. The address is considered to be found and the user has saved typing *n* characters, being *n* the difference between the address text length and the user query length.

The test process simulates the user behavior described above. It tries to find the addresses in the test address file. For each address in the file, the test process adds characters at the end of query and requests the geocoder (either Nominatim or the proposed geocoder) until the desired address appears in the suggestions. When the geocoder returns the desired address, the test process calculates various metrics for that search: precision, keystroke saving, time spent, Etc. (the metrics definitions can be found in section 2.2.3). When all the addresses have been tested, the average values of the metrics are computed. The described procedure is repeated 10 times for each number of errors introduced. The resulting values are used later to compare the geocoders.

The tests are setup using the parameters listed in Table 19:

| **Parameter** | **Values** |
|---|---|
| Geocoding service | {Proposed geocoder, Nominatim geocoder} |
| Number of addresses | 100 |
| Number of errors in query | [0, 4] |
| Number of addresses in the response | {1, 5} |
| Number of executions | 10 |

**Table 19: Test parameters**

The geocoder sorts the suggestions by similarity with the user query, therefore the more similar addresses appear first in the suggestions list. The more suggestions the geocoder can return per request (Number of addresses

in the response), the sooner the user will find the address among the suggestions, and the less characters the user needs to type in. In the other hand, if the geocoder returns too many suggestions it will be difficult for the user to find the desired address among the suggestions, and the user will need to keep typing to filter out suggestions.

### *5.1.5* Web test interface

Illustration 1 is a snapshot of the test user interface to evaluate the system. In the left panel (panel number 1, Illustration 2) it is possible to select the file containing the test addresses in JSON format, turn on and off different parts of the search engine, such as phonetic search or n-grams search, and adjust weights assigned to these searches. The central panel (panel number 2, Illustration 3) shows the results after the tests are executed, percentage of addresses found, average time the search engine spent per search, precision and so on. Last, the right panel (panel number 3, Illustration 4) shows the raw JSON response sent with the test results, this is useful in case someone wants to see more detailed information like failed searches, query used for such searches or the response time of a single search.

