2021 級 信工計算機組 學生干皓丞 2101212850 人工智慧作業報告

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0. 作業說明

此報告為人工智慧課程五篇閱讀報告中的第二篇 search，全報告包含 agent、search、Markov decision process、Bayesian Network、Reinforcement Learning。第一篇所佔的領域涵蓋 search 和 Reinforcement Learning。因為考量自身到對該領域知識的掌握程度不足，全報告採心得與翻譯。
* 研究團隊在 Reinforcement Learning 框架下，使用 Epsilon-Greedy 演算法進行研究。

GitHub Project : https://github.com/kancheng/kan-readpaper-cv-and-ai-in-2021

1. 原文獻資訊與作者
2. 報告內容心得與講述
3. 原研究文獻

1. 原文獻資訊與作者

Performance Effectiveness of Multimedia Information Search Using the Epsilon-Greedy Algorithm
使用 Epsilon-Greedy 演算法進行多媒體資訊搜尋的表現上的效能
(研究者想要看這玩意會不會比較棒)

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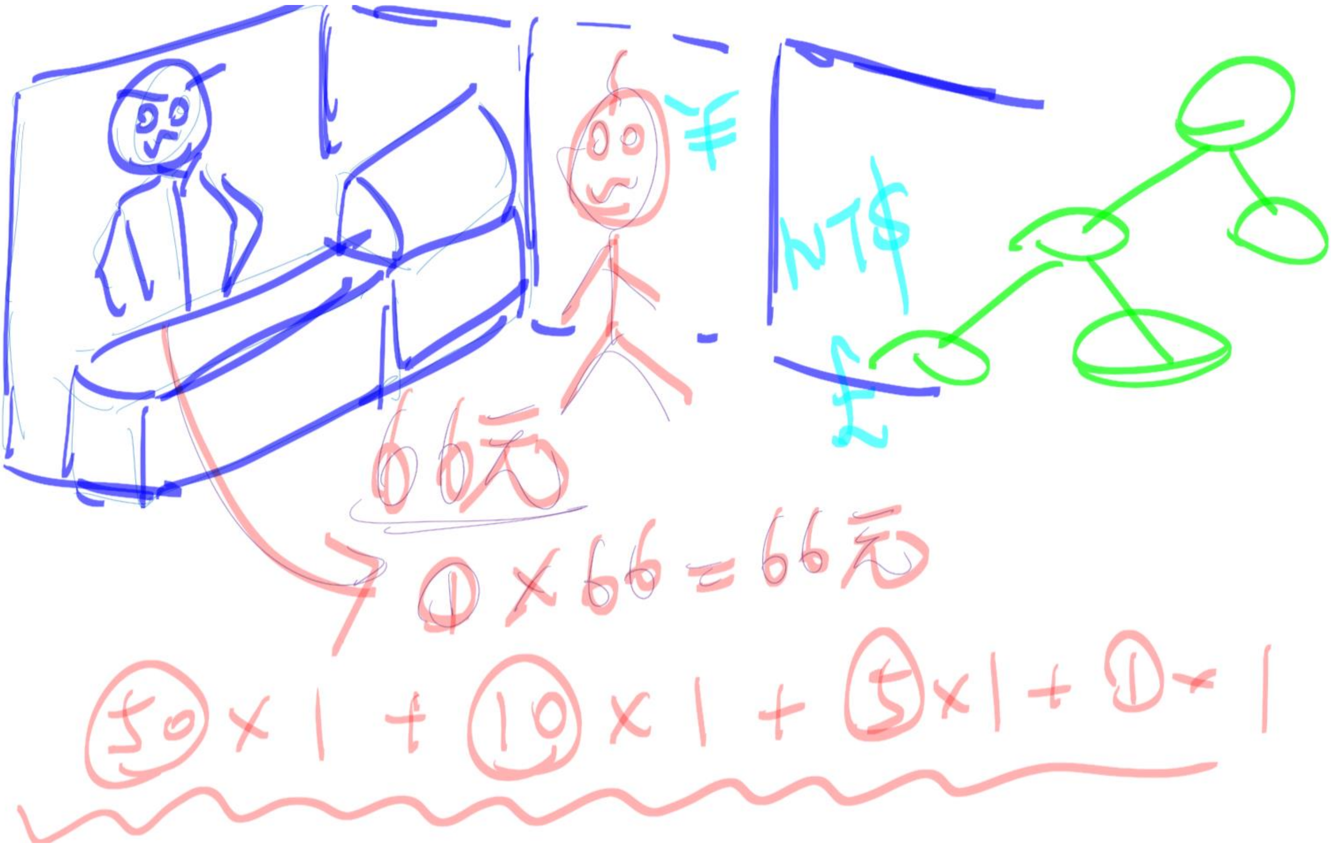
2. 報告內容心得與講述

(1) Motivation 动机
該研究提出嘗試在多媒體資訊搜尋上使用 Epsilon-Greedy 演算法，也就是所謂的貪心演算法，此算法會在每一小步的節點上，做出對當下結果最佳的解決方案，雖然整體上並不一定是最優解，但只要該問題能夠使用 Epsilon-Greedy 演算法來解決，或者局部最優的解決方案，那就能決定整體最佳解決方案，在生活上最直觀就是找零錢的方式。一個人進超商購物後，需要找 66 元，店員找零必

然不會給 66 個一元，必然是給 1 個 50 元、1 個 10 元、1 個 5 元、1 個 1 元。

當然在日常生活中，店員還是能夠找 66 個 1 元，因為這是政府規定的法定貨幣，但此問題是貨幣與政府政策領域，不在貪心演算法的討論範圍內。若真要討論全找 66 個 1 元，那個店員在臺灣地區會被顧客打，而在大陸地區則不會有這個問題，因為大陸地區用微信支付。

在此該研究團隊是想要利用貪心算法來處理多媒體搜尋的問題，也就是所謂的多媒體信息檢索 (MIR; multimedia information retrieval)，因為在搜尋上使用人工或者自動化搜尋太過費力，而且多媒體如是視頻、圖像、音檔，很難像是文字一樣去進行處理，而動用人力進行手工分類又費時費力。該研究團隊想要將貪心演算法跟現在的索引的搜索方法相結合，來嘗試看看能否獲得更好的呈現。Here, we are interested in the effective exploration in the context of index-based multimedia search that encapsulates mental judgment from users to capture high-level linguistic semantics.



(2) Intuition 直觉

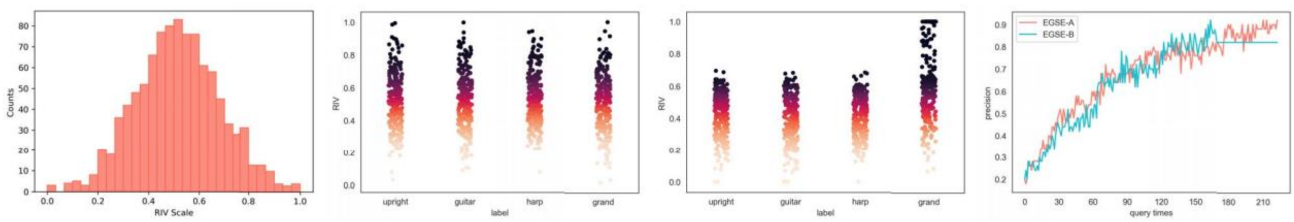


Fig. 3. Distribution of Initial RIV Scores. Fig. 4. Distribution of Initial RIV Scores for Each Category (EGSE-B). Fig. 5. Distribution of RIV Scores for Each Category When Hidden Object X is Discovered (EGSE-B). Fig. 6. Evolution of Query Precisions against Query Times. Settings: $N = 1000, M = 50, \epsilon = 0.1$.

Fig. 3. Distribution of Initial RIV Scores.

圖 3. 初始 RIV 分數分佈。

Fig. 4. Distribution of Initial RIV Scores for Each Category (EGSE-B).

圖 4. 每個類別 (EGSE-B) 的初始 RIV 分數分佈。

Fig. 5. Distribution of RIV Scores for Each Category When Hidden Object X is Discovered (EGSE-B).

圖 5. 發現隱藏對象 X 時每個類別的 RIV 分數分佈 (EGSE-B)。

Fig. 6. Evolution of Query Precisions against Query Times.

圖 6. 查詢精度隨查詢時間的演變。

Settings: N = 1000,M = 50, Є= 0.1.

本研究利用在強化學習情況下廣泛使用的 Є-greedy 算法來指導整個搜索空間的系統探索。通過在這些算法中明智地設置 Є 的值，可以實現開發和探索之間的良好平衡。我們考慮了 Є-greedy 算法的兩種變體，代表了對容錯和效率的不同重視，並從理論上和實驗上研究了它們的性能。

(3) Justification 理由

多媒體資料處裡很複雜，導致很難完全被索引。而使用者所看到的搜尋結果不一定是最佳的搜尋結果，因為一些相關的目標並不容易被檢視和搜索。就該研究的結論敘述，為了避免結果會降落在局部最大值上，導致只有次佳對象的分數增加，相關對象永遠不會有機會出現狀況，該研究認為應該「應該探索搜索空間，同時不損害搜索引擎的能力」

Consequently, to overcome this problem, the search space should be explored, while at the same time the competence of the search engine is not compromised.

