# Image Retrieval

# What is Image retrieval?

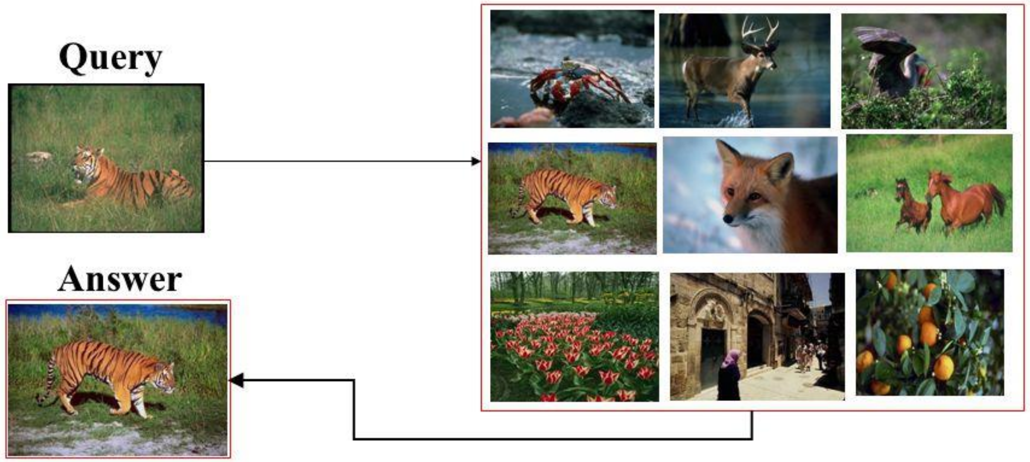
- The process of browsing, searching and retrieving images from a large database of digital images.
- Is a process of searching for digital images in large image scale image data, which is computer based for browsing, searching and retrieving images from digital images.
- An image retrieval system is a computer system used for browsing, searching and retrieving images from a large database of digital images.

https://www.igi-global.com/dictionary/image-retrieval/13836
https://en.wikipedia.org/wiki/Image_retrieval

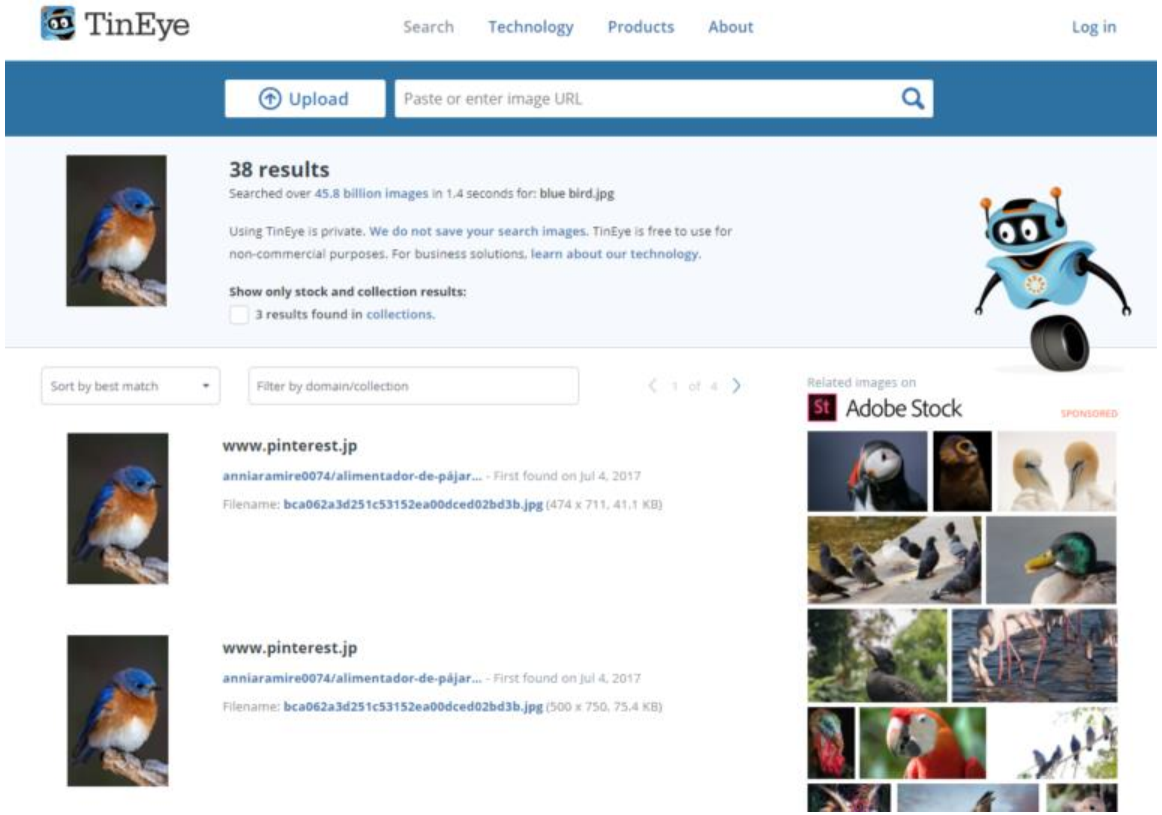
# What is Image retrieval?