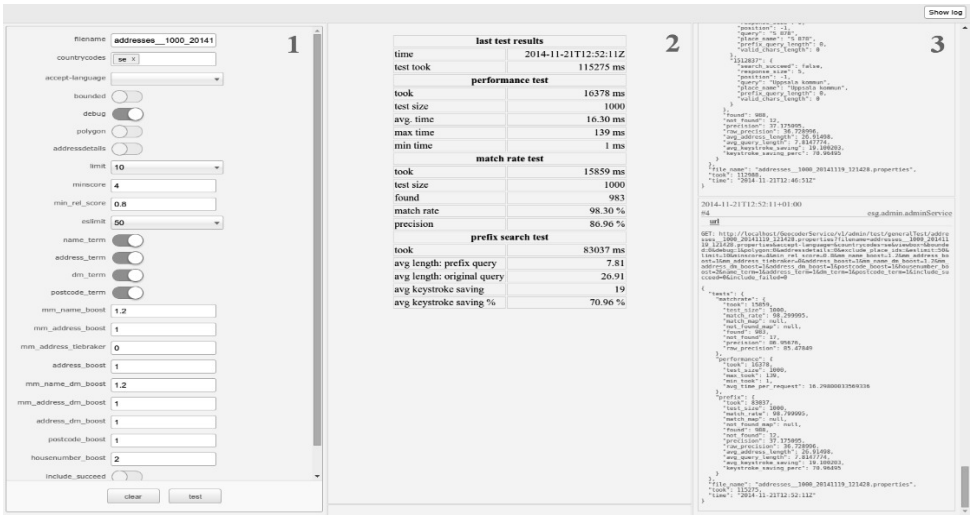


**Illustration 1: Web test interface**

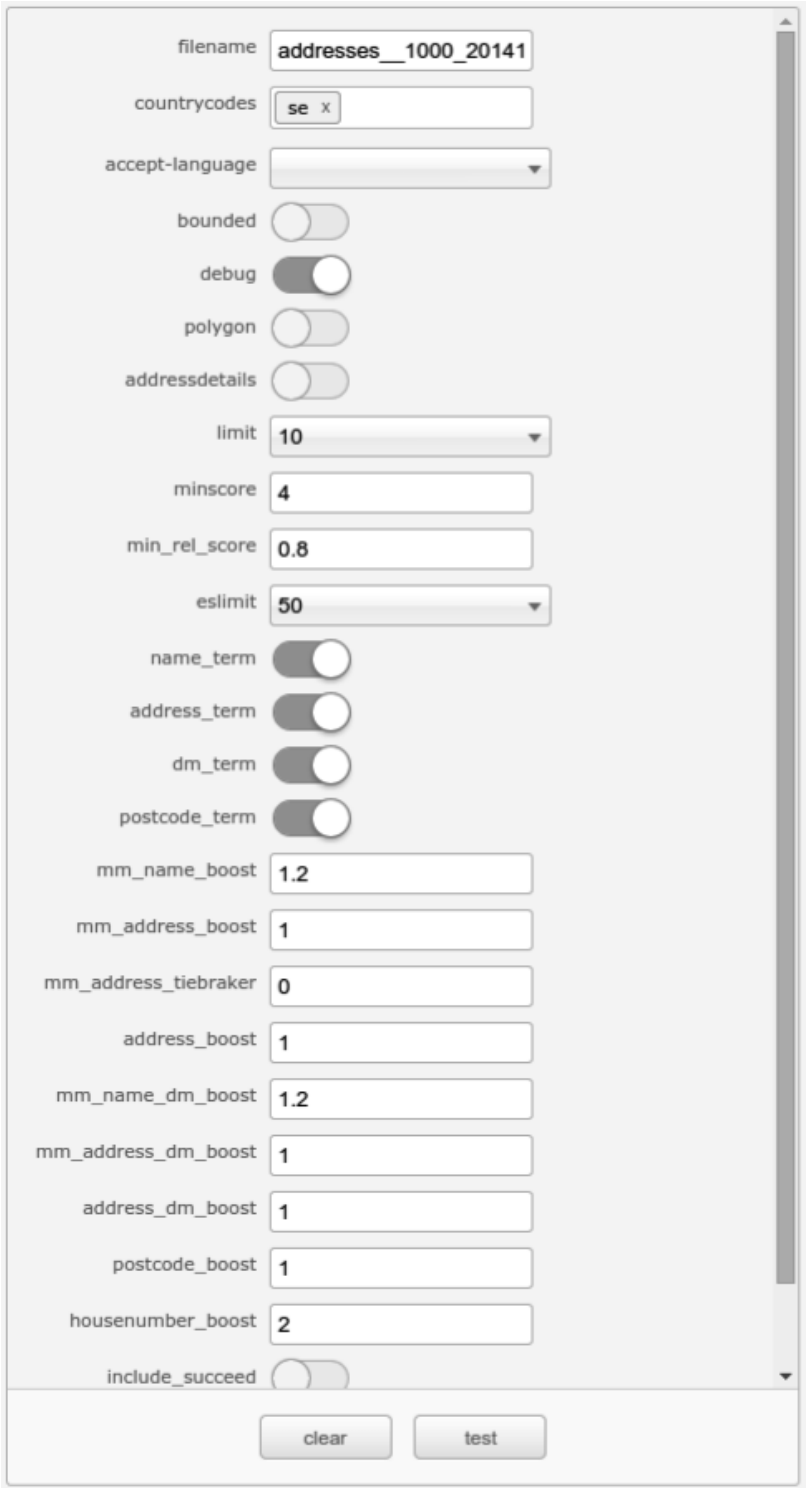


**Illustration 2: Detailed view of the panel number 1**

| last test results | |
|---|---|
| time | 2014-11-21T12:52:11Z |
| test took | 115275 ms |
| **performance test** | |
| took | 16378 ms |
| test size | 1000 |
| avg. time | 16.30 ms |
| max time | 139 ms |
| min time | 1 ms |
| **match rate test** | |
| took | 15859 ms |
| test size | 1000 |
| found | 983 |
| match rate | 98.30 % |
| precision | 86.96 % |
| **prefix search test** | |
| took | 83037 ms |
| avg length: prefix query | 7.81 |
| avg length: original query | 26.91 |
| avg keystroke saving | 19 |
| avg keystroke saving % | 70.96 % |

**Illustration 3: Detailed view of the panel number 2**


**Illustration 4: Detailed view of the panel number 3**

## *5.2* Results

### *5.2.1* Proposed geocoder results

Table 20 shows the results of geocoding 100 addresses using the proposed geocoder, with a maximum number of results returned set to 1. The number of errors introduced in the prefix query varies from 0 to 4.

| max results: 1 | | | | | |
|---|---|---|---|---|---|
| # of errors | 0 | 1 | 2 | 3 | 4 |
| search time (ms) | 23,37 | 18,54 | 15,85 | 13,87 | 14,33 |
| match rate % | 98,00 | 98,00 | 98,00 | 97,34 | 96,64 |
| precision % | 100,00 | 100,00 | 100,00 | 100,00 | 100,00 |
| address length | 49,66 | 49,66 | 49,66 | 49,88 | 50,00 |
| query length | 11,15 | 12,21 | 13,71 | 15,91 | 18,71 |
| keystroke saving | 38,51 | 37,45 | 35,95 | 33,97 | 31,29 |
| keystroke saving % | 77,55 | 75,41 | 72,39 | 68,10 | 62,58 |

**Table 20: Elasticsearch test results for max 1 address returned**

Table 21 shows the results of geocoding 100 addresses using the proposed geocoder. In this case the maximum number of results returned is set to 5. The number of errors introduced in the prefix query varies from 0 to 4.