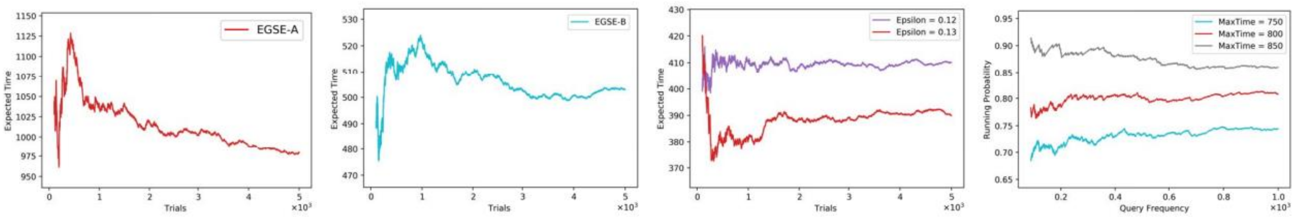


Fig. 7. Expected Discovery Time of EGSE-A. Fig. 8. Expected Discovery Time of EGSE-B. Settings: N = 10000, M = 100, ϵ = 0.1. Fig. 9. Expected Discovery Time of EGSE-B with ϵ = {0.12, 0.13}. Fig. 10. Probability of Discovering the Most Relevant Object in EGSE-B with Time Constraints.

Fig. 7. Expected Discovery Time of EGSE-A.

圖 7. EGSE-A 的預期發現時間。

Fig. 8. Expected Discovery Time of EGSE-B. Settings: N = 10000, M = 100, Є= 0.1.

圖 8. EGSE-B 的預期發現時間。 設置：N = 10000，M = 100，Є= 0.1。

Fig. 9. Expected Discovery Time of EGSE-B with = {0.12, 0.13}.

圖 9. EGSE-B 的預期發現時間 Є = {0.12, 0.13}。

Fig. 10. Probability of Discovering the Most Relevant Object in EGSE-B with Time Constraints.

圖 10. 在具有時間約束的 EGSE-B 中發現最相關對象的概率。

(4) Framework 框架

Algorithm 1 EGSE-A: Search Space Exploration with Constant Probability Require: epsilon E, length of result list M, query max counter C

算法 1 EGSE-A：具有恆定概率的搜索空間探索要求：epsilon E，結果列表長度 M，查詢最大計數器 C

Algorithm 1 EGSE-A: Search Space Exploration with Constant Probability

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Require: epsilon E, length of result list *M*, query max counter *C*

Initialize terminating condition $\Delta \leftarrow False$,
Initialize query counter $\Theta \leftarrow 0$,
Initialize exploration proportion $R \leftarrow E \times M$,
Initialize exploitation proportion $K \leftarrow (1 - E) \times M$,
while Δ == **False do**
    Retrieve and parse new user query Q
    Determine $S_1 = \{O_i \mid$ objects with the highest relevant scores$\}_{i=1}^{k}$, where $|S_1| = K$
    Determine $S_2 = \{O_j \mid O_j \in S_1^{\complement}\}_{j=1}^{R}$, where $|S_2| = R$
    Present M-list := $S_1 \cup S_2$ to user
    Capture object click information from user
    Increment the score of clicked objects
    $\Theta \leftarrow \Theta + 1$
    if $\Theta == C$ **then**
        $\Delta \leftarrow True$

Algorithm 2 EGSE-B: Search Space Exploration with Variable Probability

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Require: epsilon E, length of result list *M*, query max counter *C*

Initialize terminating condition $\Delta \leftarrow False$,
Initialize query counter $\Theta \leftarrow 0$,
Initialize exploration proportion $R \leftarrow E \times M$,
Initialize exploitation proportion $K \leftarrow (1 - E) \times M$,
Initialize previously presented M-list for Query Q_i as $S_i \leftarrow \emptyset$, for all possible i
while Δ == **False do**
    Retrieve and parse new user query Q_i
    Determine $S_1 = \{O_l \mid$ objects with the highest relevant scores$\}_{l=1}^{k}$, where $|S_1| = K$
    if $|(S_1 \cup S_i)^{\complement}| \geq R$ **then**
        Determine $S_2 = \{O_j \mid O_j \in (S_1 \cup S_i)^{\complement}\}_{j=1}^{R}$, where $|S_2| = R$
    else
        Determine $S_2 = (S_1 \cup S_i)^{\complement}$, where $|S_2| = |(S_1 \cup S_i)^{\complement}|$
    Present M-list := $S_1 \cup S_2$ for query Q_i to user
    $S_i \leftarrow S_i \cup S_1 \cup S_2$
    Capture object click information from user
    Increment the score of clicked objects
    $\Theta \leftarrow \Theta + 1$
    if $\Theta == C$ or $(S_1 \cup S_i)^{\complement} == \emptyset$ **then**
        $\Delta \leftarrow True$

Algorithm 2 EGSE-B: Search Space Exploration with Variable Probability Require: epsilon E, length of result list

list M, query max counter C
算法 2 EGSE-B：具有可變概率的搜索空間探索要求：epsilon E，結果列表長度 M，查詢最大計數器 C

(5) Result 结果

Fig. 1. Sample Images from Dataset (Size = 50). Fig. 2. Final Returned M-list using EGSE-A. Settings: $N = 1000, M = 50, \epsilon = 0.1$.

Fig. 1. Sample Images from Dataset (Size = 50).
圖 1. 來自數據集的示例圖像（大小 = 50）。
Fig. 2. Final Returned M-list using EGSE-A. Settings: N = 1000,M = 50, Є= 0.1.
圖 2. 使用 EGSE-A 的最終返回 M 列表。 設置：N = 1000，M = 50，Є= 0.1。

3. 原研究文獻

Abstract 摘要
在對多媒體物件的搜尋(search)和取得(retrieval)， 用手動或自動化方式去取得內容來給索引的用，是一件很不實際的事情，因為多數多媒體內容無法用機器去取得。而手动提取往往非常费力和费时。然而，藉由系統化方式去捕捉和分析，人類使用者的反饋模式。也就是說人類使用者反應所組成的模式。跟這些多媒體內容的有關的重要資訊，是可以被取得來做有效率的索引和後續搜尋使用。藉由學習使用者人類判斷與大腦評估。可以逐步开发和建立有效的搜索索引，然后利用它来查找最相关的多媒体对象。

为了避免在局部最大值附近徘徊，我们应用 Є-greedy 方法来系统化地來探索搜索空间。藉由通过这种有条不紊的探索，我们證實所提出的方法能够保证始终可以发现最相关的对象，即使一開始的時候，這些搜尋結果或方法可能被忽视或不被认为是相关的。
* it 寫錯，應該用 they.
為了執行 Є-greedy algorithm 的兩個變數值，也就是 EGSE-A 和 EGSE-B，我們現在的搜尋方法的搜尋行為是被量化分析(quantitatively analyzed)，而且還得取得封闭形式表达式(closed-form expressions)。我們已經進行了對實際數據的模擬和實驗，其結果與理論上的數據有非常大的一致。現有的這個方法可以很有效的增強搜尋來大幅的提升多媒體資訊搜尋的表現，而且可以確切地發現原本找不到的一些相關的物件。
Index Terms—multimedia search, exploration, performance analysis, content indexing
索引词—多媒体搜索、勘探、性能分析、内容索引

I. INTRODUCTION 前言

由於多樣化的異構模式導致內在的複雜性，多媒體內容的有效搜索和檢索長期以來一直是一項具有挑戰性的任務。用戶嘗試執行的越來越具有表現力和智能的搜索進一步放大了難度。
與傳統的無歧義查詢詞相比，這種查詢在自然語言模式中往往是啟發式和多語義的(heuristic and multi-semantic)，其中上下文和隱含信息通常可以發揮重要作用。
Examples can be, ”a song of jazz pop without saxophone” and ”images of superbloom in California with humans wearing hats”.
例如，“一首沒有薩克斯管的爵士流行歌曲”和“加利福尼亞州人們戴著帽子的超級盛開的圖像”。

The presence of user intent [1]– [3] therefore widens even more the semantic gap between low-level features and high-level semantics [4]–[6] in multimedia information retrieval (MIR).
因此，用戶意圖 [1]-[3] 的存在進一步擴大了多媒體信息檢索 (MIR; multimedia information retrieval) 中低級特徵和高級語義 [4]-[6] 之間的語義差距。

To address the semantic gap in MIR, indexing technique empowered by user feedback patterns has led to a different yet promising direction [7], [8].
為了解決 MIR 中的語義差距，由用戶反饋模式授權的索引技術導致了一個不同但有希望的方向 [7], [8]。

Unlike content-based information retrieval, indexing in MIR is typically used with available textual metadata or implicit user information for efficient access.
與基於內容的信息檢索不同，MIR 中的索引通常與可用的文本元數據或隱式用戶信息一起使用，以實現高效訪問。

However, existing algorithms typically aim to retrieve multimedia objects from the search space purely based on their relevance to the proposed queries.
然而，現有算法通常旨在純粹基於多媒體對象與建議查詢的相關性從搜索空間中檢索多媒體對象。

