

# LEVERAGING BIG DATA TO IMPROVE SEARCH PERFORMANCE

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- FULL PROFESSORSHIPS at
  - Chinese University of Hong Kong, Shenzhen, China
  - University of London, UK
  - Victoria University, Australia
  - Hong Kong Baptist University
  - National University of Singapore
- Two US patents & published five books and over 150 research articles
- Program Chair, Keynote Speaker, Panel Expert of major International Conferences
- Editorial Board of ten International Journals
- Listed in Who's Who in the World and Great Minds of the 21st Century
- Fellow of the British Computer Society, Fellow of the Royal Society of Arts, and Fellow of the International Academy, Research, and Industry Association

# CONCEPT-BASED SEARCH

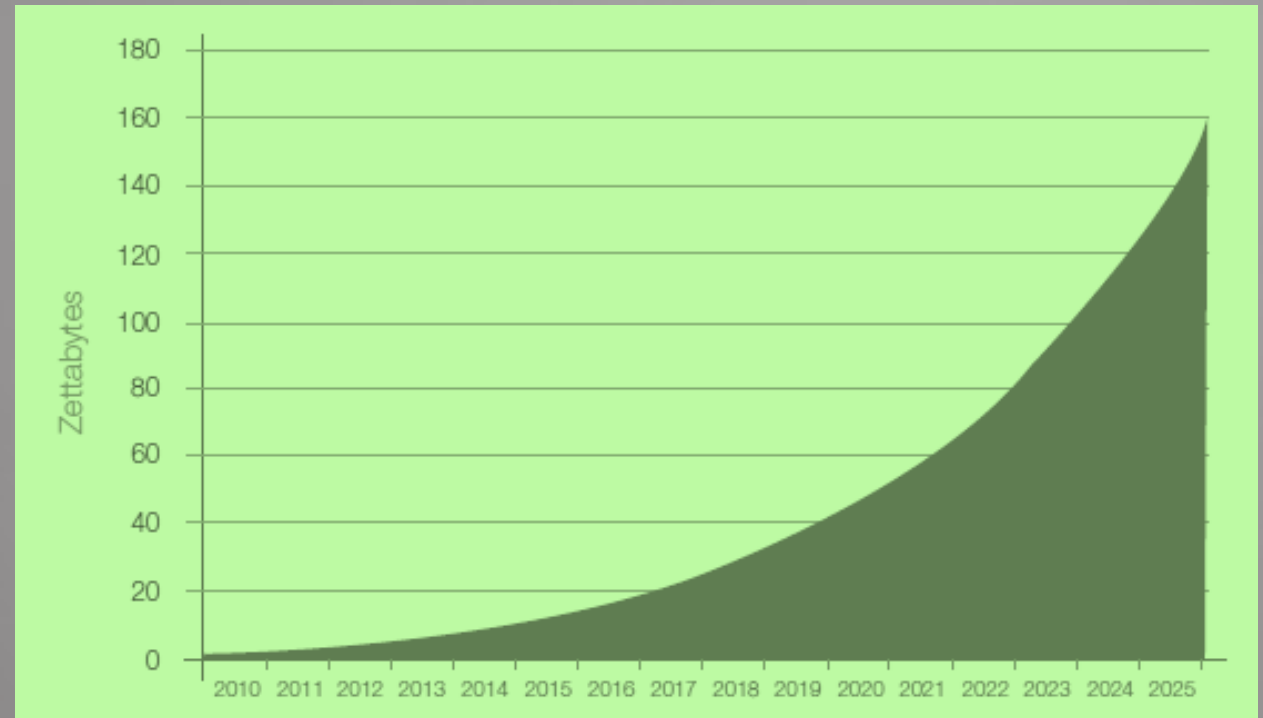


Deep Knowledge



Semantic  
Search

# EXPONENTIAL GROWTH OF THE DIGITAL UNIVERSE

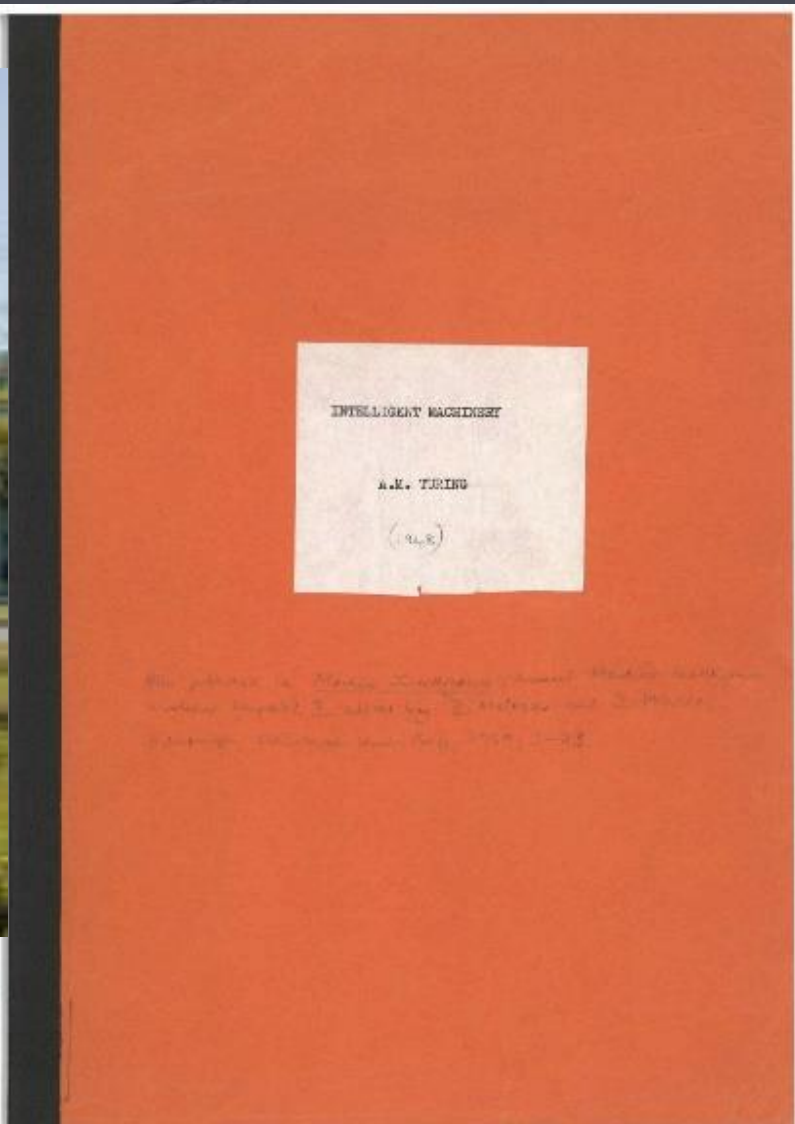
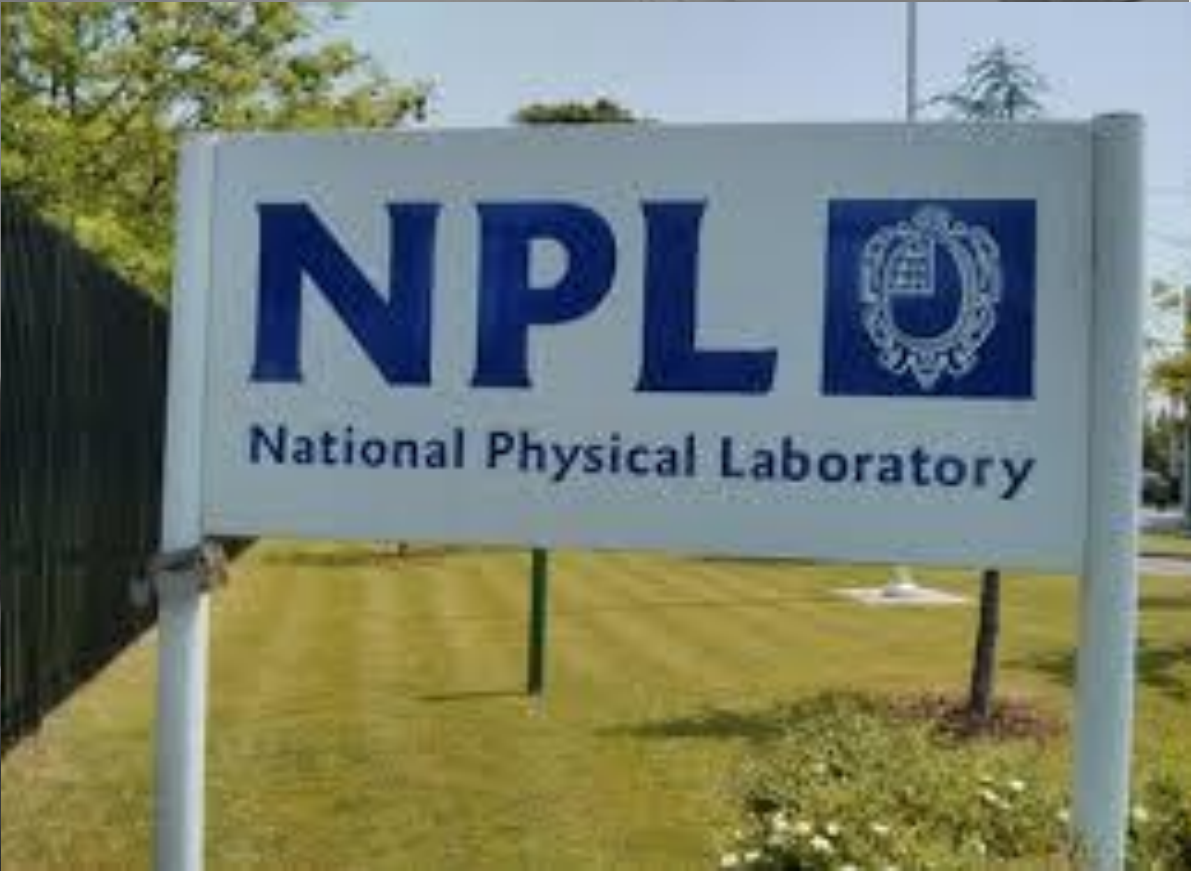