## Content-based Image Retrieval

Given a query image, try to find visually similar images from an image database

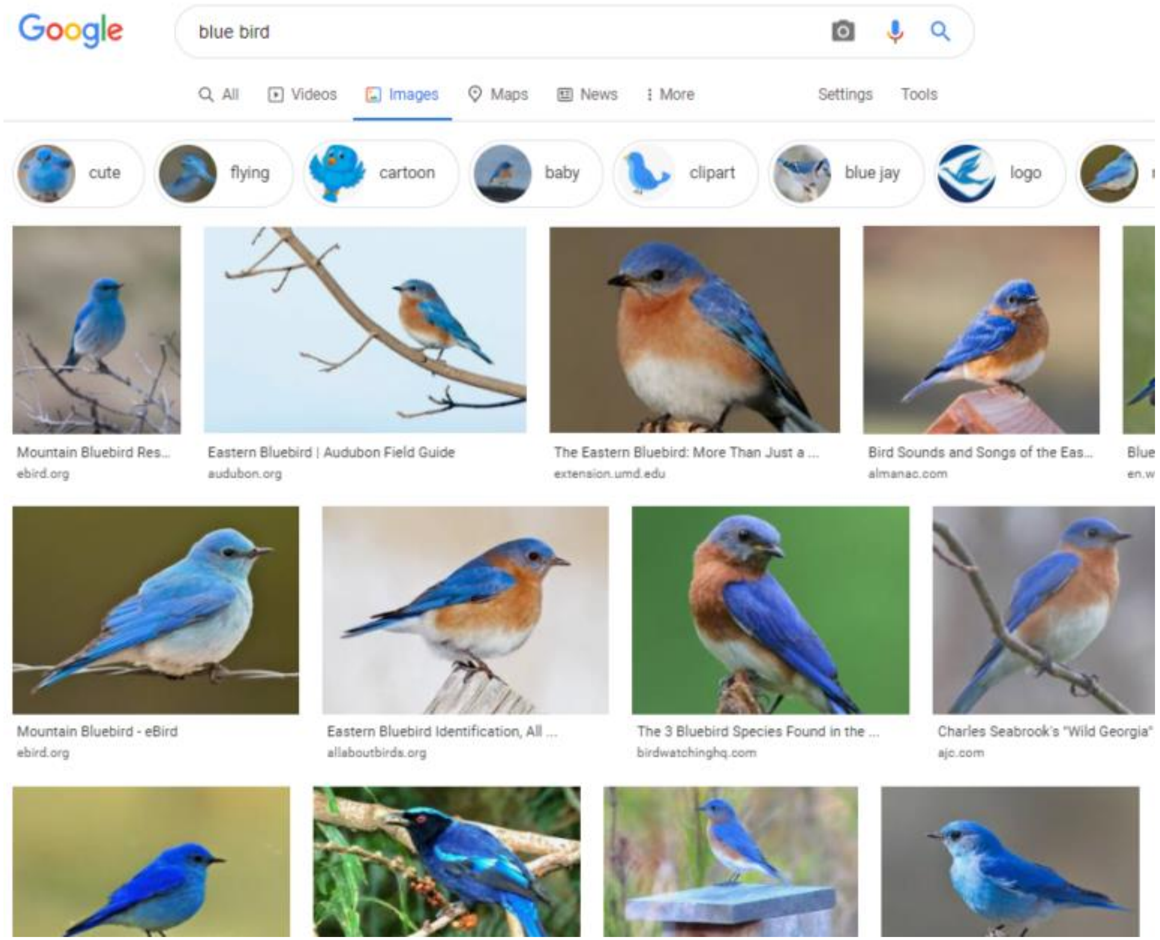


# Image Search Engines




https://www.searchenginejournal.com/best-image-search-engines/299963/#close

# Image Search Engines

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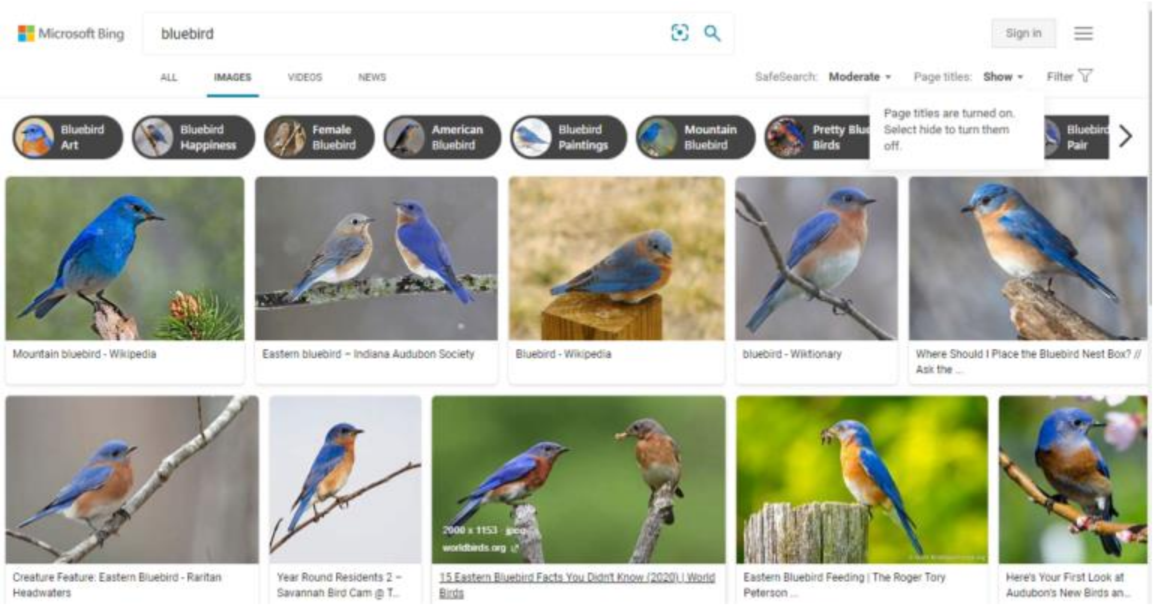
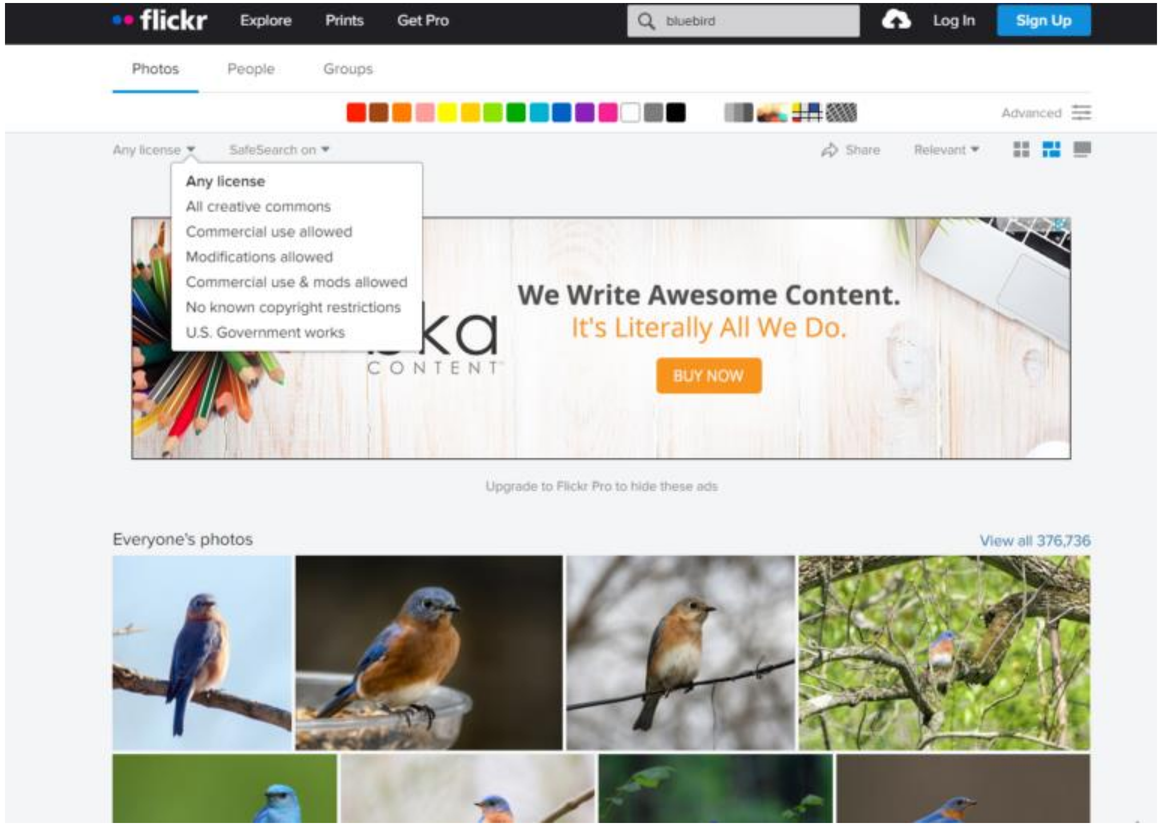
# Image Search Engines