With measures such as tfidf, objects indicated to be the most relevant are returned to form search results.
使用諸如 tfidf 之類的度量，返回指示最相關的對像以形成搜索結果。

因此，初始索引(The initial indexing)在呈現的搜索結果的演變中起著至關重要的作用。由於對像是根據索引分數排名的，具有初始大值的對象往往會主導所呈現的列表，因此幾乎不可能發現可能具有更大相關性的隱藏對象。

同時，局部最優的問題也導致搜索結果不能隨著時間的推移適應最新的用戶興趣。在本文中，我們向前邁出了一步，通過平衡開發和探索來解決上述問題。開發和探索的困境無處不在，並且在強化學習 (RL) 和控制系統中得到了廣泛的研究 [9]-[11]。

Here, we are interested in the effective exploration in the context of index-based multimedia search that encapsulates mental judgment from users to capture high-level linguistic semantics.
在這裡，我們對基於索引的多媒體搜索上下文中的有效探索感興趣(context of index-based

multimedia search)，該搜索封裝了用戶的心理判斷以捕獲高級語言語義(capture high-level linguistic semantics.)。

By learning from implicit user feedback, search indexes are built up to reflect the latest user intent and information needs, which can then be further exploited to uncover the most relevant objects.
通過從隱式用戶反饋中學習，構建搜索索引以反映最新的用戶意圖和信息需求，然後可以進一步利用這些信息來發現最相關的對象。

We aim to enable possible discovery of hidden relevant objects, where unfavorable initial indexes are bound with them, resulting in the failure of roll-out for selection.
我們的目標是能夠發現隱藏的相關對象，其中不利的初始索引與它們綁定，導致選擇失敗。

Specifically, we are interested in the worst case scenario that for a specific query, the ground-truth of most relevant objects are initially hidden due to inadequacies in initial indexes.
具體來說，我們對最壞的情況感興趣，即對於特定查詢，由於初始索引的不足，大多數相關對象的真實情況最初被隱藏。

By incorporating the Є-greedy algorithm [12] with index-based search methods,
通過將 Є-greedy 算法 [12] 與基於索引的搜索方法相結合，
proactive exploration in the search space becomes possible, ensuring the exposure of objects of interest.
在搜索空間中進行主動探索成為可能，確保感興趣對象的曝光。

同時，利用當前信息來呈現令人滿意的搜索結果。

Unlike entirely random methods that do not harness any useful information, we stress on the systematic evolution that achieves a balance between exploitation and exploration.
與不利用任何有用信息的完全隨機方法不同，我們強調在開發和探索之間實現平衡的系統進化。

這項工作的主要貢獻如下。

• We explore the problem of how to effectively perform exploration in index-based multimedia search methods.
我們探討瞭如何在基於索引的多媒體搜索方法中有效地進行探索的問題。

The goal here is not to devise new methodologies for MIR, but to instead balance exploitation and exploration within a widely-adopted index based frameworks, so as to provide a theoretically justified approach for effective exploration.
這裡的目標不是為 MIR 設計新的方法，而是在廣泛採用的基於索引的框架內平衡開發和探索，以便為有效探索提供理論上合理的方法。

Specifically, implicit user feedback patterns are learned and harnessed to form semantic indexes, while the Є-greedy algorithm is incorporated for discovering hidden relevant multimedia objects.

具體來說，隱式用戶反饋模式被學習並利用以形成語義索引，而 Є-greedy 算法被結合用於發現隱藏的相關多媒體對象。

• Two variants of the Є-greedy algorithms, EGSE-A and EGSE-B, are presented for exploration of hidden relevant objects.
提出了兩種 Є-greedy 算法的變體，EGSE-A 和 EGSE-B，用於探索隱藏的相關對象。

Analysis is performed to examine the worst case scenario where the evolution pattern of the most relevant objects start with unfavorable initial indexes.
執行分析以檢查最相關對象的演化模式以不利的初始索引開始的最壞情況。

Closedform expressions are obtained with detailed performance evaluation, which guarantee the discovery of interested objects in finite time.
閉式表達式(Closedform expressions)是通過詳細的性能評估獲得的，這保證了在有限時間內發現感興趣的對象。

• To validate and corroborate the effectiveness of exploration and exploitation, Monte-Carlo simulations and experiments on real data set are performed.
為了驗證和證實探索和開發的有效性，在真實數據集上進行了蒙特卡羅模擬和實驗。

本文的結構如下。第 2 節比較了當前的研究和最近的工作。
第 3 節給出了預備知識和問題表述。
第 4 節分析算法的性能，然後是第 5 節的實驗評估。
最後，第 6 節總結了工作。

II. RELATED WORKS 相關作品!? 相關工作!?

Relevance feedback in various forms [13]–[17] have been used to effect improvements in search performance [18]–[22].
各種形式的相關性反饋 [13]-[17] 已被用於提高搜索性能 [18]-[22]。

在[23]中研究了應用進化方法對圖像進行分類並將其構建到搜索架構中。在[24]-[28]中也提出了採用某種形式的進化行為的相關搜索問題。在[29]和[30]中已經採用了使用點擊信息進行相關反饋。

In [29], it infers user image search goals from the users’ response.
在 [29] 中，它從用戶的響應中推斷出用戶圖像搜索目標。

While it makes use of click information similar to our present study, it also relies on image analysis by extracting the color, texture, and shape features to produce a feature vector for each image.
雖然它利用類似於我們目前研究的點擊信息，但它也依賴於圖像分析，通過提取顏色、紋理和形狀特徵來為每個圖像生成一個特徵向量。

Unlike our method, the systematic exploration of the search space is impractical due to its substantial computational overhead.
與我們的方法不同，搜索空間的系統探索由於其大量的計算開銷而不切實際。

An interesting crossview method of learning based primarily on click-through is employed for image search in [30].
在[30]中，一種有趣的交叉學習方法主要基於點擊進行圖像搜索。

Different from the present method, the training mechanism of cross-view learning is carried out by minimizing an objective function representing the distance between query and image mappings,
與現有方法不同，交叉視圖學習的訓練機制(the training mechanism of cross-view learning)是通過最小化表示查詢和圖像映射之間距離的目標函數來進行的，

while maintaining the relationships between the training examples in the original feature space.
同時保持原始特徵空間中訓練樣本之間的關係。

In comparison with our method, the approach there will incur substantial training and optimization overheads, which can become computationally expensive.
與我們的方法相比，那裡的方法會產生大量的訓練和優化開銷，這在計算上會變得很昂貴。

Combining search with learning mechanisms are increasingly recognized as useful and have been proposed in [31]–[35].
將搜索與學習機制相結合越來越被認為是有用的，並已在 [31]-[35] 中提出。

In [31], the authors introduce a framework using feature selection, encoding, and learning, and apply these to retrieval and annotation.
在 [31] 中，作者介紹了一個使用特徵選擇、編碼和學習的框架，並將這些應用於檢索和註釋。

While the present study addresses the similar problems of multimedia retrieval and annotation (since indexing is a form of annotation),
雖然本研究解決了多媒體檢索和註釋的類似問題（因為索引是一種註釋形式），

instead of using a purely machine-based learning approach, we exploit human expertise and use them as agents for exploration,
我們沒有使用純粹基於機器的學習方法，而是利用人類的專業知識並將其用作探索的代理，

so that the entire search space may be covered.
這樣就可以覆蓋整個搜索空間。

The net result is that a precision rate close to 100% may be attained.
最終結果是可以達到接近 100% 的準確率。

Similarly, learning is applied to person identification and generalized to image retrieval in [32].
類似地，在 [32] 中，學習應用於個人識別並推廣到圖像檢索。
While that study makes use of CNN to obtain descriptors of pedestrians, our study learns directly from human inputs without requiring extensive training.
雖然該研究利用 CNN 來獲取行人的描述符，但我們的研究直接從人類輸入中學習，無需大量培訓。

In [33], the problem of ranking is considered, and a re-ranking mechanism, called click-boosting multi-modality graph-based re-ranking, is proposed.
在[33]中，考慮了排名問題，並提出了一種重新排名機制，稱為點擊提升多模態基於圖的重新排名。

That algorithm makes use of clicked images to locate similar images, and re-ranks them.
該算法利用點擊的圖像來定位相似的圖像，並對它們重新排序。

Given a query, an optimization problem needs to be solved.
給定一個查詢，需要解決一個優化問題。

The present study is different from this as algorithmically solving an optimization is not required, nor is ranking considered to be important in the search results.
本研究與此不同，因為不需要通過算法解決優化問題，搜索結果中的排名也不重要。

Whilst in [34], a label preserving multimedia hashing learning framework is presented,
在 [34] 中，提出了一個保留標籤的多媒體散列學習框架(multimedia hashing learning framework)，

which learns the associated codes by solving a series of integer programming problems.
它通過解決一系列整數規劃問題來學習相關代碼。