Source: IDC's Data Age 2025 study, sponsored by Seagate, April 2017

- By 2025, the amount of data  $\approx$  160 zettabytes ( $160 \times 10^{21}$ )
- 1 zetta seconds = 31.71 trillion years = 2300 x age of universe
- The volume of seawater in the Earth's oceans is approximately 1.37 zettalitres



# TURING: "All Problems are Essentially Search Problems"



...lligent Machinery".

...question as to whether it is possible for  
... It is usually assumed without argument  
... phrases such as 'acting like a machine'  
... his common attitude. It is not difficult to  
... risen. Some of the reasons are

...at the possibility that mankind can have any  
...ours as such amongst intellectual people as  
...e. Those who admit the possibility all agree  
...agreeable. The same situation arises in con-  
...ing superseded by some other animal species.  
...theoretical possibility is indisputable.

-2-

objections

...ction I propose to outline reasons why we do not need to be in-  
...we describe objections. The objections (a) and (b), being  
...to not really need to be refuted. If one feels it necessary to  
...is little to be said that could hope to prevail, though the actual  
...machines would probably have some effect. In so far then as we  
...such arguments we are bound to be left feeling rather uneasy about  
...at any rate for the present. These arguments cannot be wholly  
...is idea of 'intelligence' is itself emotional rather than mathe-

...tion (c) in its crudest form is refuted at once by the actual  
...very (EXIAC etc.) which can go on through immense numbers (e.g.  
...AGE) of operations without repetition, assuming no breakdown.  
...nas of this objection will be considered at length in § 11 and 12.

...nt from Gödel's and other theorems (objection (d)) rests essentially  
...at the machine must not make mistakes. But this is not a require-  
...ce. It is related that the infant Gauss was asked at school to  
...+ 18 + 21 + .... + 54 (or something of the kind) and that he  
...lown 483, presumably having calculated it as  $(15 + 54) \cdot (54 - 12) / 2 \cdot 3$   
...countances where a foolish master told the child that he ought  
...led 16 to 15 obtaining 35, then added 01 etc. From some points  
...be a 'mistake', in spite of the obvious intelligence involved.

...e a situation where the children were given a number of additions to  
...irst 5 were all arithmetic progressions, but the 6th was say  
...+ 100 + 112 + 122 + ..... + 199. Gauss might have given the  
...if it were an arithmetic progression, not having noticed that the  
...instead of 111. This would be a definite mistake, which the less  
...would not have been likely to make.

...d) that intelligence in machinery is merely a reflection of that  
...rather similar to the view that the credit for the discoveries of  
...iven to his teacher. In such a case the teacher would be pleased  
...his methods of education, but would not claim the results them-  
...d actually communicated them to his pupil. He would certainly  
...very broad outline the sort of thing his pupil might be expected  
...t expect to foresee any sort of detail. It is already possible  
...where this sort of situation arises in a small degree. One can  
...lines' for playing chess. Playing against such a machine gives a  
...at one is pitting one's wits against something alive.

...rs will all be developed more completely below.

ALL PROBLEMS ARE  
ESSENTIALLY SEARCH  
PROBLEMS



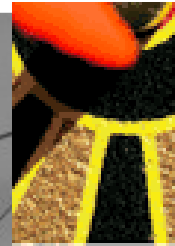
*"...intellectual activity consists mainly of various kinds of search."*

*"...evolutionary search..."*

*"indexes of experiences"*

*"...cultural search...by the human community as a whole"*

- In 2009, Google researchers publish a paper entitled “The Unreasonable Effectiveness of Data”
- The paper suggests that simple models with lots of data are better than elaborate models with less data
- No need to learn from algorithms how humans perform the tasks because the intelligence is in the data, not the algorithms



## **The Unreasonable Effectiveness of Data**

Alon Halevy, Peter Norvig, and Fernando Pereira, Google

**No explanation,  
no justification?**

## KEY ISSUES

- **D**istinct genres
  - Multimedia entities: Images, Videos, 3D Models, Stream Music...
- **S**emantic gap
  - Low-level features VS high-level semantics
  - Concept-Based VS Content-Based
- **L**ack of Efficient Methods
  - Trade-off between precision and complexity
  - Absence of a universally-accepted retrieval method



