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Image retrieval enhancement using Generalization

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To my mother , my father, my brothers, my sisters; thank you for believing in me.

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To my dear mother and my brother and my sister To all family members one by one To everyone , also To all my friends and loved ones . I dedicate this work and we ask God for success.[Zoulikha]

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Abstract

In the last few years ,there is an increase of multimedia data especially digital images. The searching or the retrievinga relevant image from ahuge dataset is a challenging research problem.In order to improve the performance of image retrievalsystems, in this thesis we propose an algorithm based on generalization, to retrieving a relevant image of the query. In our search engine the query is made up of a set of concepts .We adopted the Bayesian generalization (BG) modelto generalize the concepts queries and then extract the relevant concepts using the ontology.Our experimental evaluation of the system is based on relevant images. From the experimental results, we found out that our system outperforms other conventional systems.

Keywords: Image Retrieval,Generalization, Bayesian models of generalization,ontology.

Resumé

Au cours des dernières années, il y a eu une augmentation des données multimédias, en particulier des images numériques. La recherche ou la récupération des images pertinente à partir un largebase de données est un problème de recherche difficile. Afin d'améliorer les performances des systèmes de récupération d'images, dans cette thèse, nous proposons un algorithme basée sur la généralisation, pour récupérer des images pertinente de la requête. Dans notre moteur de recherche, la requête est constituée un ensemble de concepts. Nous avons adopté le modèle de bayésienne généralisation (BG) pour généraliser les concepts de requête, puis extraire les concepts c aché à l'aide de l'ontologie. Notre évaluation expérimentale du système est basée sur des images pertinentes. À partir des résultats expérimentaux, nous avons découvert que notre système surpasse les autres systèmes conventionnels.

Mots-clés : Recherche d'images, Généralisation, Modèles bayésiens de généralisation, Ontologie.

الملخص

في السنوات القليلة الماضية ، هناك زيادة في بيانات الوسائط المتعددة وخاصة الصور الرقمية. يعد البحث أو استرداد الصورة ذات الصلة من مجموعة البيانات الضخمة مشكلة بحثية صعبة ، ومن أجل تحسين أداء أنظمة استرجاع الصور ، نقدم في هذه المذكرة خوارمزية تعتمد على تعميم المفاهيم ، لاسترجاع صورة ذات صلة بالاستعلام. يتكون الاستعلام من مجموعة من المفاهيم ، وقد اعتمدنا نموذج لتعميم استفسارات المفاهيم ثم استخراج المفاهيم ذات الصلة باستخدام الأنطولوجيا (BG) التعميم البايزي ، ويستند تقييمنا التجريبي للنظام إلى الصور ذات الصلة. من النتائج التجريبية ، اكتشفنا أن نظامنا يتفوق على الأنظمة التقليدية الأخرى.

الكلمات المفتاحية : استرجاع الصور ، التعميم ، نماذج بايزي للتعميم ، الأنطولوجيا

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General Introduction

General Introduction

Introduction

The world around us is changing and developing at a terrible speed, the technology train is racing against time, every little while there is something new in science, the technology itself is constantly evolving, as soon as we hear about a new machine or device and due to the large number of social media (facebook,instagram ...) and other sites, seekers imageswant to know what's new in the world.

Image retrieval IR has become a very important and problematic activity in a user's life in recent years due to its potentially significant impact on both image understanding and web image search. The conventional methods of image retrieval are suffering to understanding the user intention, either by retrieving insufficient results or by retrieving results that are not related to the user's needs. In his thesis, we aim to solve the problem of image retrieval within the framework of knowledge of concepts. Taking into account those complex and unrestricted queries.

Our goal through this study in the context of shedding light on the retrieval of images from a large data based on the content of a target images, and we supported this study by applying within the environment of the “visual studio” C-Sharp (C#) program .so that we discuss in this topic the solutions that we provide to the user.

Problematic

When we have a set positive concepts in the query, in order to raw this query and get the appropriate results ,we have to answering these questions:

1-How to understand user intention?.

2-How to generalize these positive concepts?.

3-How do you find the relationship between the concepts?.

4-How do we get the hidden concepts?.

Proposed Solution

To design a reliable system for tracking the characteristic of generalization algorithm, it will be necessary to address the above four points.

We propose an algorithm based on generalization, to retrieving a relevant image of the query. We adopted the Bayesian generalization (BG) modelto generalize the concepts queries and then extract the relevant concepts (hiddenconcepts) using the ontology.

Organization of This Thesis

Continue of the thesis is organized as follows:

In the first chapter, we have focused our attention on the previous work in image retrieval, followed by information on content-based image retrieval (CBIR), text-based image retrieval (TBIR), Ontology-based image retrieval similarity, and finally query formulation in image retrieval.

In the second chapter, we will discuss to explain some of the concepts that must be recognized, because the generalization is supported by an abundance of possibilities that help in refuting false generalizations and obtaining the concepts we want to search for.

Then, in chapter three we will present our results and compare them in another way.

Finally, we suggest future work.

CHAPTER I

LITERATURE REVIEW

I.1.Introduction

A computer system for exploring, searching, and retrieving images from a database of digital images is known as an image retrieval system.

In this chapter, we provide an overview of related work, beginning with a brief introduction to image retrieval, followed by information on content based image retrieval (CBIR), text-based image retrieval(TBIR), Ontology-based image retrieval ,and finally query formulation in image retreival. Furthermore, we show the many available strategies for visual idea learning.

I.2. Image Retrieval

With the remarkable growth in the popularity of social media websites, there have been a proliferation of digital images on the internet, which have posed a great challenge for large-scale image search. Different criterias have been applied for image retrieval.

Image indexing and retrieval is very important research topic that has gained more attention in the current scenario. So in the present situation content based image retrieval is becoming necessary for exact and fast image retrieval.[1]

These features have been used till now for the image retrieval from the existing search engine. A user formulating a query usually has in mind just one topic, while the results produced to satisfy this query may belong to different topics. Therefore only parts of the search results are relevant for a user. Most image retrieval methods can be classified into two categories: content based image retrieval (CBIR) and keyword/tag based image retrieval (TBIR).

CBIR takes an image as a query, and identifies the matched images based on the visual similarity between the query image and gallery images. Various visual features, including both global features (e.g., color, texture, and shape) and local features (e.g., SIFT keypoints), have been studied for CBIR. Despite the significant efforts, the performance of available CBIR systems is usually limited, due to the semantic gap between the low-level visual features used to represent images and the high level semantic meaning behind images.[5]

To overcome the limitations of CBIR, TBIR represents the visual content of images by manually assigned keywords/tags. It allows a user to present his information need as a textual query, and find the relevant images based on the match between the textual query and the manual annotations of images. Compare to CBIR, TBIR is usually more accurate in identifying relevant images by alleviating the challenge arising from the semantic gap. TBIR is also more efficient in retrieving relevant images than CBIR because it can be formulated as a document retrieval.

I.2.1.Text based image Retrieval (TBIR)

TBIR store text in the form of keywords together with the image. Some TBIR uses Surrounding text of the image to search the keywords which are physically close to the image. This technique relies on the assumption that the surrounding text describes the image.[2]

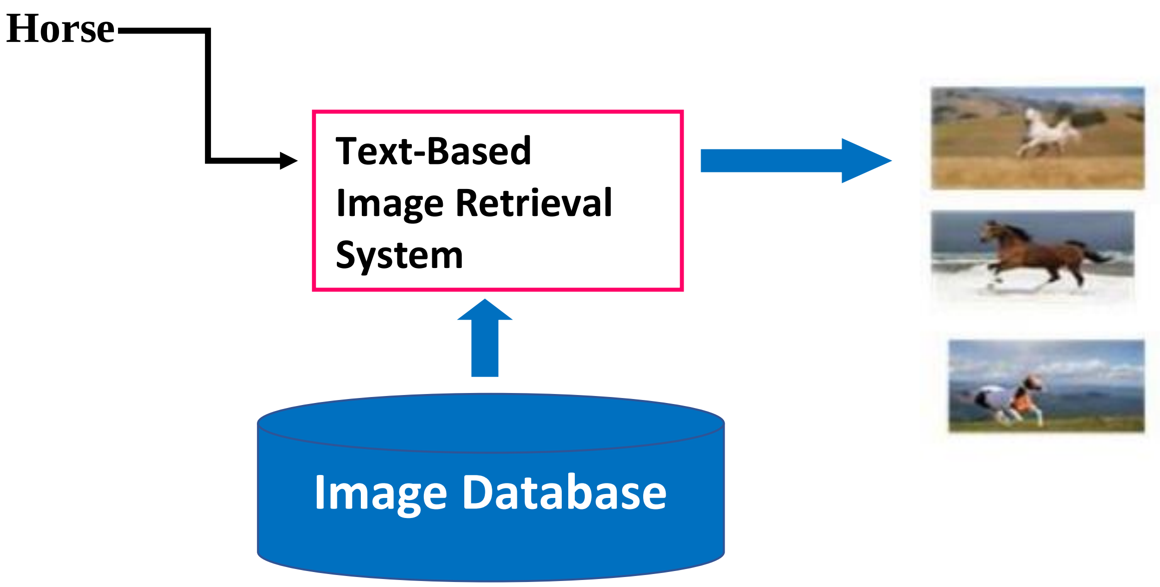


Figure I.1: Text based Image retrieval.

I.2.1.1. Advantages of TBIR

- Easy to construct queries. There is no need of drawing, example image or other advanced tools of constructing queries.
- Image retrieval is fast.
- String Matching is a relatively resource – friendly taskdvantages of TBIR.