Unlike that study which makes use of hash functions for search identification,
與使用哈希函數進行搜索識別的研究不同，

we tackle the problem directly from the intent of the human users and learn from their interaction with the presented results,
我們直接從人類用戶的意圖解決問題，並從他們與呈現結果的交互中學習，

which has been increasingly recognized as an important element in multimedia search [1], [36], [37].
它越來越被認為是多媒體搜索中的一個重要元素[1]、[36]、[37]。

The value of information captured through human behavior has been recognized in [8], [38] and [39].
[8]、[38] 和 [39] 已經認識到通過人類行為捕獲的信息的價值。

In [8], it aggregates relevance feedback from multiple users;

在[8]中，它聚合了來自多個用戶的相關性反饋；

while this study is useful in developing a versatile architecture, unlike the present study, it does not provide a mechanism to ensure that the search space is fully explored.
雖然這項研究在開發通用架構方面很有用，但與本研究不同，它沒有提供一種機制來確保充分探索搜索空間。

In [38] it highlights the importance of humans in the search process, and acknowledges that image and video retrieval should place greater emphasis on the humans users.
在 [38] 中，它強調了人類在搜索過程中的重要性，並承認圖像和視頻檢索應該更加重視人類用戶。

Our system thus further develops these approaches and provides a mechanism whereby the system learns from the humans in executing the searches.
因此，我們的系統進一步開發了這些方法，並提供了一種機制，使系統在執行搜索時向人類學習。

III. PROBLEM FORMULATION 問題表述

In a search engine system, a query needs to be input by a user via the frontend interface, through which the interaction between the system and the user triggers the dynamic involvement of the system.
在搜索引擎系統中，查詢需要用戶通過前端接口輸入，系統與用戶的交互通過前端接口觸發系統的動態參與。

In general, a specific query can be submitted multiple times by the same user or by different users, where the results returned are dynamically adjusted by the system to reflect both the interests of the users' as well as those of the system.
一般來說，一個特定的查詢可以由同一用戶或不同用戶多次提交，返回的結果由系統動態調整，以反映用戶和系統的興趣。

There is a trade-off between the short-term gain obtained for the present query, and the longterm performance that will also benefit later queries.
在為當前查詢獲得的短期收益與也有利於以後查詢的長期性能之間存在權衡。

We shall employ the Є-greedy algorithm, widely used in reinforcement learning [12], to introduce a balance between exploitation of current knowledge to find objects that are adequately relevant,
我們將採用廣泛用於強化學習 [12] 的 Є-greedy 算法，在利用當前知識以找到足夠相關的對象之間引入平衡，

and exploration of the search space to identify the objects that are most relevant.
並探索搜索空間以識別最相關的對象。

By sacrificing a certain amount of exploitation advantage and the dwelling on a local maximum, the

exploration opens the possibility of the attainment of a global maximum.
通過犧牲一定的開發優勢並停留在局部最大值上，探索開啟了實現全局最大值的可能性。

Consider a given query Q input to a multimedia search engine.
考慮一個給定的查詢 Q 輸入到多媒體搜索引擎。

We would like to examine how the dynamics of a search engine affect the returning results of the specific query Q along with time.
我們想檢查搜索引擎的動態如何隨時間影響特定查詢 Q 的返回結果。

We assume that there are N multimedia objects in total in the search space.
我們假設搜索空間中總共有 N 個多媒體對象。

In response to the query Q, a results list consisting of M objects is returned by the system, which we shall call the M-list.
作為對查詢 Q 的響應，系統返回一個由 M 個對象組成的結果列表，我們將其稱為 M-列表。

We assume N >> M; i.e., a returned list is only a very small subset of the search space.
我們假設 N >> M; 即，返回的列表只是搜索空間的一個非常小的子集。

We assume that the relevance of multimedia objects in the search space in relation to a given query Q is signified by a number in the continuous scale [0, 1], and for exploitation purposes, objects having a relevance value exceeding a given threshold h are included in the M-list, where typical values for h are 0.8 or 0.9.
我們假設搜索空間中多媒體對象與給定查詢 Q 的相關性由連續尺度 [0, 1] 中的數字表示，並且出於開發目的，具有超過給定閾值 h 的相關性值的對像是 包含在 M 列表中，其中 h 的典型值為 0.8 或 0.9。

Objects that are considered to be not relevant to the query Q typically would have a relevance value well below h, and these objects will not be included in the M-list through exploitation.
被認為與查詢 Q 不相關的對象通常具有遠低於 h 的相關值，並且這些對像不會通過利用被包含在 M 列表中。

In the Є-greedy method, a proportion of the M-list is used for exploration, while (1 − Є) is used for exploitation.
在 Є-greedy 方法中，M-list 的一部分用於探索，而 (1 − Є) 用於開發。

Here, we assume that the ordering of objects within the Mlist is not important;
在這裡，我們假設 Mlist 中對象的排序並不重要；

this is particularly true for image objects whereby users tend not to just go through the first few objects on the list, but also the remaining objects as well.

對於圖像對象尤其如此，用戶往往不僅會瀏覽列表中的前幾個對象，還會瀏覽剩餘的對象。

Repeated presentations of the M-list in response to the query Q (possibly from different users) are denoted by the M1,M2,M3, ..., where Mi signifies the ith M-list presented for the query Q.
響應於查詢 Q（可能來自不同用戶）的 M-list 的重複呈現由 M1,M2,M3, ... 表示，其中 Mi 表示為查詢 Q 呈現的第 i 個 M-list。

We let r = ЄM, and K = (1 − Є)M, i.e, M = r + K, and we include r randomly chosen objects in the M-list,
我們讓 r = M，並且 K = (1 − Є)M，即 M = r + K，我們在 M-list 中包含 r 個隨機選擇的對象，

where each available object apart from the K objects from exploitation is chosen with equal probability.
其中除了來自開發的 K 個對象之外的每個可用對像都以相等的概率被選擇。

We consider two variations of the Є-greedy exploration algorithm.
我們考慮了 Є-greedy 探索算法的兩種變體。

A Exploration with object re-selection.
對象重選的探索。
Each presentation of the M-list with the r random objects are done in such a way that when a given random object Z has been included in a previous M-list presentation,
帶有 r 個隨機對象的 M-list 的每次表示都是以這樣的方式完成的，即當給定的隨機對象 Z 已包含在先前的 M-list 表示中時，
it can be re-selected for inclusion in a subsequent M-list presentation.
它可以被重新選擇以包含在隨後的 M 列表演示中。

B Exploration without object re-selection.
B 沒有對象重新選擇的探索。
Each presentation of the M-list with the r random objects are done in such a way that when a given random object Z has been included in a previous M-list presentation, it will be excluded for inclusion in a subsequent M-list presentation.
具有 r 個隨機對象的 M 列表的每次表示都是以這樣的方式完成的，即當給定的隨機對象 Z 已包含在先前的 M 列表表示中時，它將被排除以包含在隨後的 M 列表表示中。

The details of these are given respectively in algorithms EGSE-A, and EGSE-B (Є-greedy algorithm for search exploration).
這些細節分別在算法 EGSE-A 和 EGSE-B(Є-greedy algorithm for search exploration)中給出。

Compared with EGSE-B, EGSE-A has a greater degree of fault-tolerance in that if a user inadvertently overlooks a highly relevant random object,
與 EGSE-B 相比，EGSE-A 具有更高的容錯度，因為如果用戶無意中忽略了一個高度相關的隨機對象，
it can still be discovered in a subsequent presentation.

它仍然可以在隨後的演示中發現。

On the other hand, such duplication of effort will tend to slow down search space exploration.
另一方面，這種重複工作往往會減慢搜索空間的探索速度。

Consequently, EGSE-B has the advantage that the explorationcan advance at a faster pace but supports less fault-tolerance since if the user somehow overlooks the most relevant object,
因此，EGSE-B 的優勢在於探索可以以更快的速度推進，但支持較少的容錯，因為如果用戶以某種方式忽略了最相關的對象，

它將保持隱藏狀態(remain hidden)，永遠不會被發現。

More precisely, let X be the multimedia object that is most relevant to the query Q, but the relevance value of X is currently well below the threshold value h.
更準確地說，設 X 為與查詢 Q 最相關的多媒體對象，但 X 的相關值目前遠低於閾值 h。

Under the Є-greedy algorithm, we seek to provide answers to the following questions:
在 Є-greedy algorithm 算法下，我們尋求提供以下問題的答案：

・ What is the probability that X can be first discovered on the kth presentation of the M-list?
在 M 列表的第 k 個表示中首先發現 X 的概率是多少？
That is, we would like to find the probability
也就是說，我們想找到概率

$$\mathbb{P}\{X \in M_k : X \notin M_1, ..., X \notin M_{k-1}\}$$

・ What is the average time for X to be discovered (i.e. the average time for X to be included on an M-list for the first time)?
X 被發現的平均時間（即 X 首次被包含在 M-list 中的平均時間）是多少？

That is, we wish to find k such that
也就是說，我們希望找到 k 使得

$$\min_k\{M_k : X \in M_k\}$$

In the next section, we shall derive solutions to these measures.
在下一節中，我們將推導出這些措施的解決方案。

IV. PROBABILISTIC ANALYSIS 概率分析

A. Performance Analysis of Algorithm EGSE-A 算法 EGSE-A 的性能分析

Consider Є-greedy Algorithm EGSE-A.
考慮 Є-greedy 算法 EGSE-A。

The probability that X is included in a particular M-list is given by:
X 包含在特定 M 列表中的概率由下式給出：

$$a_{r,M} = \frac{\binom{N-M+r-1}{r-1}}{\binom{N-M+r}{r}}$$

,

得到如下。

The number of objects in the pool of objects from which the r random objects are selected is N−(M−r) = N−M+r.
從中選擇 r 個隨機對象的對像池中的對像數量是 N−(M−r) = N−M+r。

The total number of combinations in choosing r objects from (N − M + r) objects including X is

$$\binom{N-M+r-1}{r-1}$$

, since we are excluding X from the pool of selections, and then always including X in the resultant chosen r objects by selecting only (r − 1) remaining objects and reserving a place for X.