# DEEPER SEMANTICS



Need to have significant background knowledge to retrieve this image (David and Goliath)

- Objective factual description
- Interpretation of the objects in the picture based on prior knowledge
- Familiarity with the subject matter

### Primary Level

- Objective description of content

### Secondary Level

- Basic level of interpretation/summary of some/all entities

### Tertiary Level

- Knowledge-based elements

## Perception and interpretation of semantic content

- Depends on user knowledge & experience
- Degree of content richness can be distinguished into 3 levels
- Information encoded in a multimedia object can be potentially unlimited

# LEVELS OF SEMANTICS

# Learning from Big Data

**INDEX  
LEARNING AND  
EVOLUTION**

**ADOPTION OF  
REINFORCEMENT  
LEARNING  
ARCHITECTURE**





- More than 2 billion people are connected to the Internet
- 20 sec of their time is more than 10 million man hours
- Empire State Building took 7 million man hours to build
- One Empire State Buildings built every 15 seconds

## INDEX BUILDING THROUGH EXPLOITING BIG DATA



# EXPLOITING BIG DATA

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- System continuously learns and evolves
- Adapts its answer lists to queries
- Satisfies latest user preferences
- Incorporates deep knowledge from users
- Unsupervised Reinforcement Learning
- Semi-Markov Decision Process framework



# EXPLOITING BIG DATA

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- Capture subtle nuances of human perceptions and deep knowledge
- Degree of reinforcement is suitably calibrated
- Indexes evolve naturally to accommodate dynamic user interests
- Continuously develop indexes
- Injecting progressive improvement in search performance



# INDEX EVOLUTION

- Dynamically builds semantic indexes to associate query terms with multimedia objects
- Construction of new Indexes and Deconstruction of existing Indexes
- Advantages
  - Addresses newly-emerged concerns (e.g. privacy, legitimacy) in social networks
  - Automatic evolution without human invention



# INDEX EVOLUTION

- A learning function  $\mathcal{L}$  between the object space and the term space to measure the relevance liaison:

$$\mathcal{L}: T \times O \rightarrow \mathbb{R}^+ \cup \{0\}$$

- For each link between an index term  $\tau$  and a multimedia object  $o$ :
  - $\mathcal{R}$ : relevance base;  $\omega$ : normalized weight

$$\mathcal{L}(\tau, o) \rightarrow \omega\mathcal{R}, \omega \in (0, 1)$$

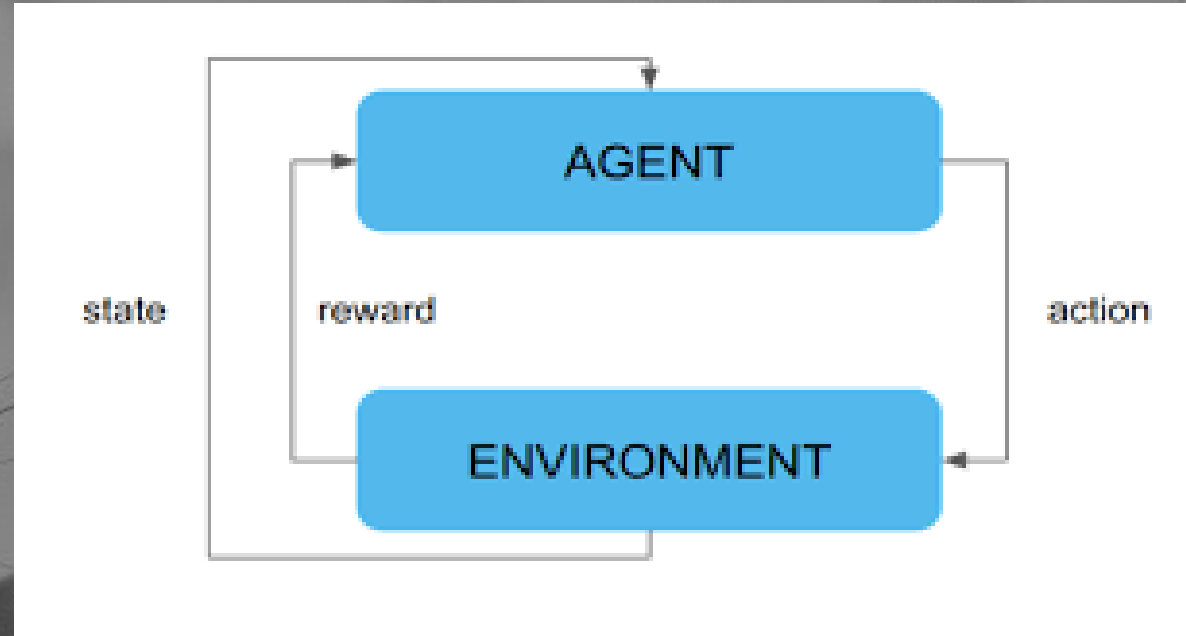
- Output – Relevance Index Value (RIV):  
non-negative real numbers that specify corresponding relevance with 0 indicating complete irrelevance