| max results: 5 | | | | | |
|---|---|---|---|---|---|
| # of errors | 0 | 1 | 2 | 3 | 4 |
| search time (ms) | 20,90 | 19,94 | 16,94 | 15,24 | 15,07 |
| match rate % | 100,00 | 99,30 | 98,68 | 98,66 | 98,33 |
| precision % | 47,09 | 51,24 | 55,55 | 61,53 | 64,56 |
| address length | 49,60 | 49,63 | 49,76 | 49,76 | 49,87 |
| query length | 8,60 | 9,88 | 11,72 | 13,91 | 13,91 |
| keystroke saving | 41,00 | 39,75 | 38,04 | 35,85 | 35,96 |
| keystroke saving % | 82,66 | 80,09 | 76,45 | 72,05 | 72,11 |

**Table 21: Elasticsearch test results for max 5 addresses returned**

### *5.2.2* Nominatim geocoder

Nominatim was only tested without errors in the user query since it does not support fuzzy search. Prefix search is not supported either so Nominatim returns addresses when there are no word prefixes in the query. Table 22

shows the results of the tests using the Nominatim geocoder, set to return 1 and 5 addresses per request.

| max results: | 1 | | 5 | |
|---|---|---|---|---|
| # of errors | 0 | 1 | 0 | 1 |
| search time (ms) | 33,29 | - | 37,98 | - |
| match rate % | 72,00 | - | 88,00 | - |
| precision % | 100,00 | - | 60,00 | - |
| address length | 85,43 | - | 86,66 | - |
| query length | 13,98 | - | 12,00 | - |
| keystroke saving | 71,45 | - | 74,66 | - |
| keystroke saving % | 83,64 | - | 86,15 | - |

**Table 22: Nominatim test results for max 1 and 5 addresses returned**

### *5.2.3* Results discussion

Search time

The average search time is well below 100ms. The proposed geocoder, using Elasticsearch as the core of the search engine, provides better search times than the Nominatim geocoder, even though it implements a more advance search algorithm.