從包括 X 在內的 (N − M + r) 個對像中選擇 r 個對象的組合總數是

$$\binom{N-M+r-1}{r-1}$$

，因為我們從選擇池中排除了 X，然後總是通過只選擇 (r − 1) 剩餘的對象並為 X 保留一個位置。

然後將其除以從 (N -M + r) 個對像中選擇任何 r 個對象的可能性總數

$$\binom{N-M+r}{r}$$

。

Letting βr,M be such that αr,M + βr,M = 1, then denoting by Ur,M the random variable signifying the time to discover X (for the first time),
令 βr,M 使得 αr,M + βr,M = 1，然後用 Ur,M 表示隨機變量，表示發現 X 的時間（第一次），

we have
我們有

$$\mathbb{P}[\mathbf{U}_{r,M} = k] = \alpha_{r,M}\beta_{r,M}^{k-1}, \qquad (1)$$

with corresponding probability generating function

$$F(z) = \frac{\alpha_{r,M}z}{1-\beta_{r,M}}.$$

we have P with corresponding probability generating function F.
我們有 P[…] = … (1) 和相應的概率生成函數 F(z) = … 。

The mean and variance of Ur,M can thus be obtained by differentiation [40]:
Ur,M 的均值和方差因此可以通過微分獲得 [40]：

$$\mathbb{E}[\mathbf{U}_{r,M}] = \frac{\binom{N-M+r}{r}}{\binom{N-M+r-1}{r-1}}, \quad (2)$$

$$\mathbb{V}[\mathbf{U}_{r,M}] = \left[\frac{\binom{N-M+r}{r}}{\binom{N-M+r-1}{r-1}}\right]^2 \times \left[\frac{\binom{N-M+r}{r} - \binom{N-M+r-1}{r-1}}{\binom{N-M+r}{r}}\right]. \quad (3)$$

Algorithm 1 EGSE-A: Search Space Exploration with Constant Probability Require: epsilon E, length of result list M, query max counter C
算法 1 EGSE-A：具有恆定概率的搜索空間探索要求：epsilon E，結果列表長度 M，查詢最大計數器 C

Algorithm 1 EGSE-A: Search Space Exploration with Constant Probability

Require: epsilon E, length of result list M, query max counter C

Initialize terminating condition $\Delta \leftarrow$ *False*,
Initialize query counter $\Theta \leftarrow 0$,
Initialize exploration proportion $R \leftarrow E \times M$,
Initialize exploitation proportion $K \leftarrow (1 - E) \times M$,
while Δ **== False do**
  Retrieve and parse new user query Q
  Determine $S_1 = \{O_i \mid$ objects with the highest relevant scores$\}_{i=1}^{k}$, where $|S_1| = K$
  Determine $S_2 = \{O_j \mid O_j \in S_1^{\complement}\}_{j=1}^{R}$, where $|S_2| = R$
  Present M-list := $S_1 \cup S_2$ to user
  Capture object click information from user
  Increment the score of clicked objects
  $\Theta \leftarrow \Theta + 1$
  if $\Theta == C$ **then**
    $\Delta \leftarrow$ *True*

The probability that X is discovered in finite time can likewise be obtained directly from the probability generating function and is found to equal to one.
X 在有限時間內被發現的概率同樣可以直接從概率生成函數中獲得，並且被發現等於 1。

B. Performance Analysis of Algorithm EGSE-B
B.算法 EGSE-B 的性能分析

To analyze EGSE-B, we shall determine the probability of X being included in an M-list for the first time, bearing in mind that objects through exploration which have been presented in earlier M-lists are marked and excluded from further presentation.
為了分析 EGSE-B，我們將首次確定 X 被包含在 M-list 中的概率，記住已經在早期 M-list 中呈現的通過探索的對像被標記並排除在進一步呈現之外。

We denote by fr,M,k the following first passage probability
我們用 fr,M,k 表示以下第一次通過概率

$$f_{r,M,k} = \mathbb{P}\{X \in M_k : X \notin M_1, \ldots, X \notin M_{k-1}\}$$

For example, we have

$$\begin{aligned} f_{r,M,3} &= \mathbb{P}\{X \in M_k : X \notin M_1, X \notin M_2\} \\ &= \frac{\binom{N-M+r-1}{r}}{\binom{N-M+r}{r}} \times \frac{\binom{N-M-1}{r}}{\binom{N-M}{r}} \times \frac{\binom{N-M-r-1}{r-1}}{\binom{N-M-r}{r}} \end{aligned}$$

The above is obtained as follows.
以上得到如下。

The first factor represents the probability of X ∉ M1: the numerator is the number of combinations of all object choices from N −M+r -1 objects, excluding X, from which the system selects r objects;
第一個因素代表 X∉M1 的概率：分子是 N-M+r-1 個對像中所有對象選擇的組合數，不包括 X，系統從中選擇 r 個對象；

the denominator represents the unrestricted choice of N −M +r objects from which the system selects r;
分母表示系統從其中選擇 r 的 N -M + r 個對象的無限制選擇；

這個因子表示在第一個 M-list 中不包括 X 的概率。第二個因素代表 X ∉ M2 的概率：

分子是現在 N – M – 1 個對像中所有對象選擇的組合數，因為 M1 中出現的前 r 個對象與 X 一起被排除，我們從中選擇 r 個對象；

分母表示系統從其中選擇 r 個對象的 N-M 個對象的無限制選擇，其中前 r 個對像已被排除；

該因子表示第二個 M-list 中不包含 X 的概率。

第三個因素代表 X ∈ M3 的概率：

分子是從現在 N – M – r – 1 個對像中所有對象選擇的組合數，因為 M1 和 M2 中出現的前 2r 個對像以及 X 被排除在外，我們從中選擇 r – 1 個對象，因為 現在為 X 預留了一個位置；分母表示系統從其中選擇 r 個對象的 N – M – r 個對象的無限制選擇，其中前 2r 個對像已被排除；

這個因子代表了第一次在第三個 M-list 中成功包含 X 的概率。使用上述推理，我們可以為 fr,M,k 建立遞推關係：

$f_{r,M,k}$:

$$f_{r,M,k+1} = f_{r,M,k} \times \frac{\binom{N-K-kr}{r}}{\binom{N-K-kr-1}{r-1}} \times \frac{\binom{N-K-kr-1}{r}}{\binom{N-K-kr}{r}} \times \frac{\binom{N-K-(k+1)r-1}{r-1}}{\binom{N-K-(k+1)r}{r}}, \qquad (4)$$

where the second factor serves to remove the successful inclusion probability in fr,M,k, and then replace
其中第二個因素用於去除 fr,M,k 中的成功包含概率，然後將該成功概率替換為包含 X 概率的失敗，這是第三個因素。

The final factor gives the successful inclusion probability at the (k+1)th presentation after k failed attempts to include X before.

最後一個因素給出了在之前 k 次嘗試包含 X 失敗後在第 (k+1) 次展示中成功包含的概率。

The solution to the above recurrence relation requires rather involved manipulations and is relegated to Appendix A,
上述遞推關係的解需要相當複雜的操作，並歸入附錄 A，

which also provides the derivation for the mean and variance of Vr,M, the random variable signifying the time to discover X (for the first time) under EGSE-B,
它還提供了 Vr,M 的均值和方差的推導，該隨機變量表示在 EGSE-B 下發現 X（第一次）的時間，

$$\mathbb{E}[\mathbf{V}_{r,M}] = \frac{N-M+2r}{2r}, \tag{5}$$

$$\mathbb{V}[\mathbf{V}_{r,M}] = \frac{1}{12} \times \left\{ \left[\frac{N-M+r}{r}\right]^2 - 1 \right\}. \tag{6}$$

Since EGSE-B explores the complete search space faster than that of EGSE-A,
由於 EGSE-B 比 EGSE-A 更快地探索完整的搜索空間，
and since EGSE-A exhausts the search space in finite time with probability one, EGSE-B will also exhaust the search space in finite time with probability one.
由於 EGSE-A 在有限時間內以概率 1 耗盡搜索空間，EGSE-B 也將以概率 1 在有限時間內耗盡搜索空間。

V. EXPERIMENTS AND RESULTS INTERPRETATION 實驗和結果解釋

In this section, we describe both the experimental work performed on real dataset and simulations to evaluate the effectiveness and performance of the above algorithms.
在本節中，我們描述了在真實數據集上執行的實驗工作和模擬，以評估上述算法的有效性和性能。