# KNOWLEDGE EXTRACTION



- Clicking Model - implicit clicking information
- Click depends on pertinence of objects
- Reward Function
  - Scalar positive or negative reward
- Iterative learning process
  - Robustness: eliminate random errors and fault tolerant



- **Reward is observed via the clicking information**
- **Take actions based on current states**
- **Learn from useful evaluative information provided by users**

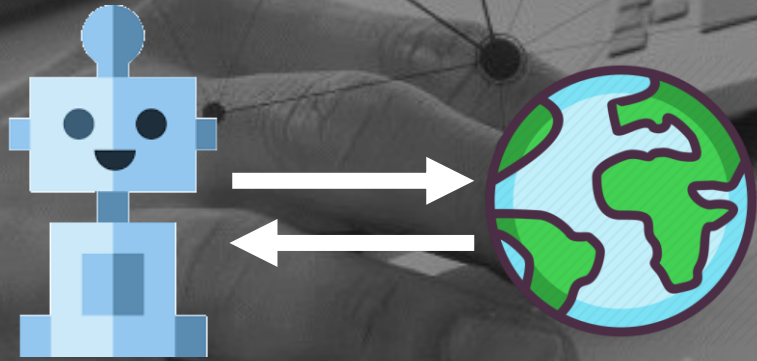
# REINFORCEMENT LEARNING

### Action Space A:

- Agent selects a set of objects and presents to user
- Intuitively huge due to a large number of combinatorial possibilities

### State space S:

- A set of all indexes in dynamic indexing
- Include explored and unexplored Indexes



## Semi-Markov Decision Process

## Reinforcement

- If a click results in a reinforcement made to a particular element  $x$ , then we have for its new value  $x' = x + \Delta$ , where  $\Delta$  is a parameter calibrated to represent the extent of the reinforcement
  - A large value of  $\Delta$  signifies strong reinforcement, while a small value of  $\Delta$  signifies weak reinforcement

# Semi-Markov Decision Process



## Rewards

- If  $n$  elements from the results list  $x_1, \dots, x_n$  receive reinforcement, then the reward would be  $n\Delta$ .
- If no clicking response is received from the user on a given list, then all the relevant elements between the submitted query terms and retrieved objects will be decremented by a given amount  $\Delta$ .
  - If there are  $q$  query terms, then for an object list of  $K$  objects, the total decrement will be  $qK\Delta$ , which corresponds to a (negative) reward of  $-qK\Delta$ .

# Semi-Markov Decision Process

- The entire process

$$\{Z(t), t > 0\}$$

gives the state the process at time  $t$  and is a semi-Markov process, with the transition epochs being the *embedded Markov chain* of the process

- Here, the embedded Markov chain characteristics are such that a transition will trigger a move of the RIV of certain indexes an amount  $\pm\Delta$

## Semi-Markov Decision Process

- Letting  $\{\pi_i\}$  denote the stationary probabilities of the embedded Markov Chain, then it can be shown that the limiting state probabilities are given by

$$P_i = \frac{\pi_i \mu_i}{\sum_j \pi_j \mu_j}$$

where  $\mu_i$  is the average time the process spends in state  $i$

## Semi-Markov Decision Process



- The semi-Markov process takes into account the real time elapsed between state transitions, as simply sampling the system at transition points will not give a full picture
- The semi-Markov process is no longer memoryless because given the present state, the future evolution of the process is no longer independent of the past
  - In order to predict the future, it is not sufficient to just know the present state, but also the length of time that the process has been in the present state

**No Longer  
Memoryless**



# LEARNING CONVERGENCE



**T**he problem of *learning convergence* is concerned with whether unexplored indexes will eventually evolve to become explored indexes. The index learning behaviour is considered to be convergent if the vast majority of unexplored indexes become explored indexes in the learning process

# LEARNING CONVERGENCE



- **TOR-Tuple** [ $\tau_i, o_j, r_{ij}$ ]
  - represent the relationship between a query term  $\tau_i$  and an object  $o_j$ , with  $r_{ij}$  as RIV
- **Index Criteria**
  - $r_{ij}$  must attain or surpass the pre-defined threshold value  $h$
- **Two categories of indexes**
  - Unexplored indexes: reside in the index generator
  - Explored indexes: promoted from index generator into the index pool