https://www.searchenginejournal.com/best-image-search-engines/299963/#close

# Image Search Engines




https://www.searchenginejournal.com/best-image-search-engines/299963/#close

# Image retrieval

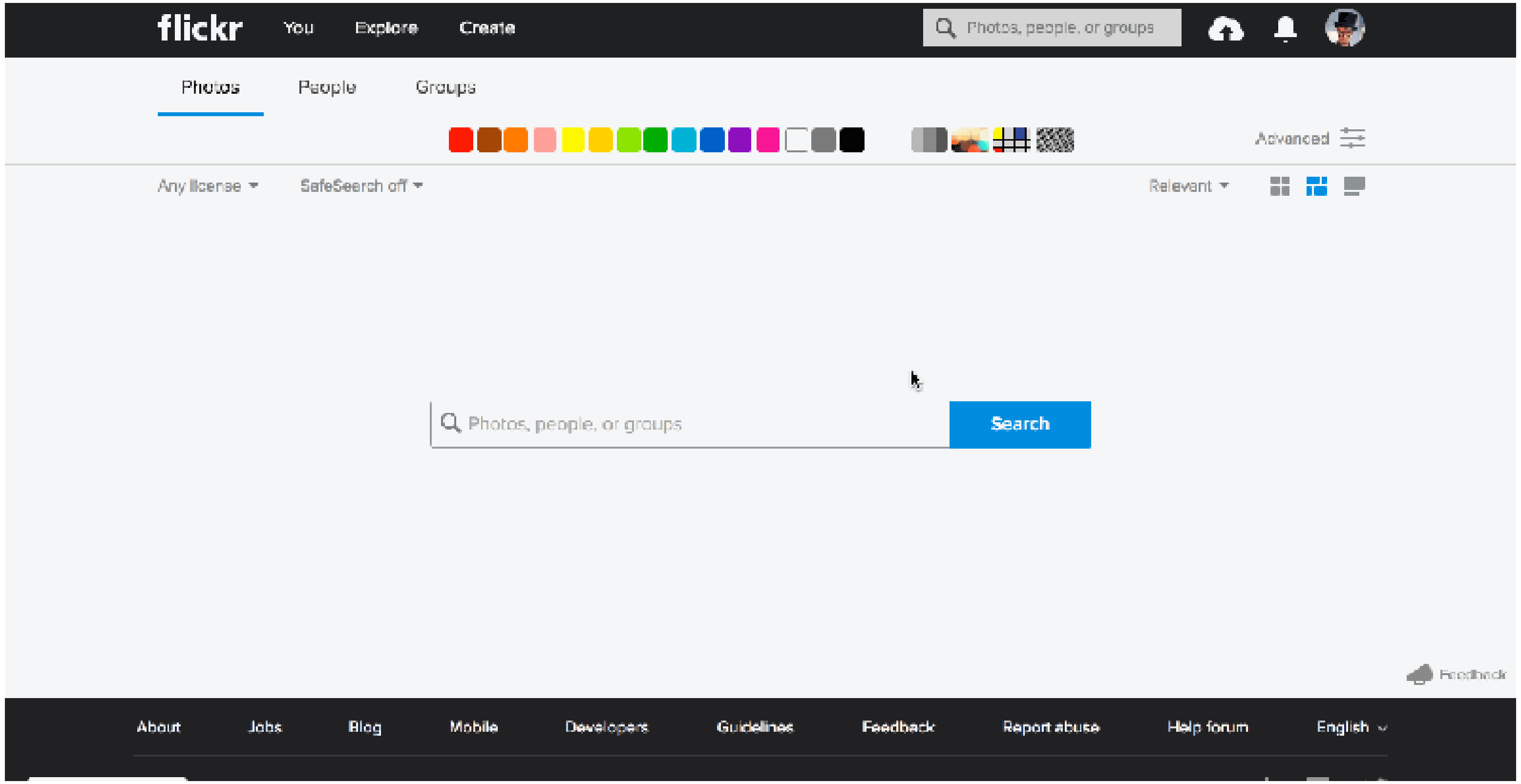
- Most traditional and common methods of image retrieval utilize some method of adding metadata such as captioning, keywords, title or descriptions to the images so that retrieval can be performed over the annotation words.

# Search methods

- To search for images, a user may provide query terms such as keyword, image file/link, or click on some image, and the system will return images "similar" to the query.

- The similarity used for search criteria could be meta tags, color distribution in images, region/shape attributes, etc.

# Search methods



# Search methods

1. Image meta search (Concept-based)
2. Content-based image retrieval (CBIR)
3. Image collection exploration

# Search methods

## 1. Image meta search (Concept-based)

- search of images based on associated metadata such as keywords, text, etc.

# Search methods

## 1. Image meta search (Concept-based)

→provides tags and keywords suggesting the content of an image

**Figure 1:** Let's assign some keywords and tags to this image: *dinosaur, velociraptors, kitchen, restaurant kitchen, boy, scared*

https://www.pyimagesearch.com/2014/01/15/the-3-types-of-image-search-engines-search-by-meta-data-search-by-example-and-hybrid/

# Search methods

## 1. Image meta search (Concept-based)

- → Searches that rely purely on metadata are dependent on annotation quality and completeness.

- → Having humans manually annotate images by entering keywords or metadata in a large database can be time-consuming, tedious, and expensive and may not capture the keywords desired to describe the image.

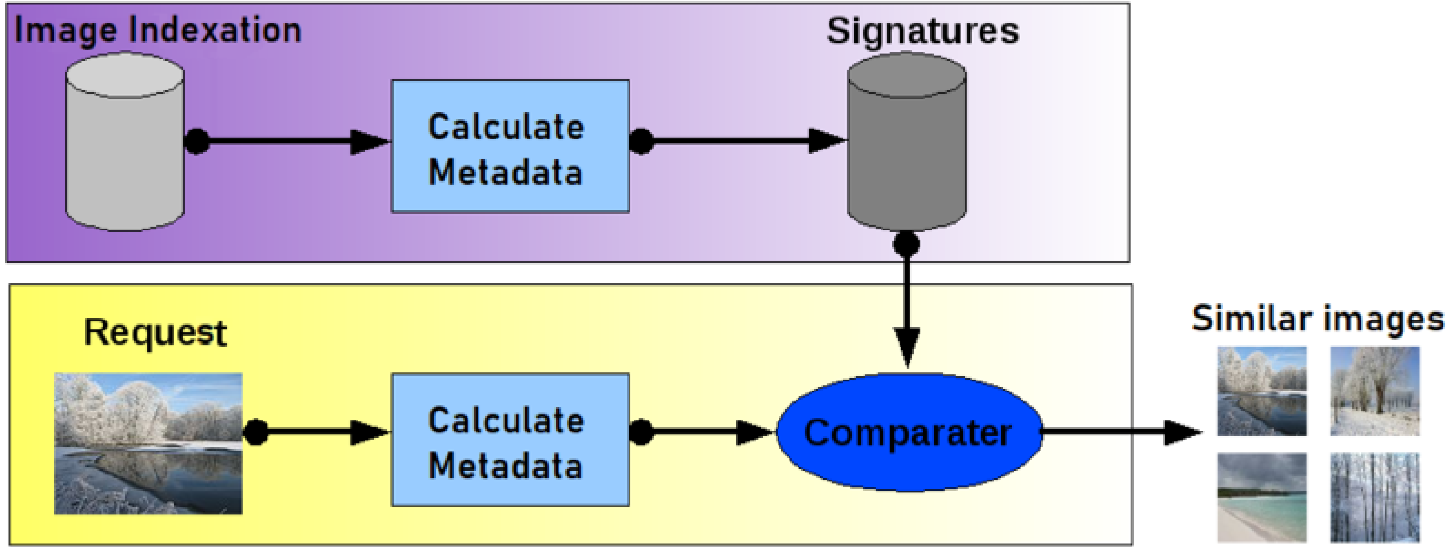
# Search methods

## 2. Content-based image retrieval (CBIR)

- CBIR aims at avoiding the use of textual descriptions and instead retrieves images **based on similarities in their contents** (textures, colors, shapes/object etc.) to a user-supplied query image or user-specified image features.