While real dataset experiments stress on the worst case scenario analysis, simulations aim to verify the theoretical results on the average performance.
雖然真實數據集實驗強調最壞情況下的情景分析，但模擬旨在驗證平均性能的理論結果。

A. Real dataset Experiments 真實數據集實驗

Dataset and Preprocessing.
數據集和預處理。

為了建立適合基於索引的多媒體搜索的真實數據集，我們同時抓取 Google 和 Bing 以檢索具有描述性信息的同一主題下的多媒體對象。
使用爬取的原始數據，我們通過仔細選擇相關圖像及其真實標籤來形成基於音樂主題的圖像數據集。

Specifically, each image falls into one of four categories: {”grand piano”,” upright piano”, ”classical guitar”, ”harp”}, where each category takes up 25% of the whole dataset.
具體來說，每張圖像屬於四類之一：{“三角鋼琴”、“立式鋼琴”、“古典吉他”、“豎琴”}，其中每個類別佔整個數據集的 25%。

Algorithm 2 EGSE-B: Search Space Exploration with Variable Probability Require: epsilon E, length of result list M, query max counter C
算法 2 EGSE-B：具有可變概率的搜索空間探索要求：epsilon E，結果列表長度 M，查詢最大計數器 C

Algorithm 2 EGSE-B: Search Space Exploration with Variable Probability

---

Require: epsilon E, length of result list M, query max counter C

Initialize terminating condition $\Delta \leftarrow False$,
Initialize query counter $\Theta \leftarrow 0$,
Initialize exploration proportion $R \leftarrow E \times M$,
Initialize exploitation proportion $K \leftarrow (1 - E) \times M$,
Initialize previously presented M-list for Query Q_i as $S_i \leftarrow \emptyset$, for all possible i
while Δ == **False do**
  Retrieve and parse new user query Q_i
  Determine $S_1 = \{O_l \mid \text{objects with the highest relevant scores}\}_{l=1}^{k}$, where $|S_1| = K$
  if $|(S_1 \cup S_i)^{\complement}| \geq R$ **then**
    Determine $S_2 = \{O_j \mid O_j \in (S_1 \cup S_i)^{\complement}\}_{j=1}^{R}$, where $|S_2| = R$
  else
    Determine $S_2 = (S_1 \cup S_i)^{\complement}$, where $|S_2| = |(S_1 \cup S_i)^{\complement}|$
  Present M-list := $S_1 \cup S_2$ for query Q_i to user
  $S_i \leftarrow S_i \cup S_1 \cup S_2$
  Capture object click information from user
  Increment the score of clicked objects
  $\Theta \leftarrow \Theta + 1$
  if $\Theta == C$ or $(S_1 \cup S_i)^{\complement} == \emptyset$ **then**
    $\Delta \leftarrow True$

Such images are associated together in many semantic contexts and often appear together in searches such as ”Le quattro stagioni orchestra”.
此類圖像在許多語義上下文中關聯在一起，並且經常一起出現在諸如“Le quattro stagioni Orchestra”之類的搜索中。

To ensure the training quality and to deal with the significantly varied image sizes, all images are re-scaled to 512×512.
為了確保訓練質量並處理顯著變化的圖像尺寸，所有圖像都重新縮放到 512×512。

圖 1 顯示了最終數據集的示例圖像。

Experimental Details. 實驗細節

To randomize the initialization of relevance index values (RIVs) for all possible semantic index terms, a Gaussian distribution is utilized.
為了隨機化所有可能的語義索引項的相關性索引值 (RIV) 的初始化，使用了高斯分佈。

In order to study the effectiveness of exploration using the proposed Є-greedy algorithms, we are interested in the case whether a hidden object with unfavorable indexes can be successfully discovered.
為了研究使用所提出的 Є-greedy 算法進行探索的有效性，我們對是否可以成功發現具有不利索引的隱藏對象的情況感興趣。

Therefore, we randomly select one object with the true label that will be included in the input query and artificially change its label to be a misleading one.
因此，我們隨機選擇一個具有真實標籤的對象，並將其包含在輸入查詢中，並人為地將其標籤更改為具有誤導性的標籤。

To utilize the associated textual information, RIVs for images with the target true label are increased with a calibrated delta value within one standard deviation of the Gaussian distribution.
為了利用相關的文本信息，具有目標真實標籤的圖像的 RIV 增加了一個校準的 delta 值，該值在高斯分佈的一個標準偏差內。

Min-max normalization is also adopted so that RIVs are normally distributed within the [0,1] interval:
還採用了最小-最大歸一化，以便 RIV 在 [0,1] 區間內正態分佈：

$$v = \frac{v - min(v)}{max(v) - min(v)}.$$

初始 RIV 的分佈如圖 3 所示。該過程首先輸入包含上述四個分類標籤之一的查詢。
如前幾節所示，返回的列表由用於利用的貪婪部分和由 Є 定義的探索部分組成。

Each time when a Mlist is returned, evaluative information from users is provided to allow successful evolution of indexes.
每次返回 Mlist 時，都會提供來自用戶的評估信息，以允許索引的成功演變。

Here, we assume that users provide implicit feedback for the greedy part only if they find objects that are of interest, and explicit feedback would be directly given for evaluating objects from the exploratory

portion.
在這裡，我們假設用戶只有在找到感興趣的對象時才為貪婪部分提供隱式反饋，並且將直接給出顯式反饋以從探索部分評估對象。

Figures 4 and 5 demonstrate the evolution of the above process, where the input queries contain the keyword ”grand piano”.
圖 4 和圖 5 展示了上述過程的演變，其中輸入查詢包含關鍵字“三角鋼琴”。

Fig. 4 shows that initially, RIVs for each category are nearly uniformly distributed, showing no bias towards any of them.
圖 4 顯示，最初，每個類別的 RIV 幾乎是均勻分佈的，沒有顯示出對任何一個類別的偏見。

To represent the user evaluations, we randomly choose zero to five objects in the greedy part representing the clicking behavior, either boosting their RIVs with a small delta value, if their true labels are ”grand piano”, or decreasing the RIVs otherwise as punishment.
為了表示用戶的評價，我們在表示點擊行為的貪婪部分隨機選擇 0 到 5 個對象，如果他們的真實標籤是“三角鋼琴”，則用一個小的 delta 值提升他們的 RIV，或者減少 RIV，否則作為懲罰。

The same procedures apply to the explorative portion, except that all objects from this portion are evaluated explicitly.
相同的過程適用於探索部分，不同之處在於該部分的所有對像都被明確評估。

In particular, the parameters are set as N = 1000,M = 50, ϵ = 0.1.
特別地，參數設置為 N = 1000,M = 50, ϵ = 0.1。

We are interested in the analysis of the performance of EGSE-A and EGSE-B under the worst case scenario, which can be measured by the number of queries required to discover the target hidden object X.
我們感興趣的是分析 EGSE-A 和 EGSE-B 在最壞情況下的性能，這可以通過發現目標隱藏對象 X 所需的查詢次數來衡量。

By worst case scenario, it is meant that:
最壞的情況是指：

- X never appears in the greedy exploitation component of the M-list,

X 從未出現在 M-list 的貪婪開發組件中，

- X requires the maximum number of queries to be discovered under exploration.

X 要求在探索中發現的最大查詢數。

With the above parameters, under EGSE-B, 200 queries are needed for X to be presented with probability one.
有了以上參數，在 EGSE-B 下，X 需要 200 次查詢才能以概率 1 呈現。

In practice, X can be successfully discovered with less than 200 queries in most cases due to the relaxation of the above two conditions.
在實踐中，由於上述兩個條件的放寬，在大多數情況下，可以在少於 200 次查詢的情況下成功發現 X。

To corroborate the claim, we choose several random seeds to run the experiments for EGSE-A and EGSE-B under the same set of parameters, and report the result for the one that requires most quries for EGSE-B.
為了證實這一說法，我們選擇了幾個隨機種子在同一組參數下運行 EGSE-A 和 EGSE-B 的實驗，並報告需要對 EGSE-B 進行最多查詢的種子的結果。

With the same random seed, EGSEB runs 172 queries to discover the object X, whereas when object re-selection is permitted in EGSE-A, the number of query times increases to 223 to discover X.
使用相同的隨機種子，EGSEB 運行 172 次查詢以發現對象 X，而當 EGSE-A 中允許對象重選時，查詢次數增加到 223 次以發現 X。

We see that X can still be discovered within a reasonable number of queries with EGSE-A.
我們看到，在使用 EGSE-A 的合理數量的查詢中仍然可以發現 X。

The increase can be regarded as the price paid for supporting greater fault-tolerance for the EGSE-A algorithm.
這種增加可以看作是為支持 EGSE-A 算法的更大容錯而付出的代價。

At the time when X is discovered, Fig. 5 shows the distribution of RIVs for each category.
在發現 X 時，圖 5 顯示了每個類別的 RIB 分佈。