I.2.1.2. Disadvantages of TBIR

- A relevant image might be left out due to lack of specific keyword in the query.
- It may return irrelevant results when there is no relevant text surrounding the picture.
- Image annotation is very time consuming process and it is often manual.
- Retrieval depends on the image annotator and retriever sharing some common vocabulary or language.
- Use of synonyms would result in missed result
- Single word can mean radically different things.
- If the Query string is misspelled there are no results returned.[10]

1.2.2.Content Based Image Search (CBIR)

CBIR system makes direct use of content of the image rather than relying on the human annotation of metadata with the keywords. Current CBIR make use of low level features like shapes, color and texture to retrieve desired images from database. To have efficient image retrieval, tools like pattern recognition and statistics are well used Different implementation of CBIR make use of different types of queries.[4]

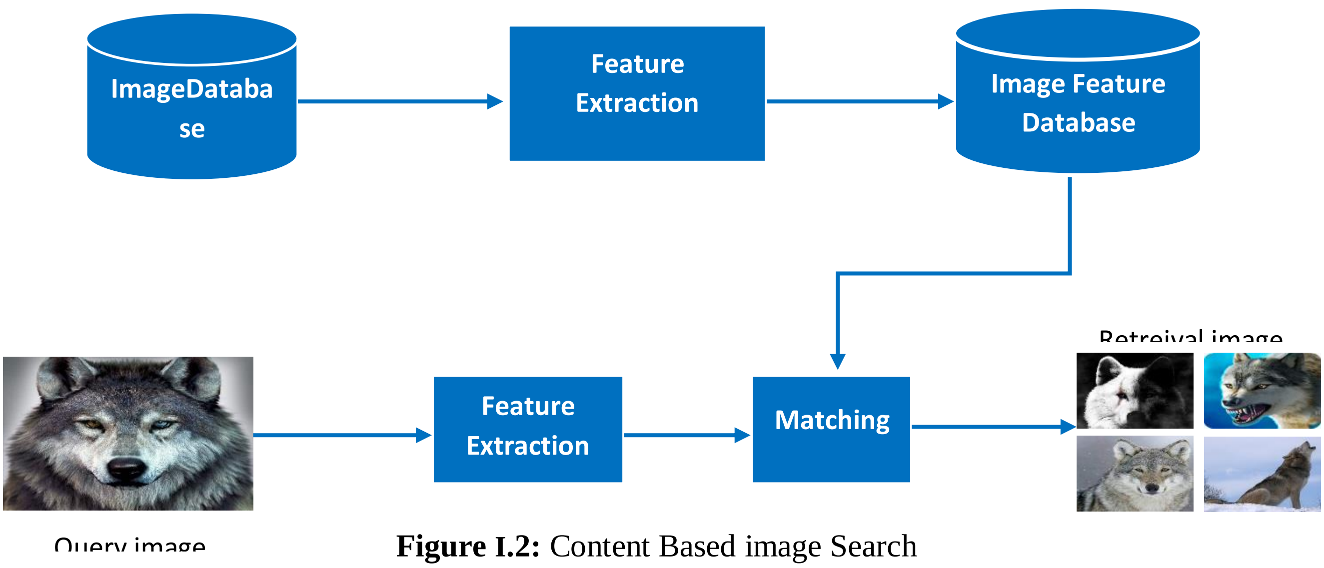


Figure I.2: Content Based image Search

I.2.2.1. Advantages of CBIR

This technique removes the difficulty that can arise upon trying to describe images with words.It does not depend upon image size or orientation for searching CBIR returns irrelevant result.[15]

I.2.2.2. Disadvantages of CBIR

- Indexing of large image repositories is time and resource consuming .A major limitation of CBIR system is that they are limited to relatively small databases.
- It is not possible to search for the semantic of the images.
- Tools to construct query image may be complicated to use.
- Due to semantic gap between low level features and high level features of the image Sometimes CBIR returns irrelevant result.

I. 3.Query formulation in image retreival

User in Image retrieval have the ability to express his/her needs by forming the query. the query can be as text we called it Query by text QBT or by image example,we called it Query by visual example QBCE. And finaly by image but the search is performed using the text attached to this image which we called Query by semantic example QBSE.We will present details of each type:

I.3.1. Query by text QBT

Allied image retrieval techniques are based on visual attributes but also rely on image text annotations which were primitive human work done manually for each image in the image database with some related text.

The image search engine will search those annotations from traditional database systems and then retrieve the corresponding images. The system searches for the annotated images with the same keywords in the query, these techniques are also called QBT because in this technique the query is presented in the form of text or keyword and the target is images.

As shown in Figure I.3 the results of the word “**FENNEC**” in Google Image.[6]

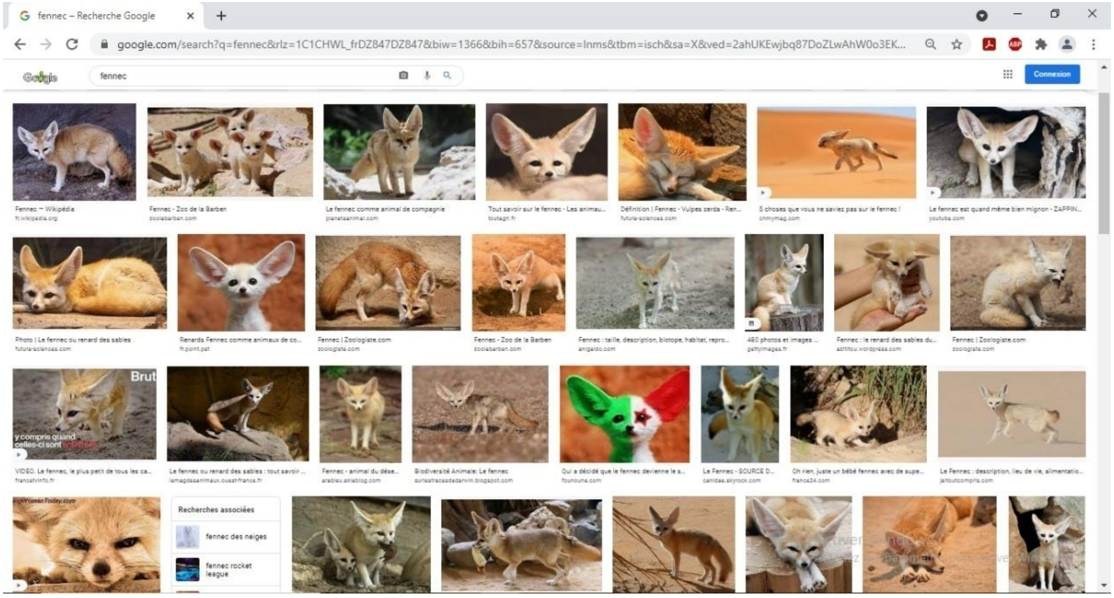


Figure I.3. The results of the Google image search for the word “FENNEC”.

I.3.1.1. Query by visual example QBVE

The basic idea of QBVE (Query by Visual Example) is retrieving images from imagedatabases using a rough sketch input as a query. Abstract images are used as pictorialindices. The images are acquired by resizing RGB images to 64x64 pixels, finding outglobal and local edge images, and thinning and shrinking the local edge images. To retrievean image, the system computes the correlation of the linear sketch provided by users andthe abstract images. The image with the highest correlation score is the best imagecandidate. The ART MUSIUM database, which is a collection of 205 paintings of fullcolour landscapes and portraits, is employed in the testing of the algorithm. The resultshows that for sketch retrieval, the possibility of retrieving the original full colour paintingwithin the best five candidates is more than 94.4% from 205 paintings. For monochromecopy retrieval, the exact image can be found from 205 paintings. In addition, similarityretrieval is efficient to find paintings with similar compositions. The experiment relies onthe painting of full colour landscapes and portraits that almost consist of line structures.The system transforms all images into edge images (abstract images), so the colourfeatures of images have been ignored. Furthermore, the features used in the ARTMUSEUM project are not invariant to scale or translation.[8]

Finally, incremental image recalland partial image recall are not available. For a medical application, a content-based indexing technique, which relates spatialrelationships among internal image entities, has been proposed .To build up an index,the algorithm extracts image "features" that describe the relative relationships amongobjects in the image in terms of distance and angle. The relationships use center of mass(COM) as a frame of reference.

A query image Q is processed in the same manner. Toaccess images similar to the query image Q, the system filters out the most similar imagesusing a so called causal based similarity tree. The information causal net (ICN) is thenformed between the best candidate images rather than all collection of images and the queryimage. ICN indicates the similarity between the image, I, and the query, Q, by computingthe probability that defines the belief in satisfying Q by giving image I . The most similarimage with respect to Q is the one with greatest probability. This research is specific toretrieve images with the same spafial relationships. It is not generic for other applications.In addition, effects of affine transformation in a given query are not considered.