# Search methods

## 2. Content-based image retrieval (CBIR)



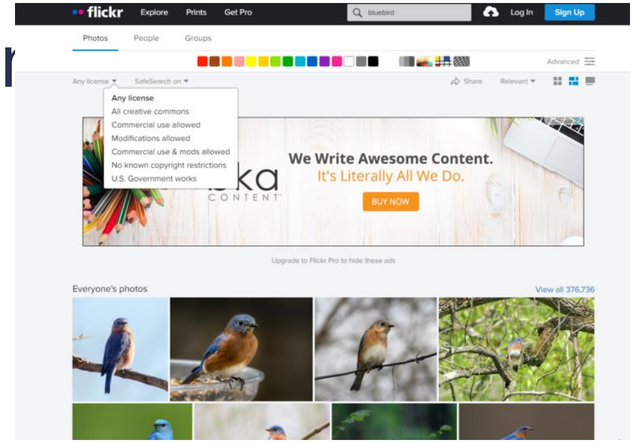

General scheme of content-based image retrieval

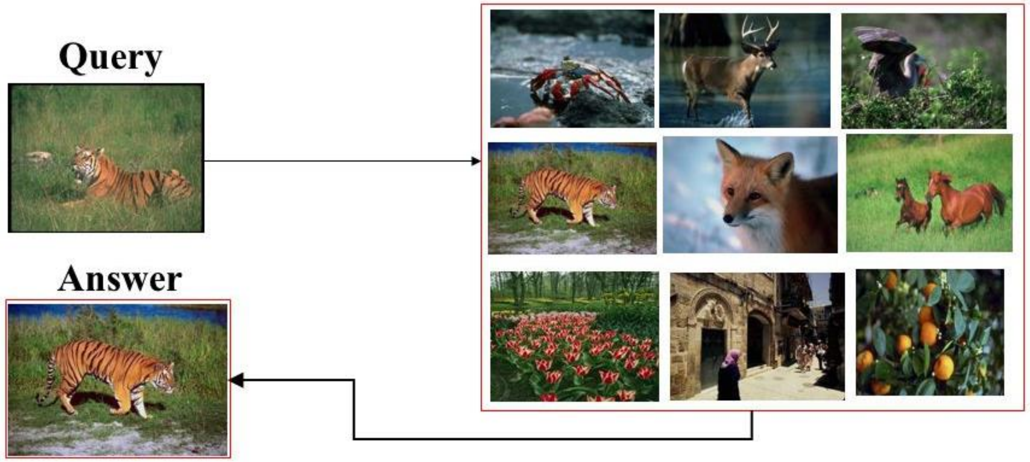
https://en.wikipedia.org/wiki/File:Principe_cbir.png

# Search methods

## 2. Content-based image retrieval (CBIR)

- The term "content" in this context might refer to colors, shapes, textures, or any other information that can be derived fro

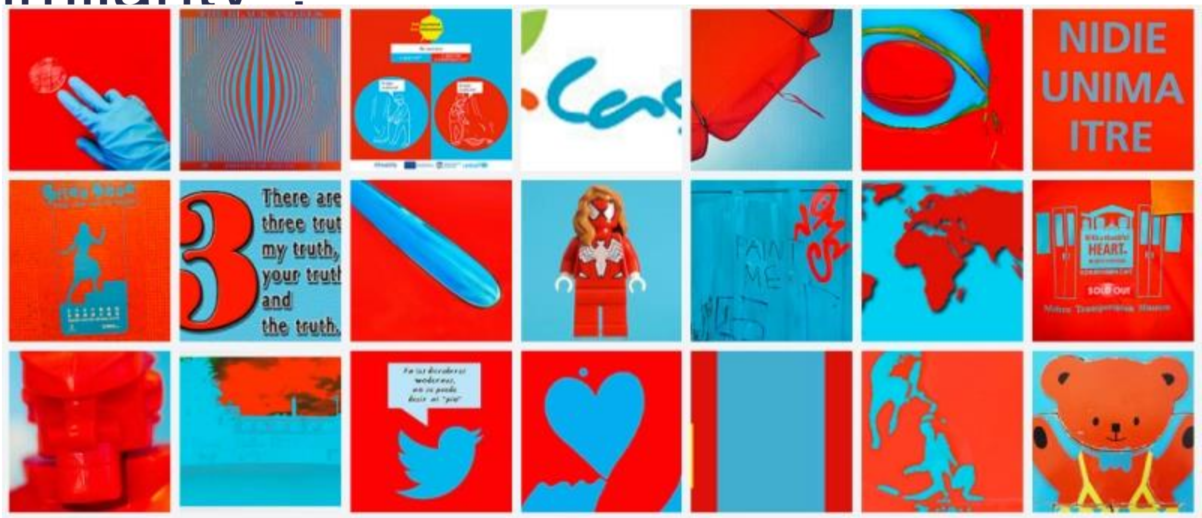


# Search methods

## 2. Content-based image retrieval (CBIR)

- What is “similarity”?




It is apparent that all of these groups of photos illustrate some notion of “similarity,” but each is different. Roughly, they are: **similarity of color**

https://code.flickr.net/2017/03/07/introducing-similarity-search-at-flickr/

# Search methods

## 2. Content-based image retrieval (CBIR)

- What is “similarity”?

It is apparent that all of these groups of photos illustrate some notion of “similarity,” but each is different. Roughly, they are: **similarity of color**, **similarity of texture**

https://code.flickr.net/2017/03/07/introducing-similarity-search-at-flickr/

# Search methods

## 2. Content-based image retrieval (CBIR)

- What is “similarity”?

It is apparent that all of these groups of photos illustrate some notion of “similarity,” but each is different. Roughly, they are: **similarity of color**, **similarity of texture**, and **similarity of semantic category**.

https://code.flickr.net/2017/03/07/introducing-similarity-search-at-flickr/

# Search methods

## 3. Image collection exploration

- search of images based on the use of novel exploration paradigms.
- Image collection exploration consists of a set of computational methods to represent, summarize, visualize and navigate image repositories in an efficient, effective and intuitive way.