The search time is lower the longer the user query. The reason for this is that longer queries provide more information to the search engine (Elasticsearch) about the address the user is looking up. Thus Elasticsearch is able to filter out more results using the Boolean model, and needs to compute fewer scores before passing the ids of the suggested addresses to the geocoder.

In a production server it would be more interesting to see the average round-trip time, which includes the search time, network time and JavaScript time. A maximum round-trip time around 300 ms lets the user experience an interactive response [28].

Match rate

The test results in Nominatim gives as best 88% match rate (See section 2.3), in the case of retrieving the top 5 addresses per request. If Nominatim only retrieves the highest scored address, the match rate drops to 72%.

The results are much better in the proposed geocoder, in which the match rate never falls below 96% even with 4 errors introduced in the user query.

We observe that when the number of errors in the user query increases, the user needs to type in more characters to find the address. I.e. the user needs to provide more information about the address.

Precision

Due to the definition of precision (See section 2.3), this metric offers no information for max addresses = 1, since the precision is measured when the right address is found, and the geocoders do not suggest more than one address. Consequently the precision is 100% when max addresses = 1.

Looking at the results when the number of suggested addresses is 5, and no errors are introduced in the query, Nominatim (60%) has a slight advantage over the proposed geocoder (47%). But the query needed to find the place with Nominatim is longer than the query sent to the proposed geocoder. I.e. the Nominatim geocoder needs more characters to find the right address among the suggestions, these extra characters added to the query of course increase the average precision.

Looking at Table 20 and Table 21, we observe that the proposed geocoder needs more characters to find the right address the more errors are introduced. The extra characters added to compensate the errors also helps to identify better the address being looked up. Thus increasing the precision of the suggestions.

Address length

The addresses computed by the proposed geocoder (49-50 characters) are in average shorter than the Nominatim addresses (86-87 characters) since the addresses calculated by the proposed solution only contain the parents specified in the address pattern as described in section 4.5.6. On the contrary, Nominatim builds the addresses by concatenating the names of all the parents of a place. However, the proposed geocoder still offers better match rate with shorter queries. The reason for this is that much of the information provided in the Nominatim addresses is irrelevant to identify them. How to improve the address computation algorithm was in fact one of the research questions stated in section 1.2.

Relative keystroke saving

The relative keystroke saving (See section 2.3) in Nominatim is higher than in the proposed geocoder. However as said in the section above (address lengths), the addresses in Nominatim are longer, but much of the text in the

addresses is irrelevant. Consequently Nominatim queries need a lower percentage of characters of the original Nominatim addresses to find the relevant address.

In the proposed geocoder, the keystroke saving varies with the maximum number of addresses returned. As expected, when the geocoder returns more suggestions per request, the user needs to type fewer characters in the query to find the desired address. If no errors are introduced and the maximum number of addresses = 5, the proposed geocoder needs only 9 characters (82.7% keystroke saving) to suggest the address the user is interested in, whereas in the case of returning only 1 address the geocoder needs 12 (77.55% keystroke saving) characters in average to find that same address.

If the number of addresses returned is set to 5, the keystroke saving decreases as the errors in the query increases. As explained before, the reason is that if the user makes a mistake while typing the address, then the geocoder needs more information (longer query) to find that address.

Extra resources needed

The new features added to the geocoder have an associated extra cost in terms of resources needed. The size of the index to support fuzzy search and autocomplete for the Swedish OSM addresses is around 100MB.

The original size of the PostgreSQL database used by Nominatim after indexing and storing the Swedish OSM address dataset is around 1 GB, so the new index increases the storing requirements by 10%. This estimation matches the approximated overhead given in the Elasticsearch documentation [35].