As shown in Figure I.4 the results of the word "**Horse**" in Google Image.[6]

Image example

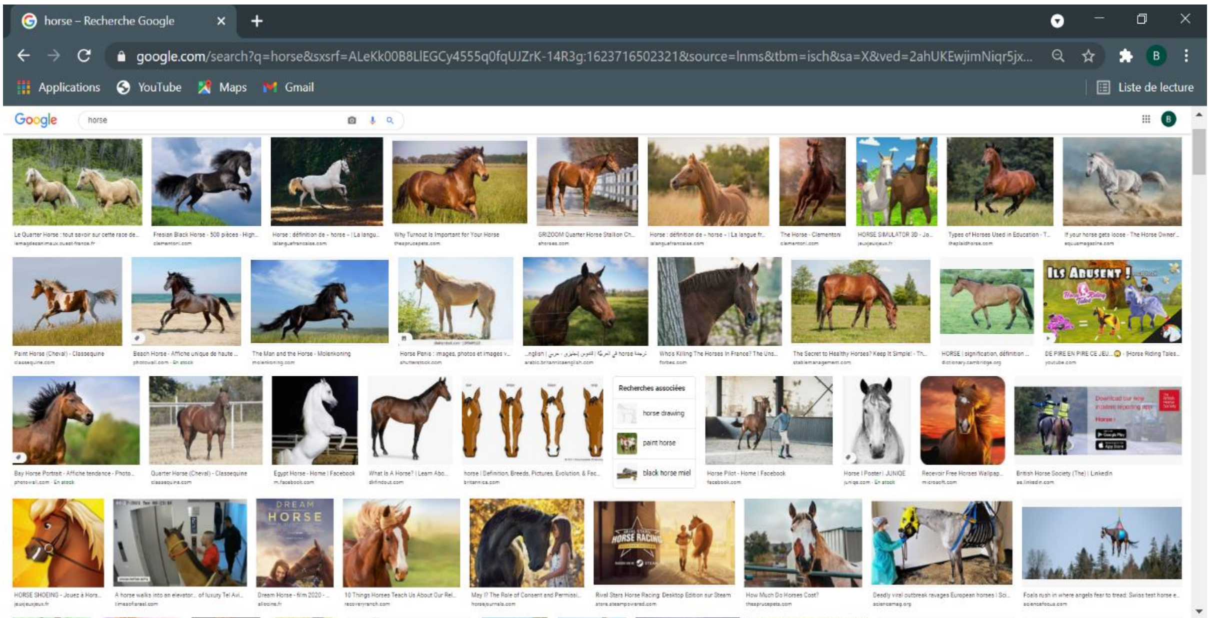


Figure I.4 . The results of the Google image search for the image of "Horse".

I. 3.1.2. Query by semantic example QBSE

The starting point for the design of a QBSE retrieval system is the combination of an image database I = {I_1,..., I_D} and a vocabulary L = {w_1,...,w_L} of semantic labels or keywords wi. All database images are annotated with a caption composed of words from L, i.e the caption ci that (in the judgment of a human labeler) best describes image Ii is available for all i. Note that ci is a binary L-dimensional vector such that ($c_{i,j}$= 1) if the i th image was annotated with the jth keyword in L. The training set D = {(I_1, c_1),...,(I_D, c_D)} of image-caption pairs is said to be weakly labeled if the absence of a keyword from caption ci does not necessarily mean that the associated concept is not present in Ii. This is usually the case in practical scenarios, since each image is likely to be annotated with a small caption that only identifies the semantics deemed as most relevant to the labeler. We assume weak labeling in the remainder of this work. The design of a QBSE retrieval systems requires two main components. The first is a semantic image labeling system that, given a novel image I, produces a vector of posterior probabilities $\pi = (\pi_1,...,\pi_L)^T$ for the concepts in L. This can be seen as a feature transformation, from the space of image measurements X to the L-dimensional probability simplex SL, i.e. a mapping Π : X→SL such that $\Pi(I) = \pi$. Each image can, therefore, be seen as a point π in SL, i.e. the probability distribution of a multinomial random variable defined on the space of semantic concepts. We will refer to this representation as the semantic multinomial (SMN) that characterizes the image. The second component is a query-by-example function on SL. This is a function that, given the SMN that characterizes a query image, returns the most similar SMN among those derived from all database images, i.e. f : SL → {1,...,D} such that(π) = arg maxi s(π, π_i) where π is the query SMN, π_i the SMN that characterizes the i th database image, and s(·, ·) an appropriate similarity function. Given that SMNs are probability distributions, a natural similarity function is the Kullback-Leibler divergence. [11]

We will explain this in this table **I.**1. [9]

table I.1. Query by semantic example QBSE, it can be more than one example.

Query	example	Raw query
	**One semantic examples**	**Flower**
  	**Several semantic examples**	**Kiwi, Orange , Mango**

I.5.Conclusion

In this chapter, we have focused our attention on the previous work in image retrieval, followed by information on content-based image retrieval (CBIR), text-based image retrieval (TBIR), Ontology-based image retrieval similarity, and finally query formulation in image retrieval.

In the next chapter, we will present Bayes' theorem.Then we will explane some basic knowledge about the Bayesian Generalization Framework, we have given details about each of these approaches. In addition, we have put the light in the computing the posterior probability of each the hypothesis.

CHAPTER II

THE BAYESIAN GENERALIZATION AND IMAGE RETRIEVAL

I.1 Introduction

The goal of this chapter is to provide an overview of Bayesian generalization modeles.First , we will present some difinition of the generalization, then we will give the ditals about the postrior probability wich we will use to findind the apropriate generalization of the query in image retrieval.Finaly ,we will present somme difinition of terms used in tree data structures (ontology); then we will finch this section by a conclusion.

II .2 **Generalization**

Generalization, which is an act of reasoning that involves drawing broad inferences from Particular observations, is widely-acknowledged as a quality standard in quantitative research, but is more controversial in qualitative research.
The goal of most qualitative studies is not to generalize but rather to provide a rich, contextualized understanding of some aspect of human experience through the intensive study of particular cases. Yet, in an environment where evidence for improving practice is held in high esteem, generalization in relation to knowledge claims merits careful attention by both qualitative and quantitative researchers. [3]

Definitions of generalization have evolved from conceptions of transfer. In particular, the next section of this chapter demonstrates how definitions of the act of transfer have shaped definitions of the activity of generalizing. The following two sections describe specifically how constructivist learning perspectives have influenced definitions of mathematical generalization. Furthermore, in the fourth section, the activity of generalizing is explained in the context of algebra as a way to support early algebra learning. Lastly, the fifth section offers example tasks as one practical way for mathematics educators to promote generalizing in their classrooms. [7]

Given these priors and likelihoods, the posterior p(h|X) follows directly from Bayes' rule.
Finally, the learner must use p(h|X) to decide how to generalize the word C to new, unlabeled objects. p(y ∈ C|X), the probability that some new object y belongs to the extension of C given the observations X, can be computed by averaging the predictions of all hypotheses weighted by their posterior probability p(h|X):[9]

$$P(y \in C|X) = \sum_{h \in H} p(y \in C|X)\, p(h/X) \qquad (1)$$

To evaluate Equation (1), note that p(y ∈ C|h) is simply 1 if y ∈ h, and 0 otherwise.

II.3 The Bayesian Generalization Framework

In our algorithm we use the Bayesian framework for concept learning and generalization introduced by Tenenbaum and his colleagues. This framework aims to explain inductive learning at the level of computational theory or rational analysis to understand in functional terms how implicit knowledge and inferential machinery guide people in generalizing from examples rather than to describe precisely the psychological processes involved.[14]

A branch of statistics, Bayesian inference is a type of inference that uses the Bayes' rule to develop an assessment of the probabilities of a hypothesis due to the discovery of new evidence. Bayesian development is an important technique in statistics, especially in mathematical statistics: the introduction of Bayesian inference to a statistical method confirms that this method is as effective as any other competing method in some cases. Bayesian development is especially important in dynamic data-sequencing analysis.

Bayesian reasoning has many applications in different fields, including: science, engineering, medicine, and also law.

Bayesian inference is directly related to debates about subjective probability, which is often called 'Bayesian probability. Bayesian probability provides a good approach in applying its properties to image retrieval. It is more feasible by applying the previous probability.

Bayes' inference based on this is conditional so that it is compatible with the application of probabilities because it provides a good approach to image retrieval, this generalization allows one to calculate the subsequent probability by looking at the hypothesis space.

II.3.1 Bayes' rule

Bayes' rule is an equation (2) from (probability theory). The various terms in bayes' rule are all probabilities, but notice that there are conditional probabilities in there. For example, the left hand side of the equation is P(A|B) and that means the probability of A given B. That is, it's the probability of A after taking into account the information B.

In other words, P(A|B) is a posterior probability, and Bayes' rule tells us how to calculate it from other probabilities. Bayes' rule is true for any statements a Bayes' rule couples the posterior to the prior via the likelihood, p(A/B), the probability of observing , given that h is the true consequential region, as follows:

$$P(A \mid B) = \frac{P(A \cap B)}{P(B)} = \frac{P(A) \times P(B \mid A)}{P(B)} \tag{2}$$

In Bayesian statistics, most of the terms in Bayes' rule have special names. Some of them even have more than one name, with different scientific communities preferring different terminology. Here is a list of the various terms and the names we will use for them:

• **P(A/B)** is the **posterior probability**. It describes how certain or confident we are that hypothesis **A** is true, given that we have observed data **B**. Calculating posterior probabilities is the main goal of Bayesian statistics.
• **P(A)** is the **prior probability**, which describes how sure we were that **a** was true, before we observed the data **B**.
• **P(B/A)** is **the likelihood**. If you were to assume that **A** is true, this is the probability that you would have observed data **b**.
• **P(B)** is the **marginal likelihood**. This is the probability of ***B*** occurring that you would have observed data **B**, whether **A** is true or not.[13]

II.3.2 **The Posterior probability**

Used in Bayesian inference to quantify an updated state of belief about the plausibility of a given model after observing data. Te ratio of prior model probabilities times the Bayes factor for these same models gives the ratio of posterior model probabilities.

Given the prior and likelihood, we can now compute the posterior distribution via Bayes theorem.

$$\text{Posterior} = \text{Likelihood} \times \text{Prior} \qquad (3)$$

The Bayesian learner evaluates these hypotheses by computing their posterior probabilities

p (h|X), proportional to a product of prior probabilities p(h) and likelihoods p(X|h) .

So the function of posterior equation (4)

$$P\ (h/X) = P(X/h) * P(h) \qquad (4)$$

II.3.3 The prior probability

Used in Bayesian inference to quantify a state of belief about some parameter values given a model before having observed any data. Priors are typically represented as a probability distribution over different states of belief.

The prior p(h) to be proportional to the branch length separating node h from its parent.