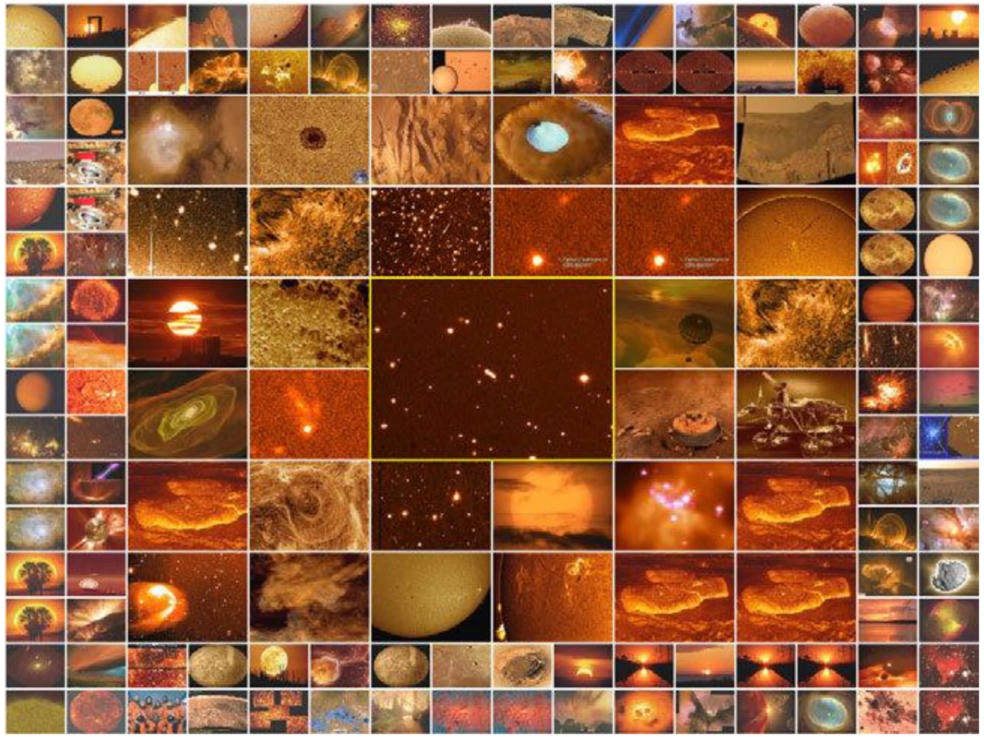
# Search methods

## 3. Image collection exploration

Image search via keyword input. Left to right: the search results corresponding to keyword(s) “spiral”, “galaxy”, “spiral” OR “galaxy”, and “spiral” AND “galaxy”, respectively. There are 222, 461, 474, and 208 images matched from left to right, respectively. The first 145 images, ordered by their dates, are shown in each search.

# Search methods

## 3. Image collection exploration



Query by color: images are ranked according to their percentages of brown pixels. F+C visualization is shown in (b) where the focused image is expanded and highlighted in the yellow boundary.

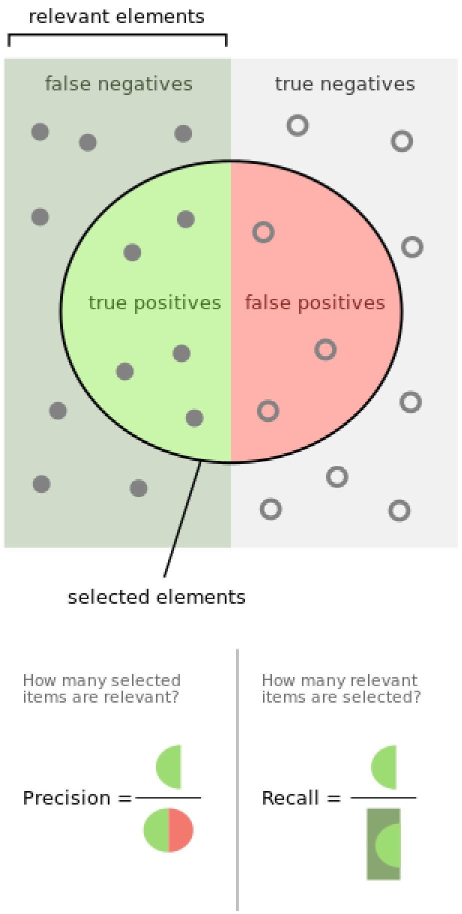
https://www.researchgate.net/publication/273919703_Similarity-based_visualization_of_large_image_collections

# Evaluation Metrics For Information Retrieval

| Metric | Formula | |
|---|---|---|
| Precision | $P=\frac{\lvert\{relevant\_docs\}\cap\{retrieved\_docs\}\rvert}{\lvert\{retrieved\_docs\}\rvert}$ | (1) |
| Recall | $R=\frac{\lvert\{relevant\_docs\}\cap\{retrieved\_docs\}\rvert}{\lvert\{true\_relevant\_docs\}\rvert}$ | (2) |
| F-measure | $F=2\cdot\frac{precision\cdot recall}{precision+recall}$ | (3) |
| Coverage | $C=\frac{\lvert\{true\_relevant\_docs\_returned\}\rvert}{\lvert\{true\_relevant\_docs\}\rvert}$ | (4) |

# Evaluation Metrics For Information Retrieval

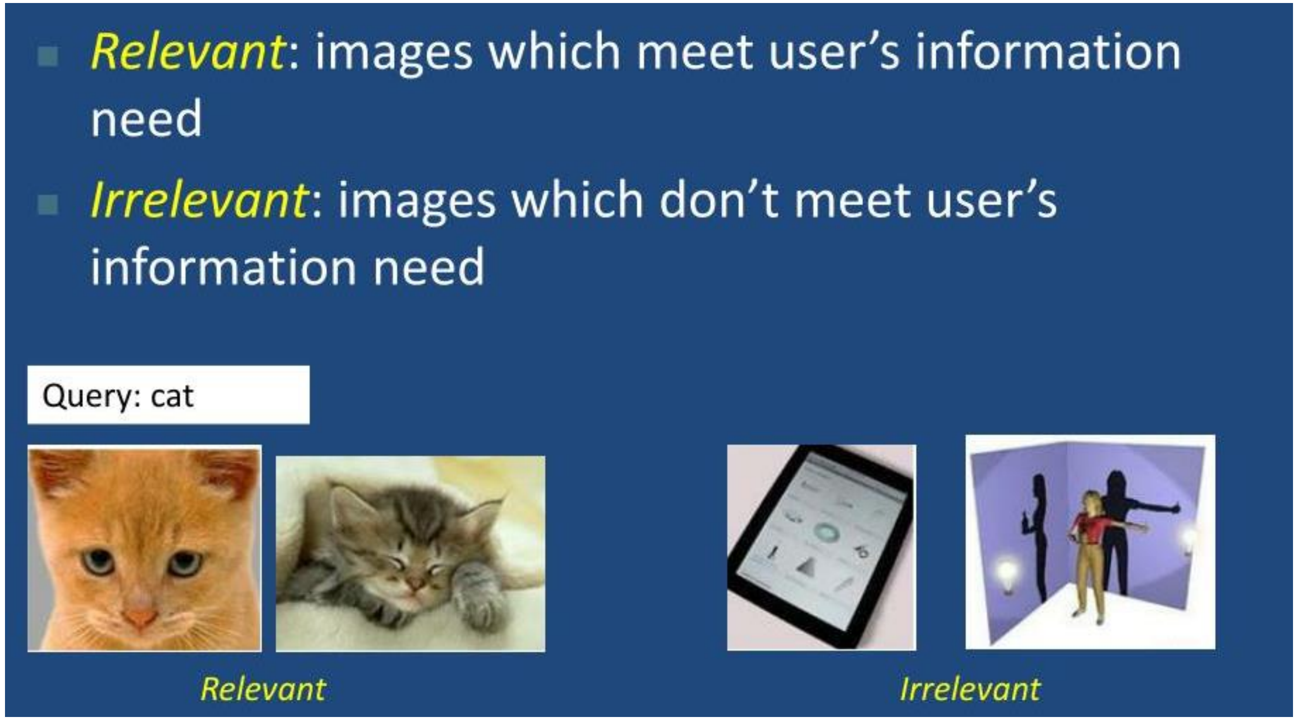
| | | Predicted condition | |
|---|---|---|---|
| | Total population = P + N | Positive (PP) | Negative (PN) |
| Actual condition | Positive (P) | True positive (TP), hit | False negative (FN), type II error, miss, underestimation |
| | Negative (N) | False positive (FP), type I error, false alarm, overestimation | True negative (TN), correct rejection |




https://en.wikipedia.org/wiki/Precision_and_recall

# Evaluation Metrics For Information Retrieval

- **Problem Setup 1: Binary Relevance**




Source: https://amitness.com/2020/08/information-retrieval-evaluation/

# Evaluation Metrics For Information Retrieval

- **Problem Setup 1: Binary Relevance**
  - We have a ranking model that gives us back 5-most relevant results for a certain query. The first, third, and fifth results were relevant as per our ground-truth annotation.