# CHAPTER 6

# 6 Conclusions and future work

## *6.1* Conclusions

This thesis adds two *must have* features to the Nominatim geocoder that many of the main online geocoders support already, fuzzy search and autocomplete. The proposed geocoder is an extension to the Nominatim geocoder, in which I based my work. The solution offered in this thesis answers the research question of how to improve the search algorithm in the Nominatim geocoder by applying mathematical models commonly used in information retrieval systems. In practice, this is done by combining the general purpose search engine called Elasticsearch with the Nominatim geocoder.

Applying mathematical models to the reference dataset of the proposed geocoder leads to a more flexible and interactive search algorithm than the original search algorithm implementation in Nominatim. With the proposed solution, the users get suggestions as they type searching for addresses. The geocoder suggests the right addresses even if the user makes any misspelling and/or typing error. During the tests, the proposed geocoder successfully found the right addresses even with up to 4 errors in the query in a 98% of the cases for the case of 5 addresses returned.

Besides the main contributions, fuzzy search and autocomplete, the proposed geocoder also offers a solution to return more concise addresses than the ones returned by the original Nominatim geocoder. Having tested one 100 addresses, the addresses computed by the proposed geocoder are a 42% shorter than the ones provided by Nominatim (The proposed geocoder average address length is 50 characters vs 87 characters average length of the Nominatim addresses).

Also, the algorithm to build the address is more flexible than in the original version, allowing to build the addresses based on patterns. These patterns can

be specified one for each country, depending on how the addresses are usually written for each country.

## *6.2* Future work

There are many things that can improve the proposed geocoder system.

Some features that are still not implemented in the geocoder are search by categories, i.e. searching addresses or places by the type of the place, for instance "restaurants in Lund", categories are not indexed yet into the proposed geocoder. This could also help to index and search places without a name, or possibly only a reference, as in many bus stops for instance, in which the only information available besides the category is a 1 character reference in many instances.

Also, the system needs to be tested against addresses in other languages. This thesis only uses Swedish addresses as reference dataset. It would be interesting to evaluate the geocoder with addresses written in an alphabet different than Latin.

In the thesis, two new search types were added to the geocoder: addresses under a postcode and street intersections. However, the proposed solution does not allow many other types of addresses being used nowadays in some countries. For instance, in Colombia, addresses can be given as relative to an intersection, as in "50 meters from the intersection between [street 1 and street 2]".

The ranking algorithm can be improved to take into account the distance from the user to the suggested addresses, or by boosting the relevance of the suggested addresses that appear within the part of the map the user is currently looking at.

Another possible future work could be the evaluation of the distributed geocoder. In the simple case of this research, the number of documents was small enough to index them all in the same node. Indexing the whole set of map features in OSM is a much harder task. It can be solved by dividing the index in different servers. This arises multiple questions such as, how is the distributed index divided, and how does this affect the search performance?

# References

[1] Manning, Christopher D., Prabhakar Raghavan, and Hinrich Schütze. *Introduction to information retrieval*. Vol. 1. Cambridge: Cambridge university press, 2008.

[2] Dong, Hai, Farookh Khadeer Hussain, and Elizabeth Chang. "A survey in traditional information retrieval models." (2008).

[3] Goldberg, Daniel W. "Improving Geocoding Match Rates with Spatially-Varying Block Metrics." *Transactions in GIS* 15.6 (2011): 829-850.

[4] Roongpiboonsopit, Duangduen, and Hassan A. Karimi. "Comparative evaluation and analysis of online geocoding services." *International Journal of Geographical Information Science* 24.7 (2010): 1081-1100.

[5] Greengrass, Ed. "Information retrieval: A survey." (2000).

[6] OpenStreetMap wiki [Online]. http://wiki.openstreetmap.org/wiki

[7] Ramm, Frederik, Jochen Topf, and Steve Chilton. *OpenStreetMap: using and enhancing the free map of the world*. Cambridge: UIT Cambridge, 2011.