We have for the prior probability equation (5):

$$P\ (h) = \text{height}\ (\text{parent}\ (h)) - \text{height}\ (h) \qquad (5)$$

II.3.4 **The likelihood**

The likelihood is a quantity that will be used for calculating the posterior probabilities. In colloquial language, likelihood is synonymous with probability. It means the same thing. However, in statistics, likelihood is a very specific kind of probability.
We need to calculate two likelihoods, so you can tell from this that the likelihood is something different for each hypothesis.
We have for the likelihood equation (6) :

$$P(\mathbf{x}/\mathbf{h}) = \left[\frac{\mathbf{1}}{\boldsymbol{height}(\,\boldsymbol{h}) + \boldsymbol{\varepsilon}}\right]^{n} \qquad (6)$$

n= is the number of concepts Queries.
Where ϵ is a small constant so that the leaf hypotheses (those that refer to only a single object) do not have infinite likelihood (as their height is zero).

if xi ∈ h for all I , and 0 otherwise. (We add a small constant (∈> 0) to height (h) to keep the likelihood from going to infinity at the lowest nodes in the tree (with height 0)).The exact value of ∈ is not critical, we found best results with (∈= 0.5s).

II.3.5 **Tree Data Structures**

Tree represents the nodes connected by edges. We will discuss binary tree or binary search tree specifically. Binary Tree is a special datastructure used for data storage purposes. A binary tree has a special condition that each node can have a maximum of two children. A binary tree has the benefits of both an ordered array and a linked list as search is as quick as in a sorted array and insertion or deletion operation are as fast as in linked list.

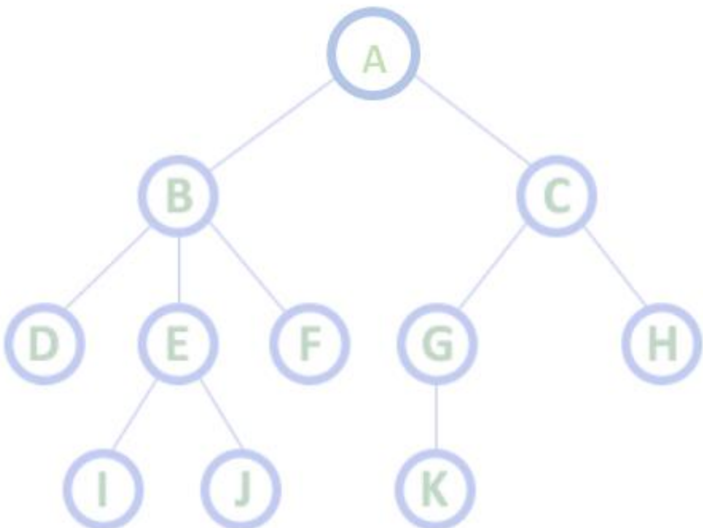


Figure **II-1**. Diagram of Tree Data Structures.

Tree with 11 nodes and 10 edges.

- In any tree with ‘N’ nodes there will be maximum of ‘N-1’ edges.
- In a tree every individual element is called as ‘NODE’.

Important Terms

Following are the important terms with respect to tree. Path − Path refers to the sequence of nodes along the edges of a tree.

•Root

The node at the top of the tree is called root. There is only one root per tree and one path from the root node to any node.

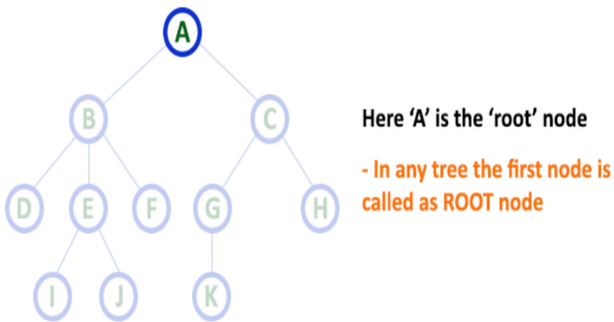


Figure **II-2**. Diagram root of a Tree Data Structures.

•Edge

In a tree data structure, the connecting link between any two nodes is called as **EDGE**. In a tree with '**N**' number of nodes there will be a maximum of '**N-1**' number of edges.

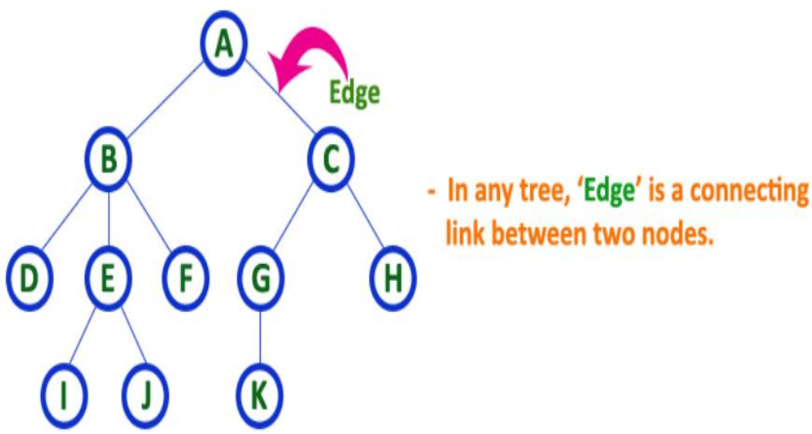


Figure **II**-3. Diagram Edge of Tree Data Structures.

•Parent

Any node except the root node has one edge upward to a node called parent.

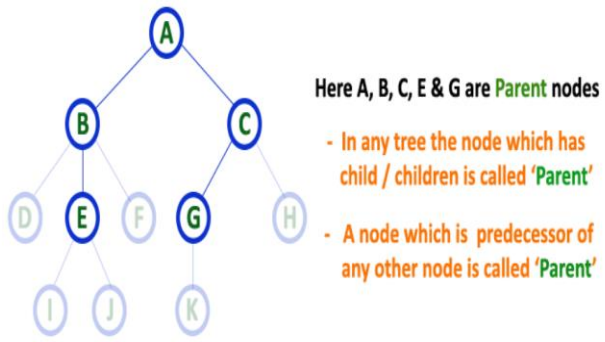


Figure **II**-4. Diagram Parent of Tree Data Structures.

•Child

The node below a given node connected by its edge downward is called its child node.

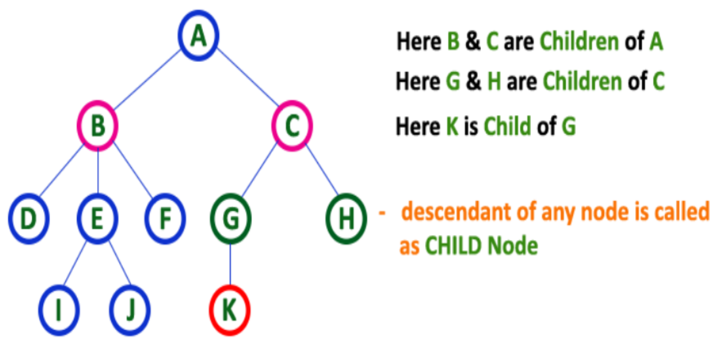
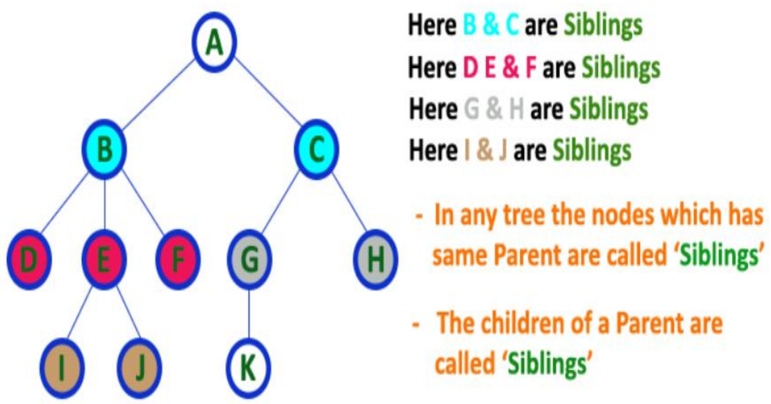


Figure **II**-5. Diagram Children of Tree Data Structures.

•Siblings

In a tree data structure, nodes which belong to same Parent are called as **SIBLINGS**. In simple words, the nodes with the same parent are called Sibling nodes.



Figure**II-6**. Diagram Siblings of Tree Data Structures.

•Height

In a tree data structure, the total number of edges from leaf node to a particular node in the longest path is called as HEIGHT of that Node. In a tree, height of the root node is said to be height of the tree. In a tree, height of all leaf nodes is '0'.

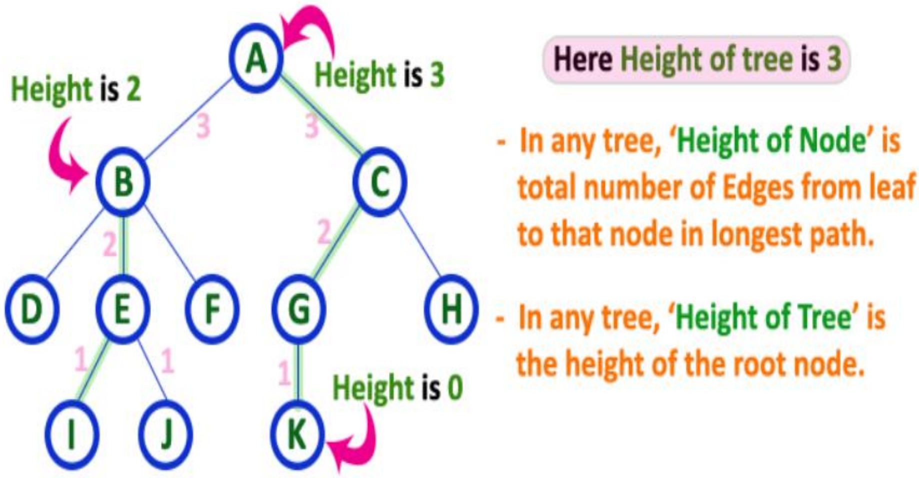


Figure **II**-7. Diagram Height of Tree Data Structures.