Source: https://amitness.com/2020/08/information-retrieval-evaluation/

# Evaluation Metrics For Information Retrieval

## A. Order-Unaware Metrics

### 1. Precision@k

- This metric quantifies how many items in the top-K results were relevant.

$$Precision@k = \frac{true\ positives@k}{(true\ positives@k) + (false\ positives@k)}$$


| k | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Precision@k | $\frac{1}{1} = 1$ | $\frac{1}{2} = 0.5$ | $\frac{2}{3} = 0.67$ | $\frac{2}{4} = 0.5$ | $\frac{3}{5} = 0.6$ |

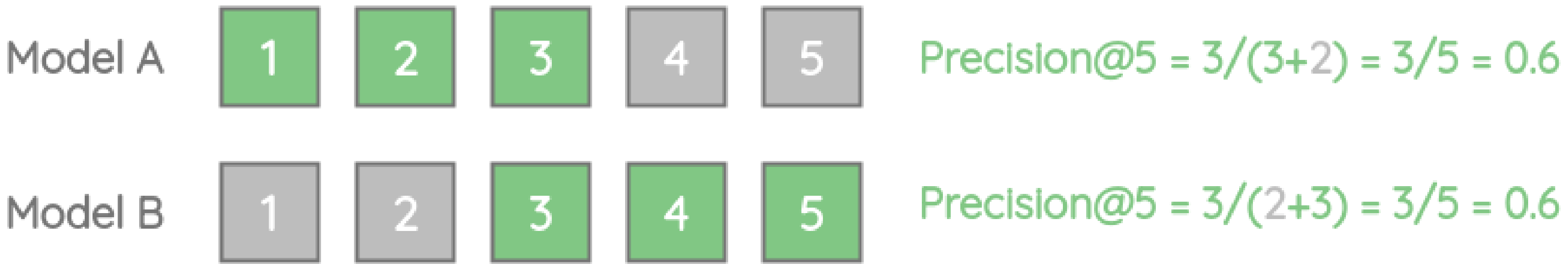
Source: https://amitness.com/2020/08/information-retrieval-evaluation/

# Evaluation Metrics For Information Retrieval

A. Order-Unaware Metrics

## 1. Precision@k

- A limitation of precision@k is that it doesn't consider the position of the relevant items.




Source: https://amitness.com/2020/08/information-retrieval-evaluation/

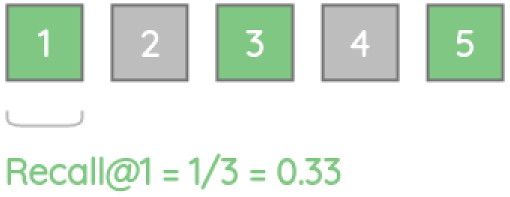
# Evaluation Metrics For Information Retrieval

## A. Order-Unaware Metrics

### 2. Recall@k

- This metric gives how many actual relevant results were shown out of all actual relevant results for the query.

$$Recall@k = \frac{true\ positives@k}{(true\ positives@k) + (false\ negatives@k)}$$




Recall@1 = 0.33 as only one of the 3 actual relevant items are present.

Source: https://amitness.com/2020/08/information-retrieval-evaluation/

# Evaluation Metrics For Information Retrieval

## A. Order-Unaware Metrics

## 2. Recall@k

- This metric gives how many actual relevant results were shown out of all actual relevant results for the query.

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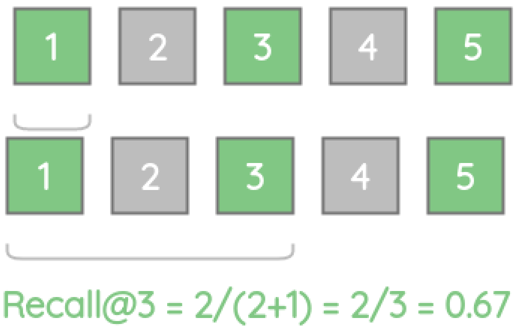



Recall@3 = 0.67 as only two of the 3 actual relevant items are present..

Source: https://amitness.com/2020/08/information-retrieval-evaluation/

# Evaluation Metrics For Information Retrieval

## A. Order-Unaware Metrics

### 2. Recall@k


| k | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Recall@k | $\frac{1}{(1+2)} = \frac{1}{3} = 0.33$ | $\frac{1}{(1+2)} = \frac{1}{3} = 0.33$ | $\frac{2}{(2+1)} = \frac{2}{3} = 0.67$ | $\frac{2}{(2+1)} = \frac{2}{3} = 0.67$ | $\frac{3}{(3+0)} = \frac{3}{3} = 1$ |

Source: https://amitness.com/2020/08/information-retrieval-evaluation/

# Evaluation Metrics For Information Retrieval

A. Order-Unaware Metrics

## 3. F1@k

- This is a combined metric that incorporates both Precision@k and Recall@k by taking their harmonic mean.

$$F1@k = \frac{2 * (Precision@k) * (Recall@k)}{(Precision@k) + (Recall@k)}$$

| k | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Precision@k | 1 | 1/2 | 2/3 | 1/2 | 3/5 |
| Recall@k | 1/3 | 1/3 | 2/3 | 2/3 | 1 |
| F1@k | $\frac{2*1*(1/3)}{(1+1/3)} = 0.5$ | $\frac{2*(1/2)*(1/3)}{(1/2+1/3)} = 0.4$ | $\frac{2*(2/3)*(2/3)}{(2/3+2/3)} = 0.666$ | $\frac{2*(1/2)*(2/3)}{(1/2+2/3)} = 0.571$ | $\frac{2*(3/5)*1}{(3/5+1)} = 0.749$ |

Source: https://amitness.com/2020/08/information-retrieval-evaluation/

# Evaluation Metrics For Information Retrieval

B. Order Aware Metrics

- While precision, recall, and F1 give us a single-value metric, they don’t consider the order in which the returned search results are sent. To solve that limitation, people have devised order-aware metrics given below:

  1. Mean Reciprocal Rank(MRR)
  2. Average Precision(AP)
  3. Mean Average Precision(MAP)

# Evaluation Metrics For Information Retrieval

B. Order Aware Metrics

## 1. Mean Reciprocal Rank(MRR)

- This metric is useful when we want our system to return the best relevant item and want that item to be at a higher position.

$$MRR = \frac{1}{|Q|}\sum_{i=1}^{|Q|}\frac{1}{rank_i}$$

where:

- $||Q||$ denotes the total number of queries
- $rank_i$ denotes the rank of the first relevant result

Source: https://amitness.com/2020/08/information-retrieval-evaluation/

# Evaluation Metrics For Information Retrieval

B. Order Aware Metrics

**1. Mean Reciprocal Rank(MRR)**

- To calculate MRR, we first calculate the **reciprocal** rank. It is simply the reciprocal of the rank of the first correct relevant result and the value ranges from 0 to 1.