The fact that the overall value scale for ”grand piano” is significantly higher than other categories suggests during the evolution process, the proposed EGSE-A and EGSE-B algorithms not only allow successful discovery of object X,
在進化過程中，“三角鋼琴”的整體價值尺度顯著高於其他類別的事實表明，所提出的 EGSE-A 和 EGSE-B 算法不僅允許成功發現對象 X，

but also successfully separate out the indexes of true interest from the irrelevant ones compared to the initial uniform pattern across different categories.
但與不同類別的初始統一模式相比，也成功地將真正感興趣的指標與不相關的指標區分開來。

Notably, the initially unrealistically high RIVs for irrelevant labels are flattened in the end, confirming the efficacious balance between exploration and exploitation.
值得注意的是，不相關標籤的最初不切實際的高 RIV 最終被扁平化，證實了探索和利用之間的有效平衡。

Meanwhile, it is also interesting to find that the evolution of query precision for EGSE-A and EGSE-B

manifests the same pattern, as shown in Fig. 6.
同時，有趣的是發現 EGSE-A 和 EGSE-B 的查詢精度的演變表現出相同的模式，如圖 6 所示。

Generally, the precision for the index-based multimedia search climbs up from extremely low levels to much more precise values, ending in providing satisfactory search results.
通常，基於索引的多媒體搜索的精度從極低的水平上升到更精確的值，最終提供令人滿意的搜索結果。

As EGSE-B typically discovers X much faster than EGSE-A, the time that the system spent on evolution starting from the initial state is not as long as that of EGSE-A.
由於 EGSE-B 通常比 EGSE-A 發現 X 快得多，因此系統從初始狀態開始進化所花費的時間沒有 EGSE-A 長。

If we are only concerned with the discovery of X, the query precision would converge to around 82%.
如果我們只關心 X 的發現，查詢精度會收斂到 82% 左右。

On the other hand, if longer time for learning and searching development is allowed, precision can reach 92%.
另一方面，如果允許更長的學習和搜索開發時間，則精度可以達到 92%。

The final M-list using EGSE-A is provided in Fig. 2, where the hidden object is marked with a read label.
圖 2 中提供了使用 EGSE-A 的最終 M 列表，其中隱藏對象標有讀取標籤。

B. Monte-Carlo Simulations 蒙特卡羅模擬

Experimental Setup. 實驗裝置

To evaluate how EGSE-A and EGSEB perform in environments with a large degree of stochastic influence, we adopt the Monte-Carlo method to efficiently generate samples for simulating the formation of query results.
為了評估 EGSE-A 和 EGSEB 在具有較大隨機影響的環境中的表現，我們採用蒙特卡羅方法來有效地生成樣本以模擬查詢結果的形成。

In particular, four different simulations that examine different aspects of the problem are presented:
特別是，提供了四種不同的模擬來檢查問題的不同方面：

・ Case I: Evaluate E[Ur,M] for EGSE-A.
案例 I：為 EGSE-A 評估 E[Ur,M]。
・ Case II: Evaluate E[Vr,M] for EGSE-B.
案例 II：為 EGSE-B 評估 E[Vr,M]。
・ Case III: Effect of varying for E[Vr,M] of EGSE-B.
情況 III： EGSE-B 的 E[Vr,M] 變化的影響。

- Case IV: Probability of discovering X with constraints.

案例 IV：發現 X 的概率有約束。

To ensure that the behavior is in accordance with the corresponding real-world scenario in the long run, each testing scenario is simulated with 5,000 trials for Cases I to III, and 1,000 trials for Case IV,
從長遠來看，為了確保行為符合相應的現實世界場景，每個測試場景都模擬了案例 I 到 III 的 5,000 次試驗，以及案例 IV 的 1,000 次試驗，

where the the convergence behavior can be observed.
可以觀察到收斂行為。

Because of the presence of randomness, the discovery time of the interested object X can vary even with the same settings of parameters.
由於隨機性的存在，即使參數設置相同，感興趣對象 X 的發現時間也會有所不同。

Examining the expected discovery time can reveal the general effectiveness of the strategies.
檢查預期的發現時間可以揭示策略的總體有效性。

Meanwhile, ϵ is varied to check whether the strategy involved is able to converge effectively under various circumstances.
同時，改變 ϵ 以檢查所涉及的策略是否能夠在各種情況下有效收斂。

在實驗過程中，我們發現具有不同值的 EGSE-A 和 EGSE-B 表現出一些相似的模式，因此為簡潔起見，我們僅報告 EGSEB 的結果。
同時，設置時間約束來評估是否可以在有限的時間步長內完成 X 的發現。

Results and Interpretations. 結果和解釋。

The expected discovery time of EGSE-A and EGSE-B under the same parameter settings are shown in Fig. 7 and Fig. 8.
EGSE-A 和 EGSE-B 在相同參數設置下的預期發現時間如圖 7 和圖 8 所示。

Here, we let N = 10,000, M = 100 and ϵ= 0.1.
在這裡，我們讓 N = 10,000，M = 100 和 ϵ = 0.1。

The evolution of the expected discovery time is plotted against the number of trials.
預期發現時間的演變是根據試驗次數繪製的。

In the inception of both EGSE-A and EGSE-B, the expected discovery time fluctuates tremendously and the results can be seen to vary dramatically with the relatively small number of trials.
在 EGSE-A 和 EGSE-B 的初始階段，預期的發現時間波動很大，並且可以看到結果隨著相對較少的試驗數量而發生巨大變化。

With the number of trials increasing, the patterns of EGSE-A and EGSE-B gradually become steady and finally converge to the theoretical values of 991.0 (with relative error 0.036%), and 496.0 (with relative error 1.428%) respectively.
隨著試驗次數的增加，EGSE-A 和 EGSE-B 的模式逐漸趨於穩定，最終分別收斂到理論值 991.0（相對誤差 0.036%）和 496.0（相對誤差 1.428%）。

These results suggest that when the same query is visited a sufficient number of times, both EGSE-A and EGSE-B are guaranteed to return the most relevant object in the search space regardless of the initial settings.
這些結果表明，當同一查詢被訪問足夠次數時，無論初始設置如何，EGSE-A 和 EGSE-B 都保證返回搜索空間中最相關的對象。

With the same set of parameters, EGSE-B takes a much smaller discovery time to discover the most relevant object compared to EGSE-A.
使用相同的參數集，與 EGSE-A 相比，EGSE-B 需要更短的發現時間來發現最相關的對象。

To see how the discovery time evolves with different values, Fig. 9 shows the expected discovery time of EGSE-B with values of 0.12 and 0.13.
為了了解發現時間如何隨不同值演變，圖 9 顯示了 EGSE-B 的預期發現時間，其值為 0.12 和 0.13。

Again, fluctuations exist only in the early stage when the specific query is input for relatively few times.
同樣，波動僅存在於特定查詢輸入次數相對較少的早期階段。

With the increasing number of trials, the expected discovery times are around 410.17 and 389.92 with relative errors of 0.804% and 0.655% respectively compared to the theoretical values of 413.5 and 381.77.
隨著試驗次數的增加，預期發現時間約為 410.17 和 389.92，與理論值 413.5 和 381.77 相比，相對誤差分別為 0.804%和 0.655%。

The same evolution pattern holds true for EGSE-A as well.
同樣的演化模式也適用於 EGSE-A。

As a result, no matter which variant of the Є-greedy method is adopted, the value choice of would only affect how aggressive the exploration strategy is but has no impact on uncovering the most relevant object in the end.
因此，無論採用 Є-greedy 方法的哪種變體，值的選擇只會影響探索策略的激進程度，而不會影響最終發現最相關的對象。

In real-world multimedia search systems, it is often desirable to return the most satisfactory results within limited time and resources, so that users would deem it as effective.
在現實世界的多媒體搜索系統中，通常希望在有限的時間和資源內返回最令人滿意的結果，以便用

戶認為它是有效的。

Therefore, it is of interest to know whether object X can be discovered within limited time steps.
因此，了解是否可以在有限的時間步長內發現對象 X 是很有趣的。

Specifically, we use the same settings as for Fig. 7 and Fig. 8, and set the maximum time step to be 750, 800 and 850 respectively for each query trial.
具體來說，我們使用與圖 7 和圖 8 相同的設置，並將每個查詢試驗的最大時間步長分別設置為 750、800 和 850。

The results are plotted in Fig. 10, which shows that along with time, the probabilities of discovering object X under such time constraints are respectively 75.8%, 80.5% and 86.1%.
結果繪製在圖 10 中，表明隨著時間的推移，在這種時間約束下發現對象 X 的概率分別為 75.8%、80.5% 和 86.1%。

It agrees with the intuition that tighter constraints result in smaller probability of discovering the desired object, as the unfavorable initial settings would always require longer time for the discovery.
它同意更嚴格的約束導致發現所需對象的可能性更小的直覺，因為不利的初始設置總是需要更長的時間來發現。

Nevertheless, even in systems where time resources is a significant concern, the modified Є-greedy algorithms can still lead to the promising discovery of the desired object.
儘管如此，即使在時間資源是一個重要問題的系統中，修改後的貪婪算法仍然可以導致對所需對象的有希望的發現。

This in turn corroborates the effectiveness of EGSE-A and EGSE-B.
這反過來又證實了 EGSE-A 和 EGSE-B 的有效性。