•Subtree

In a tree data structure, each child from a node forms a **subtree** recursively. Every child node will form a **subtree** on its parent node.

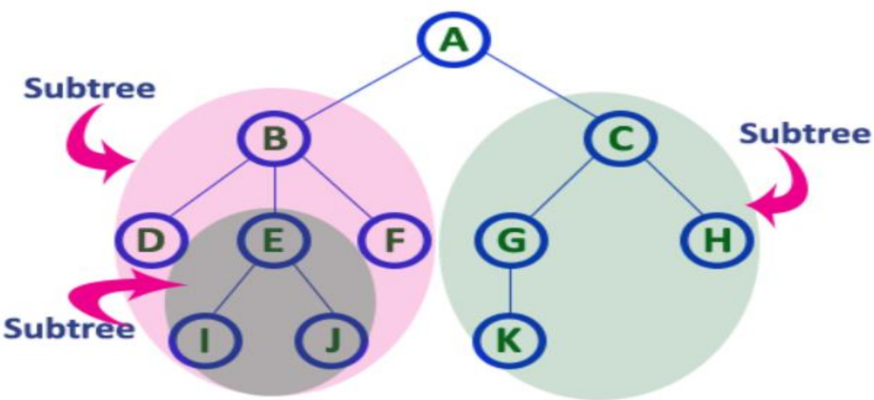


Figure **II**-8. Diagram Subtree of Tree Data Structures.

• Levels

In a tree data structure, the root node is said to be at Level 0 and the children of root node are at Level 1 and the children of the nodes which are at Level 1 will be at Level 2 and so on... In simple words, in a tree each step from top to bottom is called as a Level and the Level count starts with '0' and incremented by one at each level (Step).

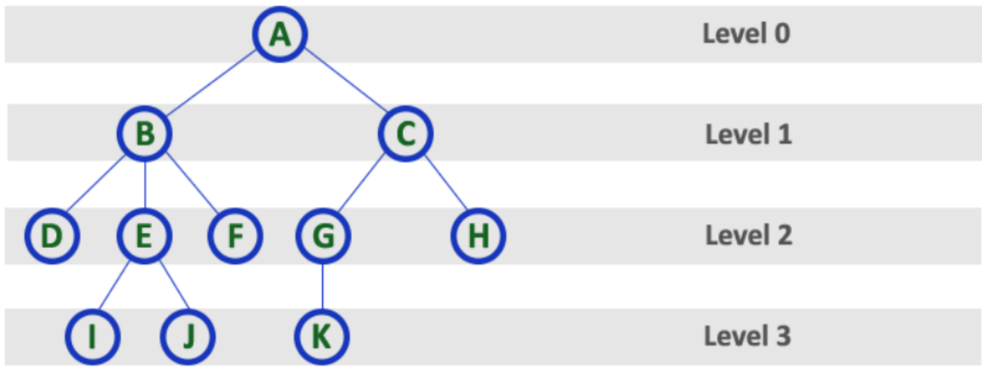


Figure **II**-9. Diagram Level of Tree Data Structures.

•Depth

In a tree data structure, the total number of egdes from root node to a particular node is called as DEPTH of that Node. In a tree, the total number of edges from root node to a leaf node in the longest path is said to be Depth of the tree. In simple words, the highest depth of any leaf node in a tree is said to be depth of that tree. In a tree, depth of the root node is '0'.

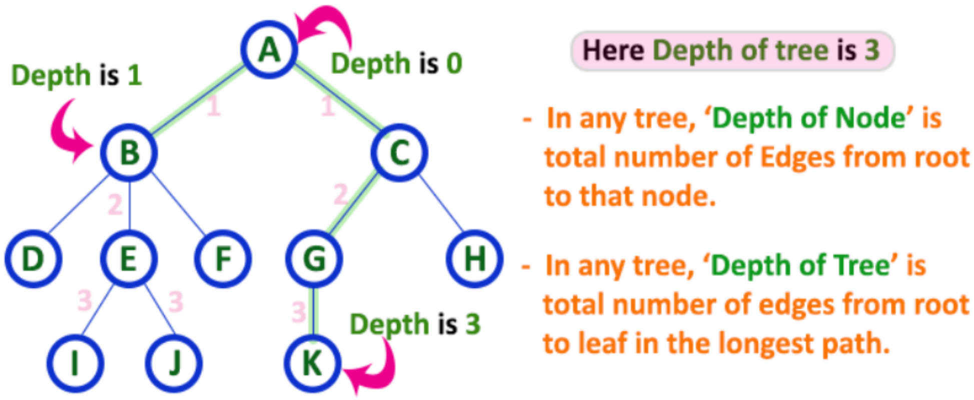


Figure **II**-10. Diagram Depht of Tree Data Structures.

•Path

In a tree data structure, the sequence of Nodes and Edges from one node to another node is called as **PATH** between that two Nodes. Length of a Path is total number of nodes in that path. In below example the path A - B - E - J has length 4.

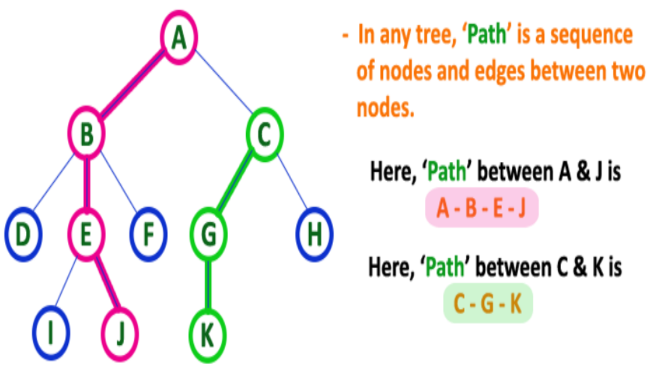


Figure **II**-11. Diagram Path of Tree Data Structures.

• **Leaf**

The node which does not have any child node is called the leaf node.

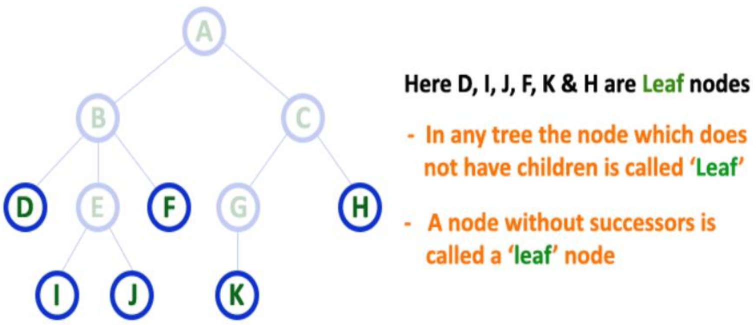


Figure **II**-12. Diagram Leaf of Tree Data Structures.

• **Internal Nodes**

In a tree data structure, the node which has atleast one child is called as **INTERNAL Node**. In simple words, an internal node is a node with atleast one child.

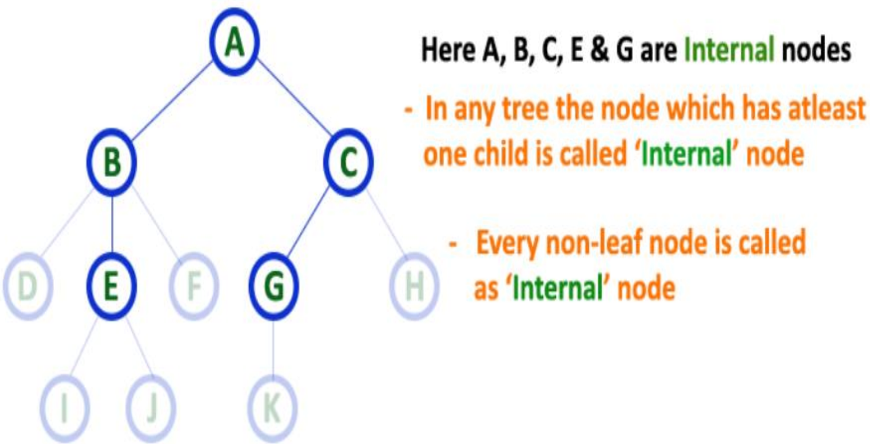


Figure **II**- 13. Diagram Internal nodes of Tree Data Structures.

II.4 Hypothesis space

The likelihood function comes from assuming that the observed positive examples are sampled at random (and independently) from the true concept to be learned.

Imagine that each hypothesis consisted of a finite set of K objects. Then the likelihood of picking any one object at random from a set of size K would be 1/K, and for n objects (sampled with replacement), 1/Kn. Hence set size is crucial for defining likelihood. While we do not have access to the "true" size of the set of all dogs in the world, or all vegetables, we do have access to a psychologically plausible proxy, in the average with incluster . Moving up in the tree, the average dissimilarity with in clusters increases as they become larger. thus equating node height with approximate cluster size.

Through our previous example, we concluded that these are the optimal possibilities for obtaining The correct data that is close to our search for the image to be searched for, and therefore, the likelihood probability p(h/x) is the one who gives us the appropriate values for the search engine. We have noticed that the further away from Root, the lower the percentage of H and vice versa.

II.5 Conclusion

In this chapter, we introduced the Bayesian generalization technique to improve the results of image retrival according to the learning concepts.The generalization based on Bayes’ rule is the basis for building intelligent algorithms by applying them in image retrieval.