→ as the first correct item is at position 1

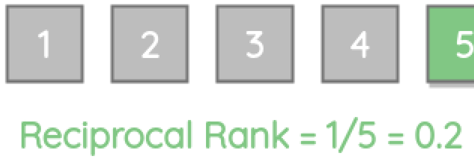
Source: https://amitness.com/2020/08/information-retrieval-evaluation/

# Evaluation Metrics For Information Retrieval

B. Order Aware Metrics

**1. Mean Reciprocal Rank(MRR)**

- To calculate MRR, we first calculate the **reciprocal** rank. It is simply the reciprocal of the rank of the first correct relevant result and the value ranges from 0 to 1.




→ as the first correct item is at position 5

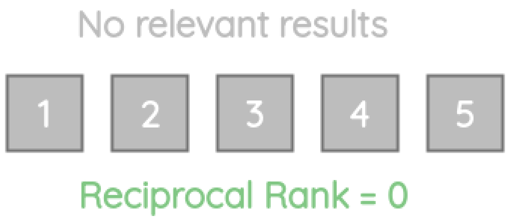
Source: https://amitness.com/2020/08/information-retrieval-evaluation/

# Evaluation Metrics For Information Retrieval

B. Order Aware Metrics

## 1. Mean Reciprocal Rank(MRR)

- To calculate MRR, we first calculate the **reciprocal** rank. It is simply the reciprocal of the rank of the first correct relevant result and the value ranges from 0 to 1.




→ none of the returned results are relevant

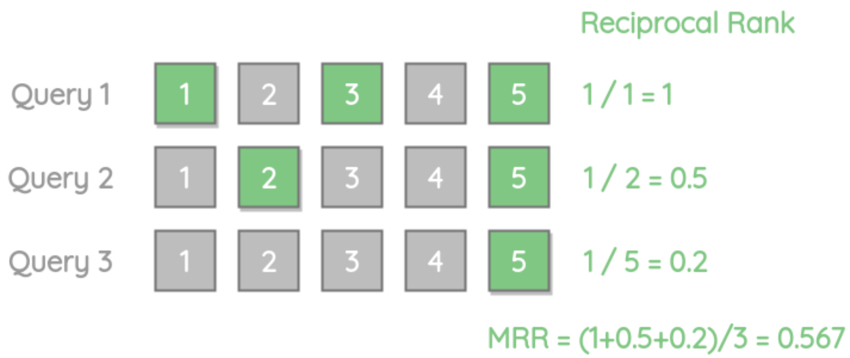
Source: https://amitness.com/2020/08/information-retrieval-evaluation/

# Evaluation Metrics For Information Retrieval

B. Order Aware Metrics

## 1. Mean Reciprocal Rank(MRR)

- For multiple different queries, we can calculate the MRR by taking the mean of the reciprocal rank for each query.




→ MRR doesn’t care about the position of the remaining relevant results

Source: https://amitness.com/2020/08/information-retrieval-evaluation/

# Evaluation Metrics For Information Retrieval

B. Order Aware Metrics

**2. Average Precision(AP)**

- Average Precision is a metric that evaluates whether all of the ground-truth relevant items selected by the model are ranked higher or not. Unlike MRR, it considers all the relevant items.

$$AP = \frac{\sum_{k=1}^{n}(P(k) * rel(k))}{number\ of\ relevant\ items}$$

where:

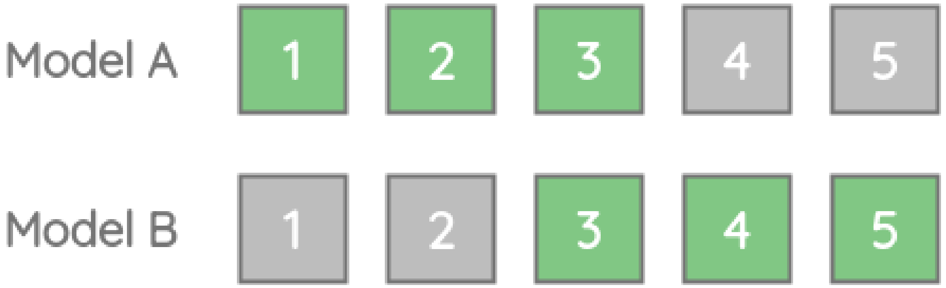
- $rel(k)$ is an indicator function which is 1 when the item at rank K is relevant.
- $P(k)$ is the Precision@k metric

Source: https://amitness.com/2020/08/information-retrieval-evaluation/

# Evaluation Metrics For Information Retrieval

B. Order Aware Metrics

## 2. Average Precision(AP)

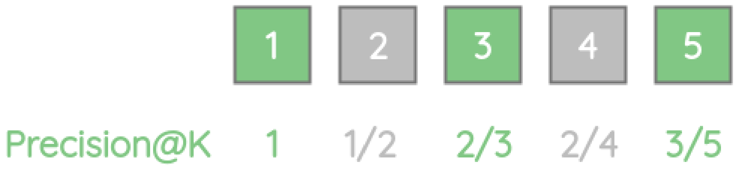



Source: https://amitness.com/2020/08/information-retrieval-evaluation/

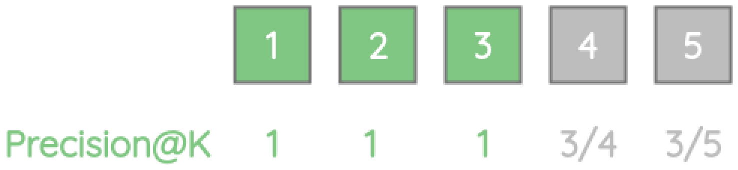
# Evaluation Metrics For Information Retrieval

B. Order Aware Metrics

## 2. Average Precision(AP)




$$AP = \frac{(1 + 2/3 + 3/5)}{3} = 0.7575$$




$$AP = \frac{(1 + 1 + 1)}{3} = 1$$

Source: https://amitness.com/2020/08/information-retrieval-evaluation/

# Evaluation Metrics For Information Retrieval

B. Order Aware Metrics

**3. Mean Average Precision(MAP)**

- if we want to evaluate average precision across multiple queries, we can use the MAP. It is simply the mean of the average precision for all queries.

$$MAP = \frac{1}{Q}\sum_{q=1}^{Q} AP(q)$$

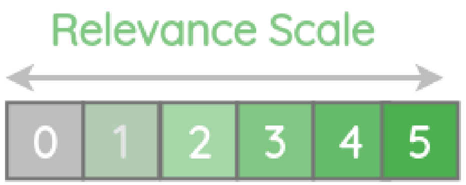
where

- $Q$ is the total number of queries
- $AP(q)$ is the average precision for query q.

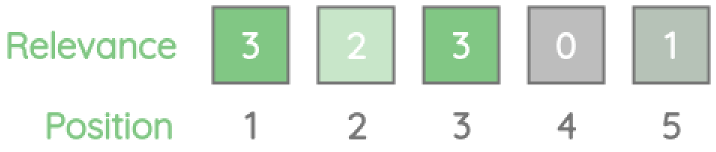
Source: https://amitness.com/2020/08/information-retrieval-evaluation/

# Evaluation Metrics For Information Retrieval

- **Problem Setup 2: Graded Relevance**
  - we annotated the items not just as relevant or not-relevant but instead used a grading scale between 0 to 5 where 0 denotes least relevant and 5 denotes the most relevant.




  - Ex: the first item had a relevance score of 3 as per our ground-truth annotation, the second item has a relevance score of 2 and so on.