# LEARNING CONVERGENCE



- Consider a query with multiple terms  $Q(\tau_1, \dots, \tau_t, \tau_{t+1}, \dots, \tau_n)$
- Explored indexes exist for  $\{\tau_1, \dots, \tau_t\}$  with a set of multimedia objects
- $\{\tau_{t+1}, \dots, \tau_n\}$  are entirely new terms
- *Returned Object List* is a union set
  - a  $k$ -object subset  $O_a: \{o_1, o_2, \dots, o_k\}$  that has the highest cumulative RIV scores
  - a subset  $O_b$  of random objects selected for exploration

- Naïve Strategy

- Returns the best  $K$  result objects ordered by index scores in decreasing order ( $k = K$ )
  - Objects with high RIV will be shown repeatedly for user evaluation
  - The RIV of these objects tends to keep increasing even though they may not be the most relevant as these are selected as relevant (clicked) by the users
- Would lead to *local maxima problem*
  - Objects that have the highest RIV may not in fact be the most relevant

**PURE  
EXPLOITATION**



The background of the slide features a grayscale image of a person's hands typing on a laptop keyboard. Overlaid on this image is a network graph consisting of several black circular nodes connected by thin black lines, representing a complex web of connections. The text is presented in a clean, sans-serif font, with the main heading in a light green color and the list items in white.

- Randomized Strategy

- Returns  $K$  result objects purely by random extractions ( $k = 0$ )
- Discover 'hidden' objects by randomness
- Exploration vs exploitation

**PURE  
EXPLORATION**

- We use a convex combination of exploration and exploitation
  - For  $0 < u < 1$ , we include a proportion of  $\alpha$  randomly chosen objects, and  $\nu$  objects from exploitation, with  $u + \nu = 1$ 
    - $u = 0$  corresponds to pure exploitation
    - $u = 1$  corresponds to pure exploration
  - The  $\beta$  objects from exploitation can be chosen according to their ranks, or picked from the retrieved list using some randomized algorithm

## Convex Combination

## State Classification

- **Exposed**: If an unexplored index is elevated into the index pool, it can be regarded as exposed.
- **Extant**: Conversely, it is regarded to be extant and still in the evolutionary process.

# ANALYSIS OF LEARNING CONVERGENCE BEHAVIOUR

## State Simplification

- The state of the process in this particular context can be simplified as the number of extant unexplored indexes.

**PROBABILITY  
A GIVEN  
UNEXPLORED  
INDEX BE  
EVENTUALLY  
EXPOSED**

$$\frac{1 - \left[\frac{1-f}{f}\right]^k}{1 - \left[\frac{1-f}{f}\right]^h}$$

where  $f (>1/2)$  is the positive feedback probability,  
 $k (< h)$  is the current score of the index,  
 $h$  is the threshold



# TIME FOR A GIVEN UNEXPLORED INDEX TO BE EXPOSED

Average time:

$$1 + \frac{2q^{h-k+1} - (h-k+1)q^2 + h-k-1}{(1-q)^2}$$

where  $q = (1 - f)/f$

# IMMIGRATION -DEATH PROCESS

## Evolutionary Behaviour

- A total of  $C$  unexplored indexes initially
- Let  $S_t$  denote the reduced system state at time  $t$ , omitting the RIV scores:  $S_0 = C$
- In the evolutionary stage,  $S_t$  decreases compared with  $S_0$

# IMMIGRATION -DEATH PROCESS

## Evolutionary Behaviour

- Whenever an unexplored index is exposed,  $S_t$  is decreased by one.
- At a particular time  $t$ , the number of remaining unexplored indexes follows an **immigration-death process** with rate  $\alpha$ :

$$P(S_t = k) = \binom{S_0}{k} (e^{-\alpha t})^k (1 - e^{-\alpha t})^{S_0 - k}$$

$$E(S_t) = S_0 e^{-\alpha t}$$

$$V(S_t) = S_0 e^{-\alpha t} (1 - e^{-\alpha t})$$

- $E(S_t)$  denotes the expected number of extant unexplored indexes after a time interval  $\Delta t$
- $V(S_t)$  gives the corresponding variance

# IMMIGRATION -DEATH PROCESS

## Evolutionary Behaviour

- Let  $t \rightarrow \infty$ :

$$\lim_{t \rightarrow \infty} E(S_t) = 0, \quad \lim_{t \rightarrow \infty} V(S_t) = 0$$

- Indicates eventually the entire collection of unexplored indexes will be fully discovered
- The limit of  $V(S_t)$  reveals that the effect of stochastic fluctuation tends to diminish in the course of the learning process, leading the system to evolve into a steady state
- The index learning behaviour acts like a deterministic evolution