In the next chapter, we will present an experimental study about the perfermence of our algorethm, and in order to evaluate our algorithm we will compare the results with the conventional algorithm.

Chapter III

Results and Discussion

III.1 Introduction

In this chapter we will see our algorethm on selecting the best generalization ,In order to know the good algorithm in image retrieval, we present the data set by translating it between tour algorithm and the conventional algorithm in image retrieval.

To evaluate our Results, several tests (Queries) have been performed , then

III.2 Experimental setup

III.2.1 Dataset

Our system's dataset contains 320 images that we extracted from the Google web site, and it also contains 54 concepts.

As shown in the figure III.1.

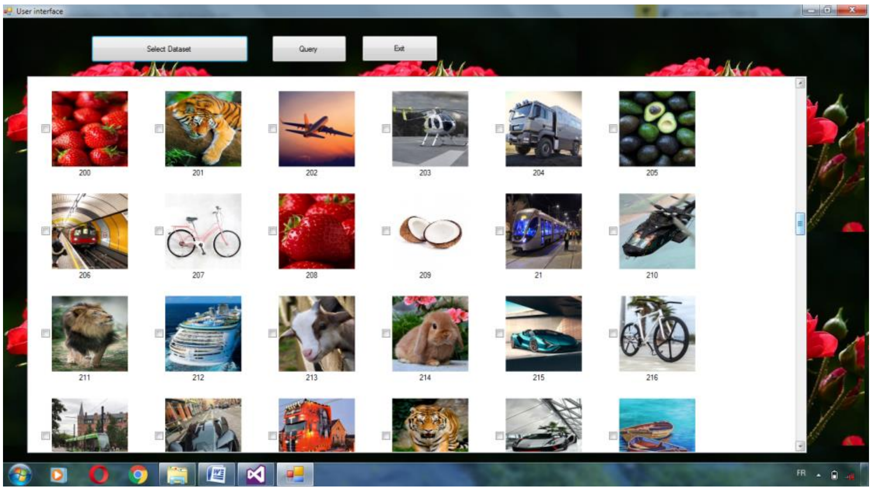


Figure III.1 . Our database.

III.2.2 Scenario of Experiments

We must implement an image retrieval system that integrates our own algorithm. we interviewed 20 users to participate in our experiments. We showed them a group from randomly selected images from the image dataset.

To evaluate the performance of our algorithm, we made a comparison between: our algorithm, and in theconventional algorithm. As performance criteria, we compute the relevant images retrieved by our algorithm.

III.2.3.Generalization the query in our algorithm

This process is depicted in **Figure 2**.

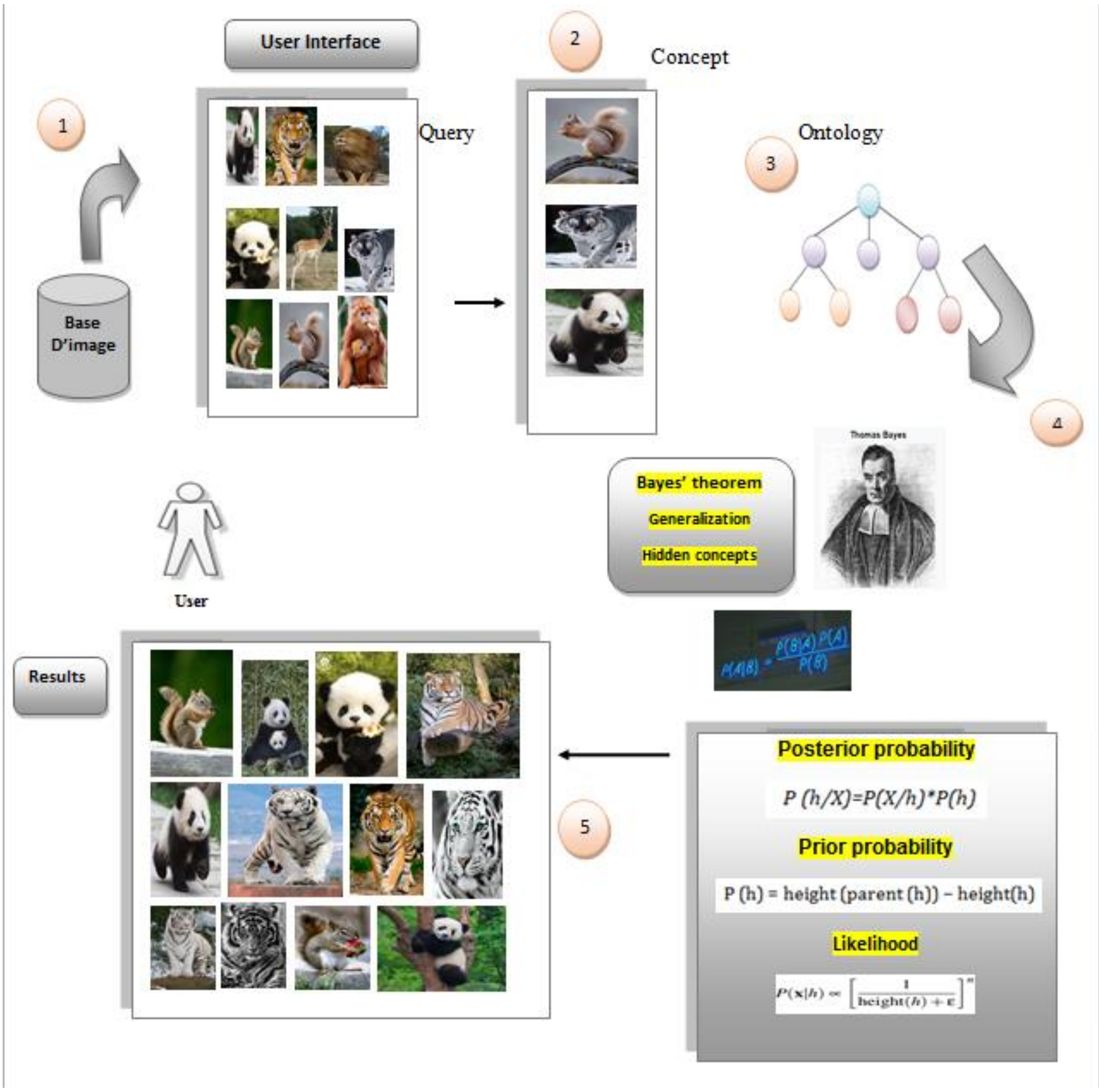


Figure III-2. General architecture of our algorithm.

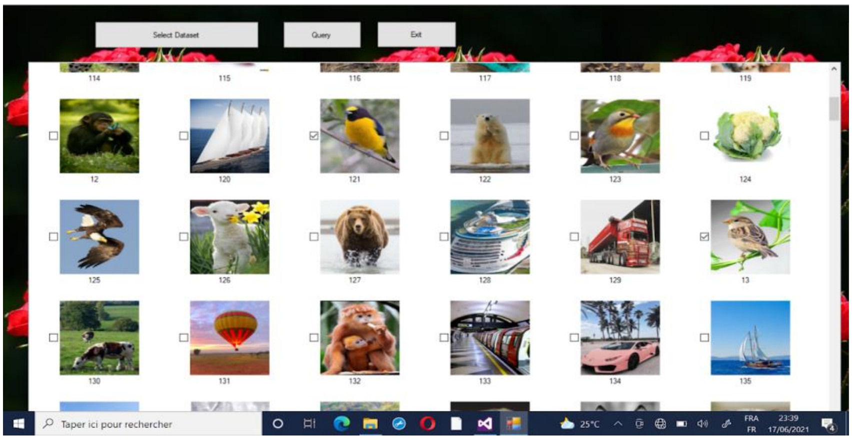
There are six main steps to generalize the query which are described as follows:

III.3 Explain the steps

1_ Input images

The user chooses from our system from the query interface few the images, for example (2-5 images). Each image expresses only one concept that represents its requirements for formulating the query.

As shown in the figure 3.



Figuer III.3. The Query chosen by the user.

2_ Concepts of images

In the data set, each image represents a concept. It is called a set of concepts 'query' and the refore each user formulates his query and our system has to do the search.

As shown in Figure 4.

Canary Sparro

Figuer III.4. The Concepts of images by the user.

3_Ontology Hypothesis space (Relationships)

After identifying the concepts, our system begins by discovering and defining the interrelationships between two concepts or a set of concepts. All relationships in all types of hierarchy of concepts are called hypothesis space.

4_Finding the appropriate relationship (h_{MAP})

The relation between Query and hypothesis space we compute the posterior probability of each hi than we chose the hypothesis wish have the max a posterior .

5_ Hidden concepts

Hidden concepts are the concepts that are linked with concepts query by the appropriate relationships selected in the concept hierarchy.

6_ Results

All images annotated with concept query and hidden concep,t as shwen in figure5.

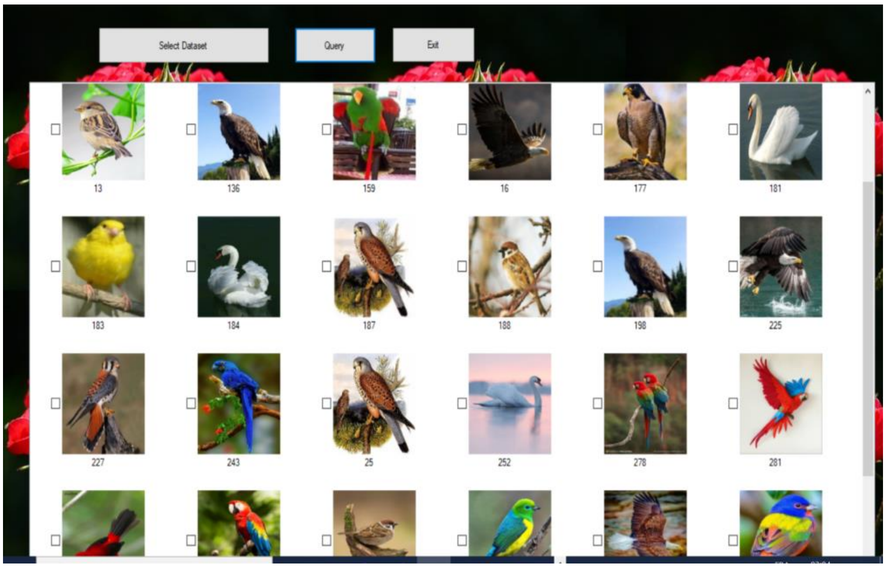


Figure III-5. Results Illustration of the Query 1.