Source: https://amitness.com/2020/08/information-retrieval-evaluation/

# Evaluation Metrics For Information Retrieval

- **Problem Setup 2: Graded Relevance**

  **1. Cumulative Gain (CG@k)**

  - This metric uses a simple idea to just sum up the relevance scores for top-K items. The total score is called cumulative gain.

$$CG@k = \sum_{1}^{k} rel_i$$


| Position(k) | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Cumulative Gain@k | 3 | 3+2=5 | 3+2+3=8 | 3+2+3+0=8 | 3+2+3+0+1=9 |

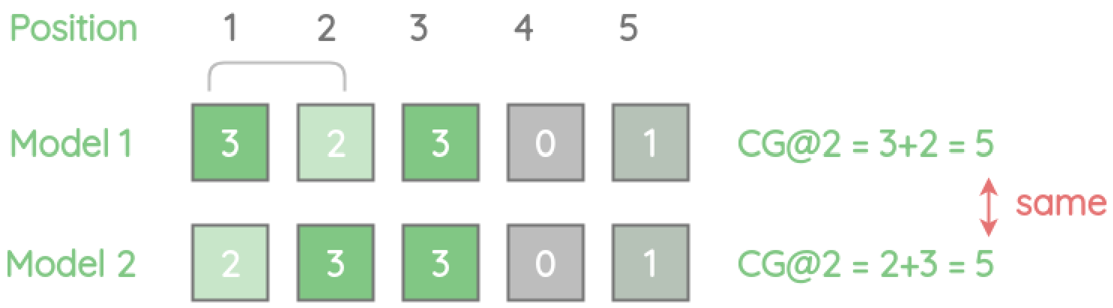
Source: https://amitness.com/2020/08/information-retrieval-evaluation/

# Evaluation Metrics For Information Retrieval

- **Problem Setup 2: Graded Relevance**

  **1. Cumulative Gain (CG@k)**

  - While simple, CG doesn't take into account the order of the relevant items. So, even if we swap a less-relevant item to the first position, the CG@2 will be the same.




Source: https://amitness.com/2020/08/information-retrieval-evaluation/

# Evaluation Metrics For Information Retrieval

```
def calc_recall_at_k(T, Y, k):
    """
    T : [nb_samples] (target labels)
    Y : [nb_samples x k] (k predicted labels/neighbours)
    """
    s = sum([1 for t, y in zip(T, Y) if t in y[:k]])
    return s / (1. * len(T))
```

- A Zero-Shot Framework for Sketch Based Image Retrieval.

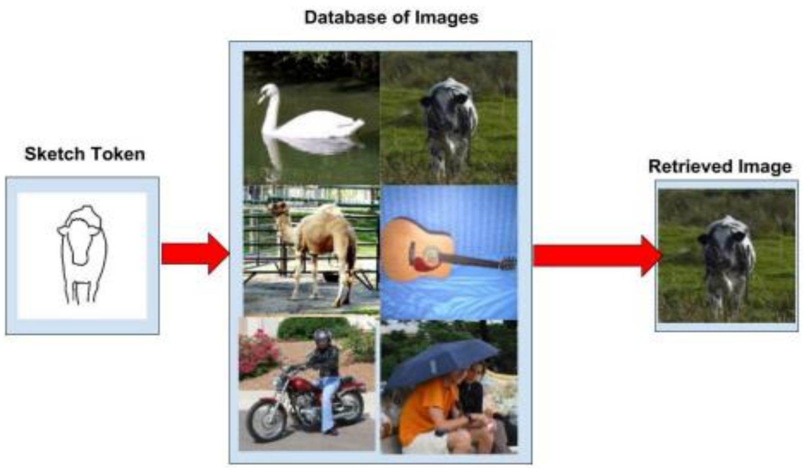



**Fig. 1.** Illustration of Sketch based Image Retrieval

https://openaccess.thecvf.com/content_ECCV_2018/papers/Sasikiran_Yelamarthi_A_Zero-Shot_Framework_ECCV_2018_paper.pdf

- Deep Image Retrieval: A Survey : https://arxiv.org/abs/2101.11282

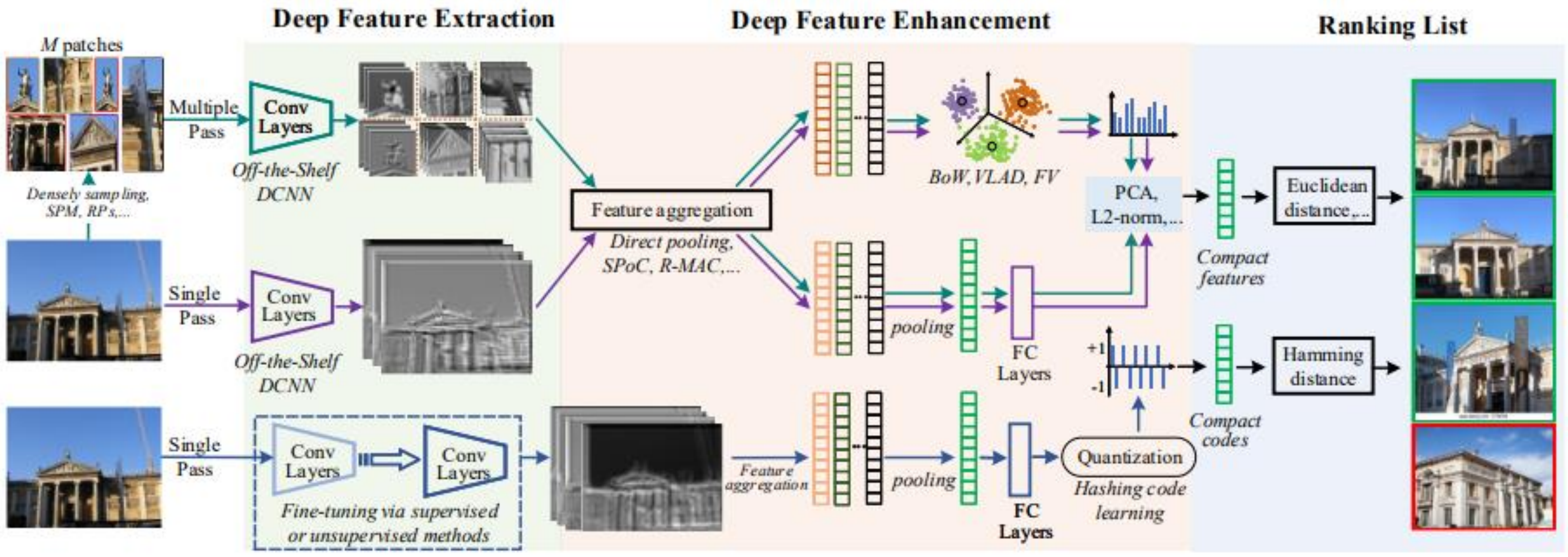



Fig. 1: In deep image retrieval, feature embedding and aggregation methods are used to enhance the discrimination of deep features. Similarity is measured on these enhanced features using Euclidean or Hamming distances.

- https://www.analyticsvidhya.com/blog/2017/11/information-retrieval-using-kdtree/
- https://code.flickr.net/2017/03/07/introducing-similarity-search-at-flickr/
- https://www.slideshare.net/kitkate/classification-and-information-retrieval-metrics-for-machine-learning

- https://www.educative.io/answers/what-is-the-mean-average-precision-in-information-retrieval
- https://www.pinecone.io/learn/offline-evaluation/