# THEORETICAL RESULTS

## Evolutionary Behaviour

- Let  $T_s$  denote the expected time spent on indexing a proportion  $p$  of unexplored indexes
- A monotonically increasing function for  $T_s$  in regard to  $p$  can be obtained:

$$T_s = d \ln \frac{1}{(1-p)}, \quad d = \frac{1}{\alpha}$$

- The time unit of days is adopted for  $\alpha$ , and  $1/\alpha$  can be seen as the average number of days spent to discover an unexplored index.
- Let  $p \rightarrow 1$ , the limit of  $T_s$  tends to be infinite, suggesting when most unexplored indexes are exposed, the indexing time for the remaining few ones tends to be large

# THEORETICAL RESULTS

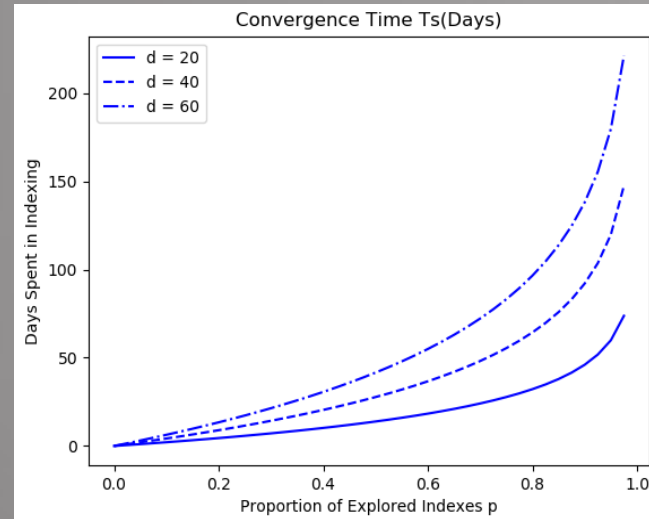
## Evolutionary Behaviour in SLSE

- Taking the derivative with respect to  $p$ , we have the incremental indexing time  $I_t$  in discovering unexplored indexes:

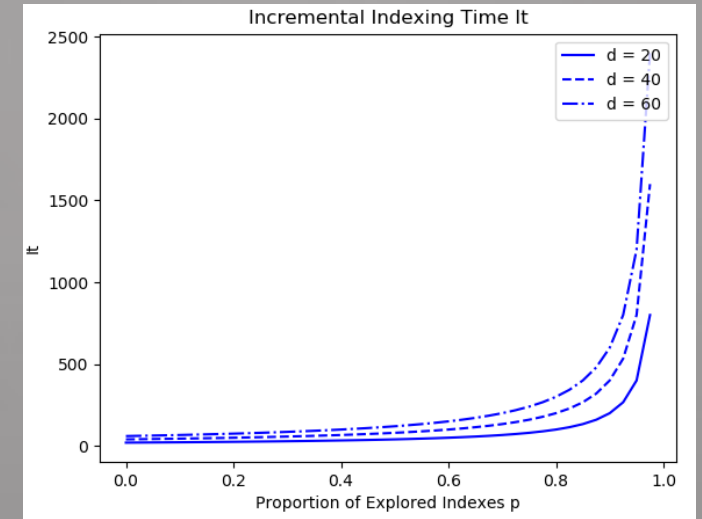
$$I_t = \left( d \ln \frac{1}{(1-p)} \right)' = \frac{d}{(1-p)}$$

- The larger the values of  $p$ , *the higher* the incremental indexing time tends to be

# THEORETICAL RESULTS



(a)  $T_s$ :  $d = 20, 40, 60$



(b)  $I_t$ :  $d = 20, 40, 60$

If 90% of the unexplored indexes needs to be indexed, approximately 2.3 times the amount of time  $d$  for discovering an individual index can be expected.

E.g. when  $d = 40$ , roughly 92 days are required for convergence. This can be seen by examining the above equation, and letting  $p = 0.9$ :

$$T_s = d \ln \frac{1}{(1 - 0.9)} = 2.3d$$

# SIMULATION EXPERIMENTS

- Consider the event that an end user submits a query and furnishes evaluative feedback by clicking interested returned objects.
- If such event streams are presented by a Poisson process with rate  $\alpha$ , the inter-event time has the following exponential density function:

$$f(t) = \lambda e^{-\lambda t}$$

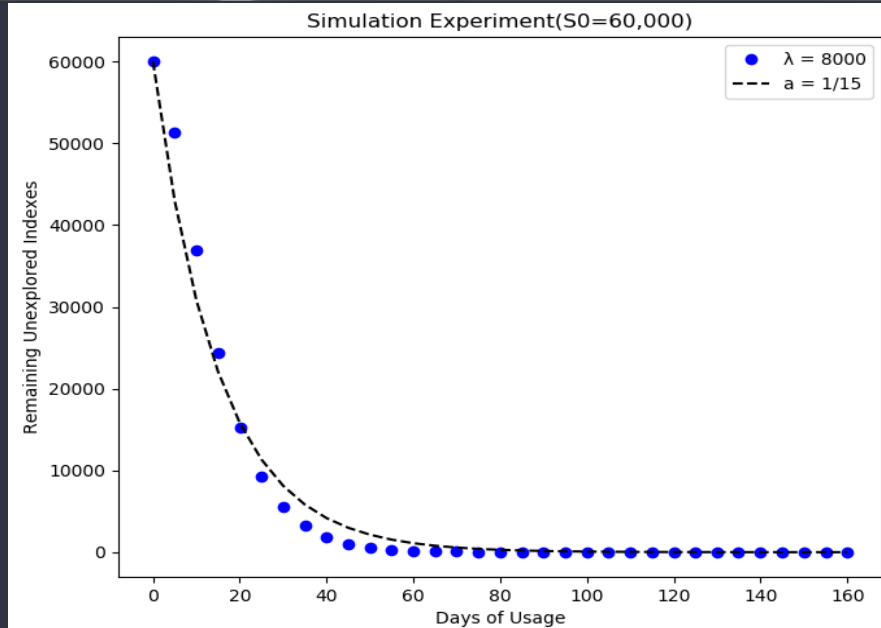
- Concerning the indexing behaviour, three different scenarios exist in regard to the submitted query  $Q(\tau_1, \dots, \tau_t, \tau_{t+1}, \dots, \tau_n)$

# SIMULATION EXPERIMENT

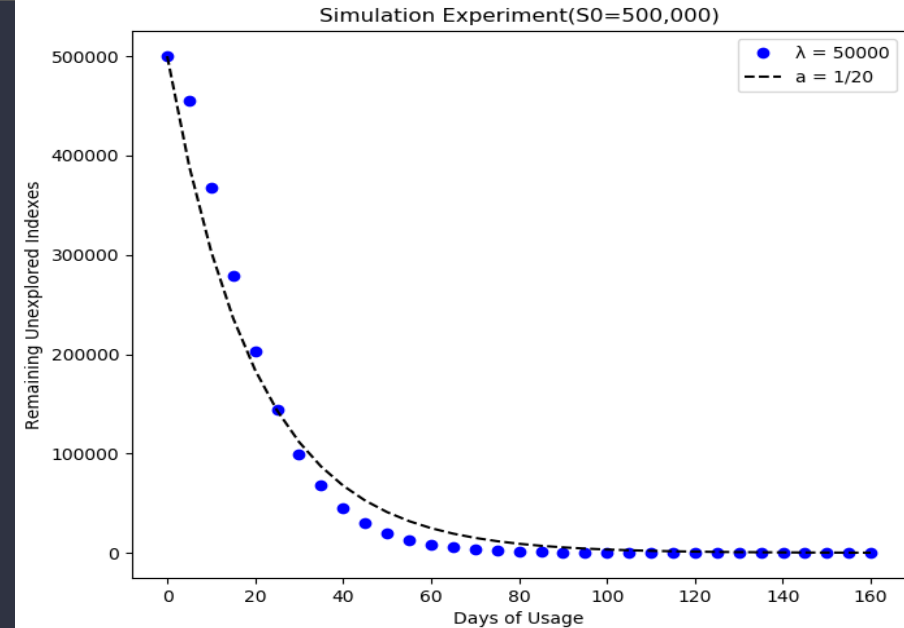
- Each time that an arrival of a user occurs, the user selection behaviour is enacted by randomly clicking on some objects in retrieved list
- Graphs of  $S_t$  at each arrival time  $t$ 
  - The blue dot series represent experimental results
  - The black lines correspond to theoretical analysis
  - Sampling frequency is set at five-day interval



# SIMULATION EXPERIMENT



(a) St:  $S_0 = 60,000$ ;  $\lambda = 8,000$ ,  $\alpha = 1/15$



(b) St:  $S_0 = 500,000$ ;  $\lambda = 50,000$ ,  $\alpha = 1/20$

Comparison between Simulation and Theoretical Results

# LEVERAGING BIG DATA

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- **Unlike text-based documents**, the indexing of multimedia entities for deep knowledge retrieval is a learning and evolutionary process
- **By applying reinforcement learning** within a semi-Markov decision process framework, the subtle nuances of human perceptions and deep knowledge are captured and learnt for evolution
- **Index evolution** enables effective retrieval of multimedia objects
- **Performance** of the system automatically improves over time

A grayscale image of a robotic hand typing on a keyboard. The hand is positioned in the upper left, with fingers pressing down on keys. The keyboard is visible in the foreground and background. A dark blue rectangular box with a white border is overlaid on the image, containing the text 'THANK YOU!' in white, bold, uppercase letters. A green gradient bar is visible on the left side of the blue box, and another green gradient bar is at the bottom of the page.

**THANK YOU!**