Annex A shows an exmple of generalization quey in our alghorthm.

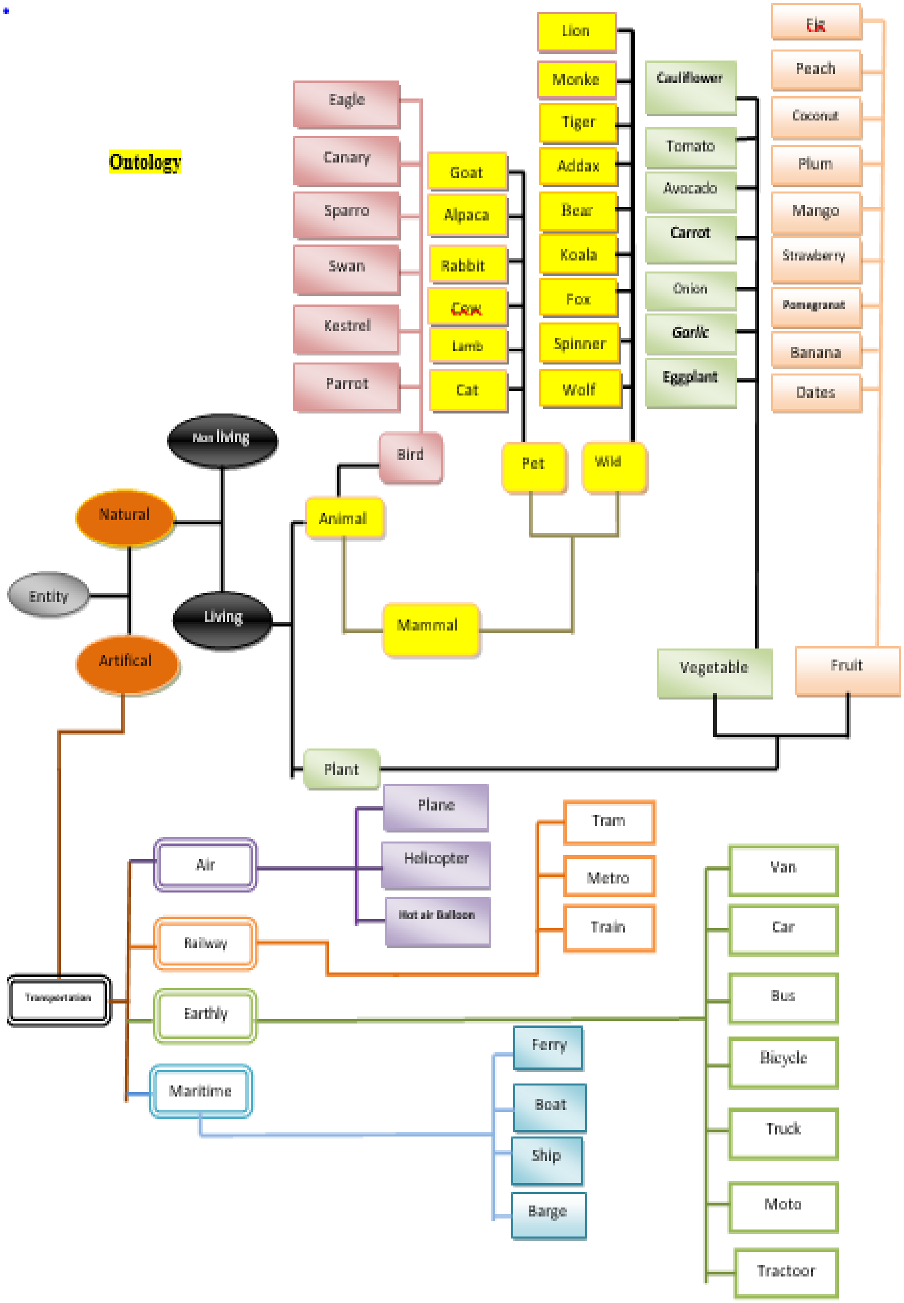


Figure III-6. Ontology.

III.3.1 Our Algorithm (Generalization of query):

The steps of our generalization of the query are summarized in the following Algorithm :

Begin
1: INPUT: $X = \{x_1, x_2, \ldots x_n\}$
2: Compute posterior probability $P(h|X)$ of all hypotheses h in ontology according to a function the posterior :

$$P(h/X)=P(X/h)*P(h)$$

3: Find the Max a posteriori h_{MAP} .
4: Find Hidden Ci .
5: OUTPUT: Result of images Ii annotated by all leaf nodes under the concept C.
End

III.4 Results

The following table (1) shows the results we obtained,of 20 queries. we compute the relevant images retrievedin our algorithm and in the conventional algorithm **[TBIR]** .

Table III 1: Relevant images retrievedin our algorithm and in the conventional algorithm of 20 queries.

Query	Relevant images retrieved in our algorithm	Relevant images retrieved in the conventional algorithm [TBIR]
1  	33	10
2  	102	12
3  	102	17

4  	61	16
5  	51	14
6  	41	10
7   	44	17
8   	71	13
9  	44	10
10  	27	9
11   	102	16
12   	71	13
13	61	18

		
14 	27	12
15 	44	14
16 	51	26
17 	114	20
18 	21	18
19 	135	12
20 	51	16

The graphs in the following Figure III-7,represent a translation of the results from the table 1.

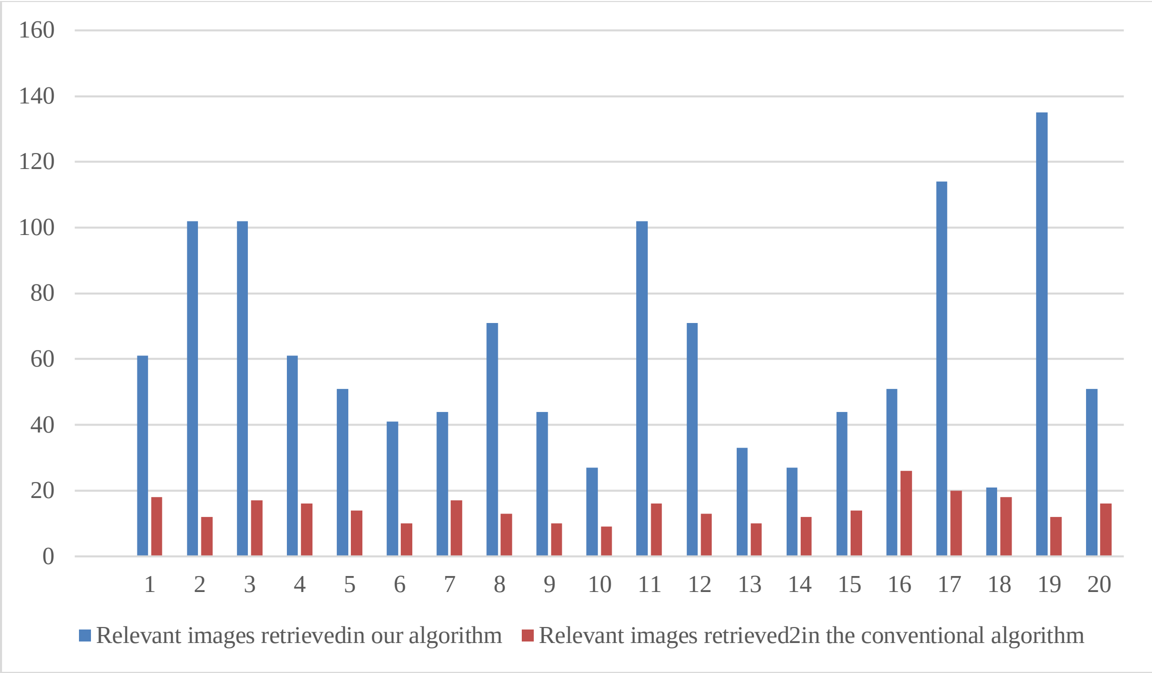


Figure III-7. R I R in our algorithm and in the conventional algorithm of 20 queries.

From Figure III.7, it can be seen that all the queries have more relevent images in our algorthm and its outperforms the state of the art algorithm[TBIR].

III.5 Discussion results

Through the results that we obtained in Figure III.9, we note the great success and success of the generalization algorithm for the number of retrieved images is greater than the number of relevant images retrieved through the conventional algorithm [TBIR], whose results do not contain any hidden concepts.

Our system searches all annotated images with a concept query and it is the hidden concepts that helped improve the quality of the relevant image retrieval product, and it shows the results to the user so that the study of the generalization algorithm provided the best results for each query concept and that the system was able to analyze and interpret to extract the essence of the concept. It relied heavily on the reliability of the examples in the query.

Our system searches all annotated images with a concept query and the hidden concepts

Thus understanding the ueser's intent,this algorithm provided the best results but the conventional algorithm [TBIR], whose results do not contain any hidden concepts.

III.6 Conclusion

In this chapter, we presented an algorithm that base on the generalization of several positive examples. We generalize the query concepts to extract more relevant concepts which linked with the concepts query.