[8] Ogawa, Yasushi, Tetsuya Morita, and Kiyohiko Kobayashi. "A fuzzy document retrieval system using the keyword connection matrix and a learning method."*Fuzzy sets and systems* 39.2 (1991): 163-179.

[9] Baeza-Yates, Ricardo, and Berthier Ribeiro-Neto. *Modern information retrieval*. Vol. 463. New York: ACM press, 1999.

[10] Janowicz, Krzysztof, Martin Raubal, and Werner Kuhn. "The semantics of similarity in geographic information retrieval." *Journal of Spatial Information Science* 2 (2014): 29-57.

[11] Jones, Christopher B., and Ross S. Purves. *Geographical information retrieval*. Springer US, 2009.

[12] Robertson, Stephen, and Hugo Zaragoza. *The probabilistic relevance framework: BM25 and beyond*. Now Publishers Inc, 2009.

[13] Goldberg, Daniel W., John P. Wilson, and Craig A. Knoblock. "From text to geographic coordinates: the current state of geocoding." *Urisa Journal* 19.1 (2007): 33-46.

[14] Hutchinson, Matthew, and B. Veenendall. "Towards using intelligence to move from geocoding to geolocating." *Proceedings of the 7th Annual URISA GIS in Addressing Conference*. 2005.

[15] OSM Admin boundaries [Online]. http://wiki.openstreetmap.org/wiki/Key:admin_level#admin_level

[16] Zandbergen, Paul A. "A comparison of address point, parcel and street geocoding techniques." *Computers, Environment and Urban Systems* 32.3 (2008): 214-232.

[17] Hoffmann, Sarah. "OpenStreetMap. State of the map, Nominatim behind the scenes". OSM annual conference. Microsoft PowerPoint file. September 2013

[18] Saini, Balwinder, Vikram Singh, and Satish Kumar. "Information Retrieval Models and Searching Methodologies: Survey." *Information Retrieval* 1.2 (2014).

[19] Salton, Gerard, Edward A. Fox, and Harry Wu. "Extended Boolean information retrieval." *Communications of the ACM* 26.11 (1983): 1022-1036.

[20] Aizawa, Akiko. "An information-theoretic perspective of tf–idf measures."*Information Processing & Management* 39.1 (2003): 45-65.

[21] Kukich, Karen. "Techniques for automatically correcting words in text." *ACM Computing Surveys (CSUR)* 24.4 (1992): 377-439.

[22] Zobel, Justin, and Philip Dart. "Phonetic string matching: Lessons from information retrieval." *Proceedings of the 19th annual international ACM SIGIR conference on Research and development in information retrieval*. ACM, 1996.

[23] Philips, Lawrence. "The double metaphone search algorithm." *C/C++ users journal* 18.6 (2000): 38-43.

[24] Wikipedia: List of postal codes format by country [Online]. http://en.wikipedia.org/wiki/List_of_postal_codes

[25] OpenStreetMap wiki: address format [Online]. http://wiki.openstreetmap.org/wiki/Addresses

[26] Goldberg, Daniel W. "Advances in geocoding research and practice."*Transactions in GIS* 15.6 (2011): 727-733.

[27] Jin, Liang, and Chen Li. "Selectivity estimation for fuzzy string predicates in large data sets." *Proceedings of the 31st international conference on Very large data bases*. VLDB Endowment, 2005.

[28] Ji, Shengyue, et al. "Efficient interactive fuzzy keyword search." *Proceedings of the 18th international conference on World wide web*. ACM, 2009.

[29] Nominatim geocoder wiki [Online]. http://wiki.openstreetmap.org/wiki/Nominatim

[30] Levenshtein, Vladimir I. "Binary codes capable of correcting deletions, insertions and reversals." *Soviet physics doklady*. Vol. 10. 1966.

[31] Salton, Gerard, and Christopher Buckley. "Term-weighting approaches in automatic text retrieval." *Information processing & management* 24.5 (1988): 513-523.