VI. SUMMARY AND CONCLUSIONS 總結和結論

多媒體數據對象往往具有豐富多樣的屬性，這使得它們難以被完全索引。

結果，直接向用戶呈現看起來相關的多媒體對象可能不是最佳的，因為給定查詢的最相關的對象可能逃過注意並且永遠不會被顯示或檢索。

This will result in the landing in a local maximum, whereby suboptimal results are repeatedly shown and received an increase in relevance score, while the most relevant objects are never exposed and stand no chance of being clicked to receive an increase in relevance score.
這將導致降落在局部最大值，從而重複顯示次優結果並獲得相關性得分的增加，而最相關的對象永遠不會暴露並且沒有機會被點擊以接收相關性得分的增加。

Consequently, to overcome this problem, the search space should be explored, while at the same time the

competence of the search engine is not compromised.
因此，為了克服這個問題，應該探索搜索空間，同時不損害搜索引擎的能力。

本研究利用在強化學習情況下廣泛使用的 Є-greedy 算法來指導整個搜索空間的系統探索。

By judiciously setting the value of Є in these algorithms, a good balance between exploitation and exploration may be achieved.
通過在這些算法中明智地設置 Є 的值，可以實現開發和探索之間的良好平衡。

We consider two variations of the Є-greedy algorithm, representing different emphasis placed on fault-tolerance and efficiency, and study their performance both theoretically and experimentally.
我們考慮了 Є-greedy 算法的兩種變體，代表了對容錯和效率的不同重視，並從理論上和實驗上研究了它們的性能。

We have shown that, through such exploration, the problem of local optima can be overcome, and the algorithms are able to guarantee that the most relevant multimedia objects to given queries can always be found.
我們已經表明，通過這種探索，可以克服局部最優問題，並且算法能夠保證始終可以找到與給定查詢最相關的多媒體對象。

Closed-form expressions of the performance of these algorithms have been derived,
已經導出了這些算法性能的閉式表達式，

which exhibit good agreements with experimental results.
與實驗結果顯示出良好的一致性。

These results show that such exploration paradigm may be usefully incorporated into multimedia search systems to enable them to enhance the performance of multimedia information search,
這些結果表明，這種探索範式可以有效地結合到多媒體搜索系統中，使它們能夠提高多媒體信息搜索的性能，

so as to achieve the certain discovery of relevant objects that may be otherwise undiscoverable.
從而實現對其他可能無法發現的相關對象的某些發現。

Fig. 1. Sample Images from Dataset (Size = 50). Fig. 2. Final Returned M-list using EGSE-A. Settings: $N = 1000, M = 50, \epsilon = 0.1$.

Fig. 1. Sample Images from Dataset (Size = 50).
圖 1. 來自數據集的示例圖像（大小 = 50）。

Fig. 2. Final Returned M-list using EGSE-A. Settings: N = 1000,M = 50, Є= 0.1.
圖 2. 使用 EGSE-A 的最終返回 M 列表。 設置：N = 1000，M = 50，Є= 0.1。

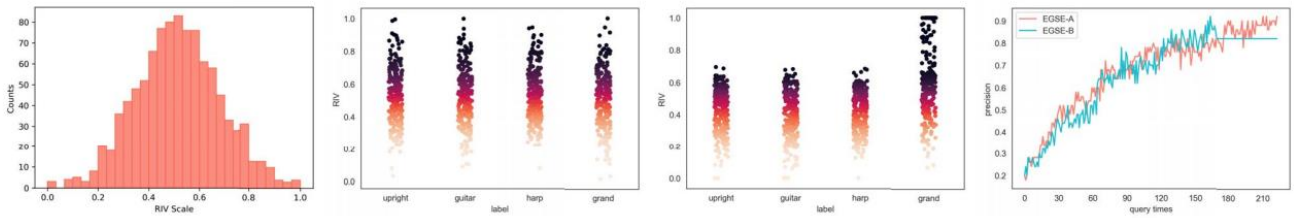

Fig. 3. Distribution of Initial RIV Scores. Fig. 4. Distribution of Initial RIV Scores for Each Category (EGSE-B). Fig. 5. Distribution of RIV Scores for Each Category When Hidden Object X is Discovered (EGSE-B). Fig. 6. Evolution of Query Precisions against Query Times. Settings: $N = 1000, M = 50, \epsilon = 0.1$.

Fig. 3. Distribution of Initial RIV Scores.
圖 3. 初始 RIV 分數分佈。

Fig. 4. Distribution of Initial RIV Scores for Each Category (EGSE-B).
圖 4. 每個類別 (EGSE-B) 的初始 RIV 分數分佈。

Fig. 5. Distribution of RIV Scores for Each Category When Hidden Object X is Discovered (EGSE-B).
圖 5. 發現隱藏對象 X 時每個類別的 RIV 分數分佈 (EGSE-B)。

Fig. 6. Evolution of Query Precisions against Query Times.
圖 6. 查詢精度隨查詢時間的演變。
Settings: N = 1000,M = 50, Є= 0.1.

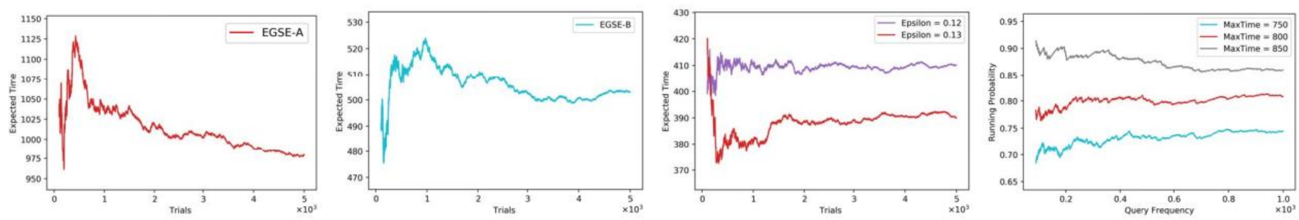

Fig. 7. Expected Discovery Time of EGSE-A. Fig. 8. Expected Discovery Time of EGSE-B. Settings: N = 10000, M = 100, $\epsilon = 0.1$. Fig. 9. Expected Discovery Time of EGSE-B with $\epsilon = \{0.12, 0.13\}$. Fig. 10. Probability of Discovering the Most Relevant Object in EGSE-B with Time Constraints.

Fig. 7. Expected Discovery Time of EGSE-A.
圖 7. EGSE-A 的預期發現時間。

Fig. 8. Expected Discovery Time of EGSE-B. Settings: N = 10000, M = 100, Є= 0.1.

圖 8. EGSE-B 的預期發現時間。 設置：N = 10000，M = 100，ϵ= 0.1。

Fig. 9. Expected Discovery Time of EGSE-B with = {0.12, 0.13}.
圖 9. EGSE-B 的預期發現時間 ϵ = {0.12, 0.13}。

Fig. 10. Probability of Discovering the Most Relevant Object in EGSE-B with Time Constraints.
圖 10. 在具有時間約束的 EGSE-B 中發現最相關對象的概率。

Appendix A

From Section IV B, we have

$$f_{r,M,k+1} = f_{r,M,k} \times \frac{\binom{N-K-kr}{r}}{\binom{N-K-kr-1}{r-1}} \times \frac{\binom{N-K-kr-1}{r}}{\binom{N-K-kr}{r}} \times \frac{\binom{N-K-(k+1)r-1}{r-1}}{\binom{N-K-(k+1)r}{r}},$$

This is expanded as

$$\begin{aligned} f_{r,M,k+1} = f_{r,M,k} &\times \frac{[N-K-(k+1)r]!(r-1)!}{(N-K-kr-1)!} \\ &\times \frac{(N-K-kr)!}{[N-K-(k+1)r]!r!} \\ &\times \frac{(N-K-kr-1)!}{[N-K-(k+1)r-1]!r!} \\ &\times \frac{[N-K-(k+1)r]!r!}{(N-K-kr)!} \\ &\times \frac{[N-K-(k+1)r-1]!}{[N-K-(k+2)r]!(r-1)!} \\ &\times \frac{[N-K-(k+2)r]!r!}{[N-K-(k+1)r]!}, \end{aligned}$$

Considerable simplification of the above shows that $f_{r,M,k+1} = f_{r,M,k} = C$. Since after $(N-K)/r$ presentations, all random objects will have been exhausted, this implies that $C = r/(N-K)$. The mean is therefore

$$C\left(1+2+...+\frac{(N-K)}{r}\right) = \frac{(N-M+2r)}{2r}.$$

The corresponding second moment is

$$C\left(1^2+2^2+...+[\frac{(N-K)}{r}]^2\right) = \left(1+\frac{(N-K)}{r}\right) \times \frac{\left(1+\frac{2(N-K)}{r}\right)}{6}. \quad (7)$$

The variance is therefore

$$\left(1+\frac{(N-K)}{r}\right) \times \frac{\left(1+\frac{2(N-K)}{r}\right)}{6} - \left(\frac{(N-M+2r)}{2r}\right)^2$$

which simplifies to

$$\frac{1}{12} \times \left\{\left[\frac{N-M+r}{r}\right]^2 - 1\right\}. \qquad \square$$