The objective of this algorithm is to improve the semantic image retrieval quality by reducing the famous problems of image retrieval: noise and miss via understanding user's intention. Our algorithm is based on the use of an ontology which allows us to exploits its semantic richness. We implemented an image retrieval system that integrates the proposed algorithm. The results obtained show our algorithm outperforms other conventional algorithms.

General Conclusion

General Conclusion

The main objective of this thesis is to suggest a way to generelaize several concepts and retrieve more relevant hidden concepts. This task is a very great importance through the translation of queries in order to enhance the understanding between the user and the search engine.

The goal of this thesis is to clarify some questions about generalization and the problem of *how we selecte the best generalization?*, whenwe obsereve severelpositive concepts in a query.

Our system is closely related to concepts learning,and performed well by generalizing the query in retrieval of a large set of relevent images that annotates with the concepts query and the hidden concepts . This way can improve the understanding of user intent in image retrieval. As for the conventional algorithm, it only retrieved the required images without containing the hidden concepts.

We performed evaluation tests for severel queris, The result obtained during the test confirms the effectiveness of our alghorthm compared with the conventional algorthms.
We hope that our alghorthm will be useful in understanding the user and improving the retrieval of the desired images.

For future work,we can expand the experiments with more databases.

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Annex A

Example of generalization Query

We assume that the user chooses the images represented below:

Query 01

Image 225 :Eagle

Image32 : Canary

We have 2 concepts so n=2

X = {Eagle , *Canary* }

Hypotheses space H:

Through our anthology ,we have 5 h
H = { *h1 :* Brid, h2 : Animal, h3 :Living, h4 :Natural, h5: Entity}

height=**5 root**

height=**4**

height=**3**

height=**2**

height=**1**

height =**0**

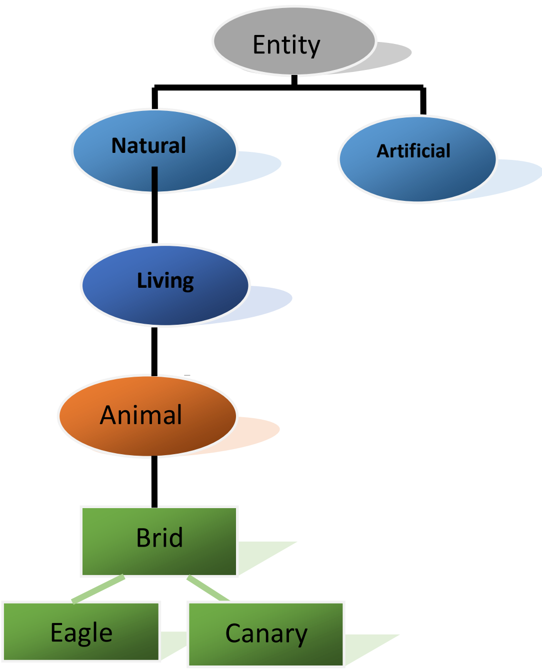

Figure A-1.Tha heightof each level in Ontology.

We compute the Posterior probability of each *hi* : from equation 4.

$$P(h/X)=P(X/h)*P(h) \quad (4)$$

P (h/X) : Conditional probability

The prior probability P(h):

$$P(h) = \text{height}(\text{parent}(h)) - \text{height}(h) \quad (5)$$

Where parent (*h*) returns the parent of node *h*.

The likelihood probability

$$P(\mathbf{x/h}) = \left[\frac{\mathbf{1}}{\boldsymbol{height}(\boldsymbol{h}) + \boldsymbol{\varepsilon}}\right]^{n} \quad (6)$$

We have :

X = {Eagle ,*Canary* } ; n=2

H: { *h1:* Bird, h2 : animal , h3 :Living, h4 :natural , h5:Entity}
Then we choose the largest value of *P(X/h)* we count:
***h1* : Bird**
$P(h_1/X) = P(X/h_1)*P(h_1)$

*P(***Bird** */X)=P(X/* **Bird***)*P(***Bird** *)*

*P(***Bird** *)*= height(parent(**Bird**))- height(**Bird**)

Parent **(Bird) =Animal**

Height **(Animal)=2**

He**ight (Bird) =1**

Look up in anthology so:

*P(***Bird** *)*= height(**Animal)** - height(**Bird**)
= 2-1=1

- **The likelihood probability**

$$P(\mathbf{x/Bird}) = \left[\frac{\mathbf{1}}{\boldsymbol{height}(\boldsymbol{Bird}) + \boldsymbol{\varepsilon}}\right]^{n}$$

We have it before : n=2
We put ϵ constant ϵ =0.5

$P(\mathbf{x/Bird}) = \left[\frac{\mathbf{1}}{\mathbf{1+0.5}}\right]^2$ **=0.44**

h2: Animal

P(h$_2$*/X) = P(X/h2)*P(h2)*

*P(***Animal** */X)=P(X/* **Animal***)*P(***Animal***)*

*P(**Animal**)*= height(parent(**Animal**))- height(**Animal**)

Parent (**Animal**) = **Living**

Height **(Living) = 3**

Height **(Animal) = 2**

Look up in anthology so:

*P(***Animal** *)* = height(**living)** - height(**Animal**)

= 3-2=1

The likelihood probability

$$P(\mathbf{x/Animal}) = \left[\frac{\mathbf{1}}{\boldsymbol{height(\ Animal) + \epsilon}}\right]^{\mathrm{n}}$$

We have it before : n=2
We put ϵ constant ϵ =0.5
So
$P(\mathbf{x/Animal}) = \left[\frac{\mathbf{1}}{\mathbf{2+0.5}}\right]^2$ **=0.16**
$P(h_2/X) = P(X/h_2)*P(h_2)=1*0.16=0.16$

- ***h3*: Living**

P(h$_3$*/X) = P(X/h*$_3$*)*P(h*$_3$*)*

*P(***Living** */X)=P(X/* **Living***)*P(***Living***)*

*P(***living** *)*= height(parent (**living**))- height(**Living**)

Parent (**Living) =Natural**

Height **(Living)=3**

Height **(Natural) =4**

Look up in anthology so:

*P(***Living***)*= height(**Natural)** - height(**Living**)

= 4-3=*1*

The likelihood probability

$$P(\mathbf{x/Living}) = \left[\frac{\mathbf{1}}{\mathbf{height(\ Living)} + \boldsymbol{\epsilon}}\right]^{n}$$

We have it before : n=2

We put ϵ constant ϵ =0.5

So

$P(\mathbf{x/Living}) = \left[\frac{\mathbf{1}}{\mathbf{3+0.5}}\right]^{2}$**=0.081**

P(h_3/X) = P(X/h_3)*P(h_3)=1*0.081=0.081

- **h4 : Natural**

*P(h_4/X) = P(X/h_4)*P(h_4)*

*P(***Natural** */X)=P(X/* **Natural***)*P(***Natural** *)*

*P(***Natural** *)*= height(parent(**Natural**))- height(**Natural**)

Parent (**Natural)=entity**

Height **(Natural) =4**

Height **(entity) =5**

Look up in anthology so:

P **(Natural***)*= height(**entity)** - height(**Natural**)

=5-4 =*1*

The likelihood probability

$$P(\mathbf{x/Natural}) = \left[\frac{\mathbf{1}}{\boldsymbol{height(\ Natural)} + \boldsymbol{\epsilon}}\right]^{n}$$

We have it before: n=2

We put ϵ constant ϵ =0.5

So

$$P(\mathbf{x/Natural}) = \left[\frac{\mathbf{1}}{\mathbf{4+0.5}}\right]^{2} = \mathbf{0.049}$$

P(h_4/X) = P(X/h_4)*P(h_4)=1*0.049=0.049

- ***h5*****: Entity**

Note here that the search engine cannot search for everything at once.

So the biggest value is :

$$P(h_1/X)max = 0.44$$

And from it the user here is looking for the relationship h1 is **Bird**.

The concepts that did not appear in query are the hidden concepts. In our example, there are 4 hidden concepts {Sparro, Swan, Kestrel, Parrot}.

They fall under the bird relationship and we will show the user all the images of birds.

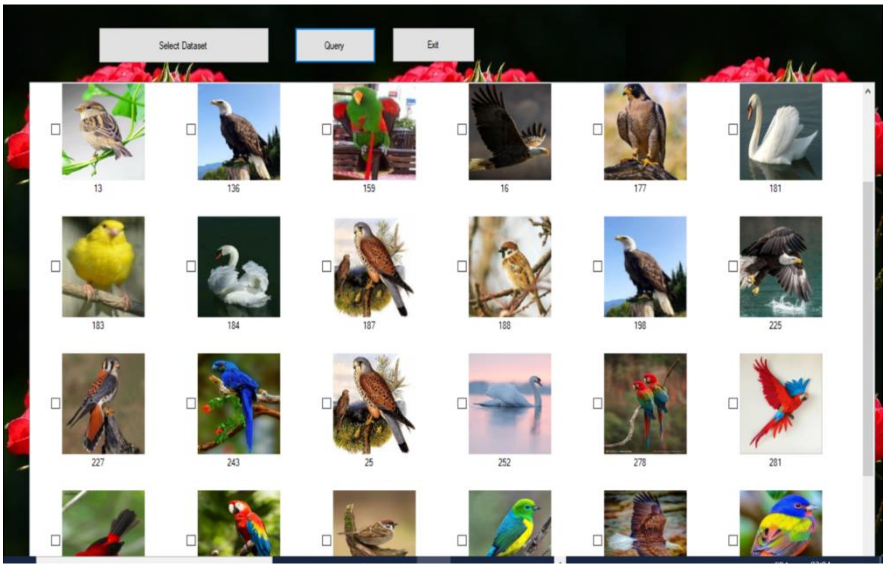

Figure **A-**2. Results Illustration of the Queries canary and eagle with the hidden concept.