[32] Faloutsos, Christos, and Douglas W. Oard. "A survey of information retrieval and filtering methods." (1998).

[33] Salton, Gerard, Anita Wong, and Chung-Shu Yang. "A vector space model for automatic indexing." *Communications of the ACM* 18.11 (1975): 613-620.

[34] OpenStreetMap wiki: map features [Online]. http://wiki.openstreetmap.org/wiki/Map_Features

[35] Elasticsearch [Online]. http://www.elasticsearch.org/

[36] Apache Lucene [Online]. http://lucene.apache.org/

[37] Hibernate [Online]. http://hibernate.org/

[38] ISO 639 [Online].
http://www.iso.org/iso/home/standards/language_codes.htm

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# List of Acronyms

| | |
|---|---|
| API | Application programming interface |
| BM | Boolean model |
| DAO | Data access object |
| Df | Document frequency |
| DSL | Domain specific language |
| ES | Elasticsearch |
| GIR | Geographical Information retrieval |
| GIS | Geospatial information system |
| HTTP | Hypertext transfer protocol |
| Idf | Inverse document frequency |
| IR | Information retrieval |
| ISO | International Organization for Standardization |
| JSON | JavaScript object notation |
| OSM | OpenStreetMap |
| Tf | Term frequency |
| URL | Uniform resource locator |
| VSP | Vector space model |
| XML | Extended markup language |

# Appendix 1

## A.1 Glossary

Boolean retrieval model
The Boolean retrieval model is a model for information retrieval in which we can pose any query which is in the form of a Boolean expression of terms, that is, in which terms are combined with the operators AND, OR, and NOT. The model views each document as just a set of words [1]

Collection or Corpus
The group of documents over which we perform retrieval [1]

Dictionary/Vocabulary/Lexicon
The set of indexed terms [1]

Document
Any piece of information the information retrieval system is built over [1]

Document frequency
Measure related to a term which says the number of documents which contain that term [1]

Geocoding
Geocoding is the process of converting postal address data into geographic coordinates, i.e. latitude and longitude pairs [3] .The software performing the geocoding process is called a geocoder, which can be divided into four components: input, output, processing algorithm, and reference database [4]

Index
Data structure containing mapping of terms to documents, whose purpose is to avoid linearly scanning documents for each retrieval operation [1]

Information need
Information need is the topic about which the user desires to know more [1]

Information retrieval
Information retrieval (IR) is finding material (usually documents) of an unstructured nature (usually text) that satisfies an information need from within large collections (usually stored on computers) [1]

Posting
An item in the posting list which records that a term appeared in a document [1]. In the simplest case, a posting is a pair of the form (term, doc Id)

Precision
Precision is the fraction of retrieved documents that are relevant to a user query

Online geocoding
An online geocoding service is a network-accessible component, sometimes a module of a GIS, which automatically performs the geocoding process. It is usually available on the Internet by utilizing a Web service interface. The data entry, such as a place name, street address, or zip code, is passed over the Internet using a communication protocol to the geocoding service [4]

Query
The information the user conveys to the computer in an attempt to communicate with it [1]. It can also be defined as a formal statement of the user information need.

Recall
Recall is the fraction of relevant documents that are retrieved [1]

Relevant document
A document is relevant if it is one that the user perceives as containing information of value with respect to their personal information need [1]

Retrieval
It is the activity of finding and providing documents from within the collection that are relevant to a user information need [1]

Term frequency
The number of times a term appeared in a document [1]

Term
The indexed units [1], if documents are of text nature, they can be sentences, words, or any other char chain resulting from processing the document (one possible document processing activity is tokenization).

Token
A token is an instance of a sequence of characters in some particular document that are grouped together as a useful semantic unit for processing [1]

Tokenization
Given a document (text document), tokenization is the task of splitting the document into pieces, called tokens [1]

Vector space model
Information retrieval model in which documents and queries are represented as vectors, and each dimension of the vector corresponds to a term in the vocabulary [2]

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