University of Zurich[UZH]

ROBOTICS & PERCEPTION GROUP

Vision Algorithms for Mobile Robotics

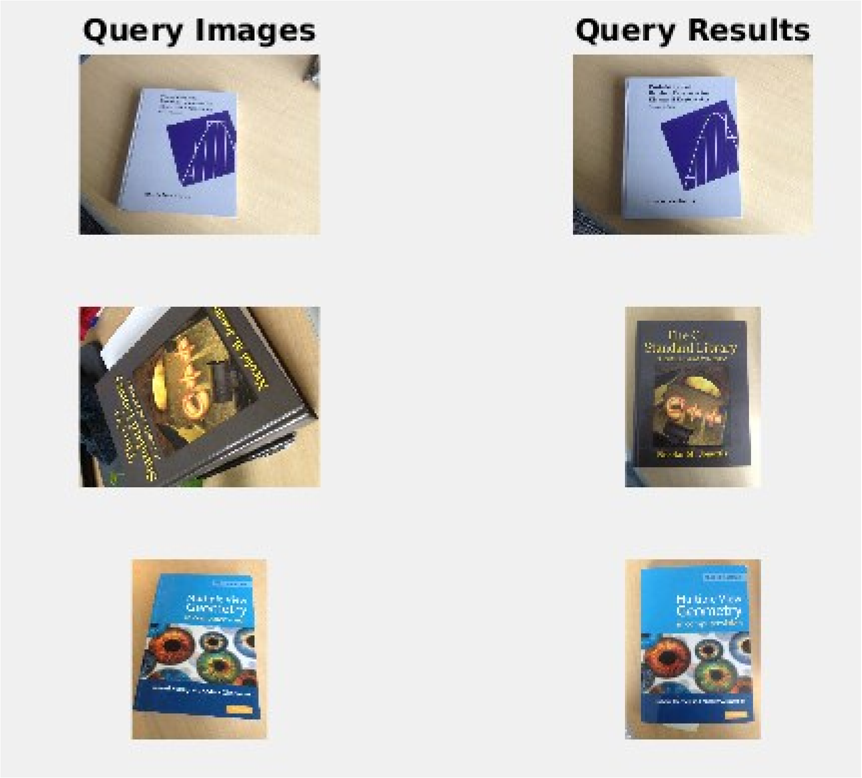
Lecture 12a
Place Recognition

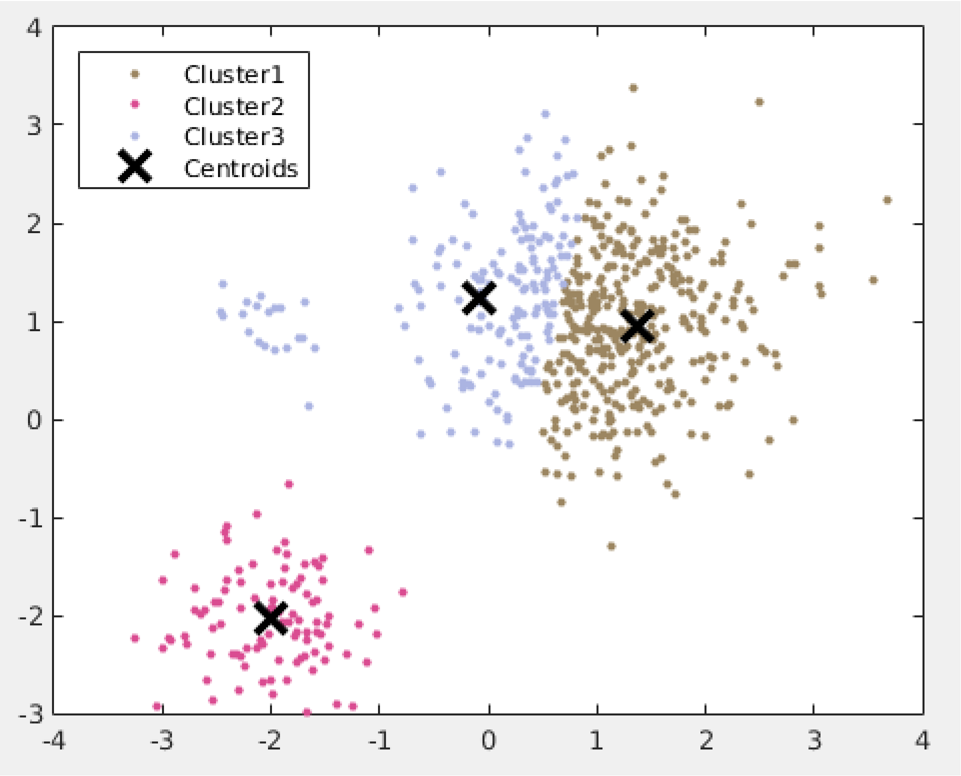
Davide Scaramuzza

http://rpg.ifi.uzh.ch

Deep Learning Tutorial Today

- **Deep Learning tutorial: 12:15 – 13:45**
- **Optional lab exercise** is online: **K-means clustering** and **place recognition** with Bag of Words



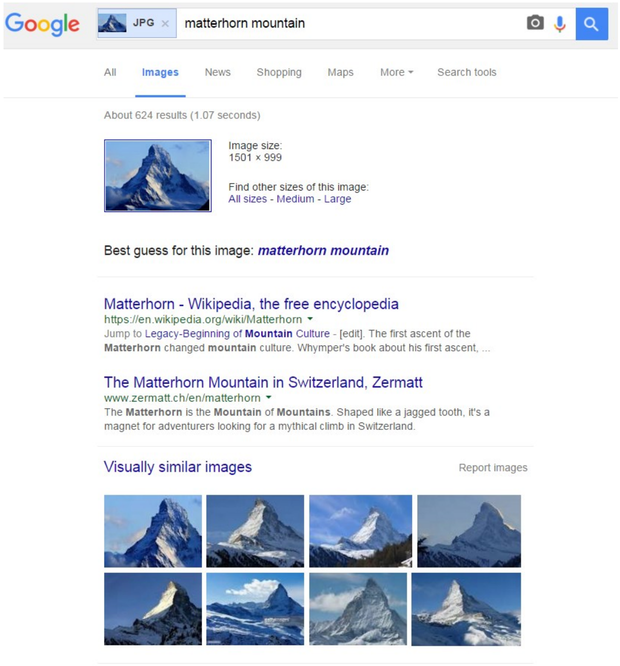


Place Recognition

Have I been
here before?

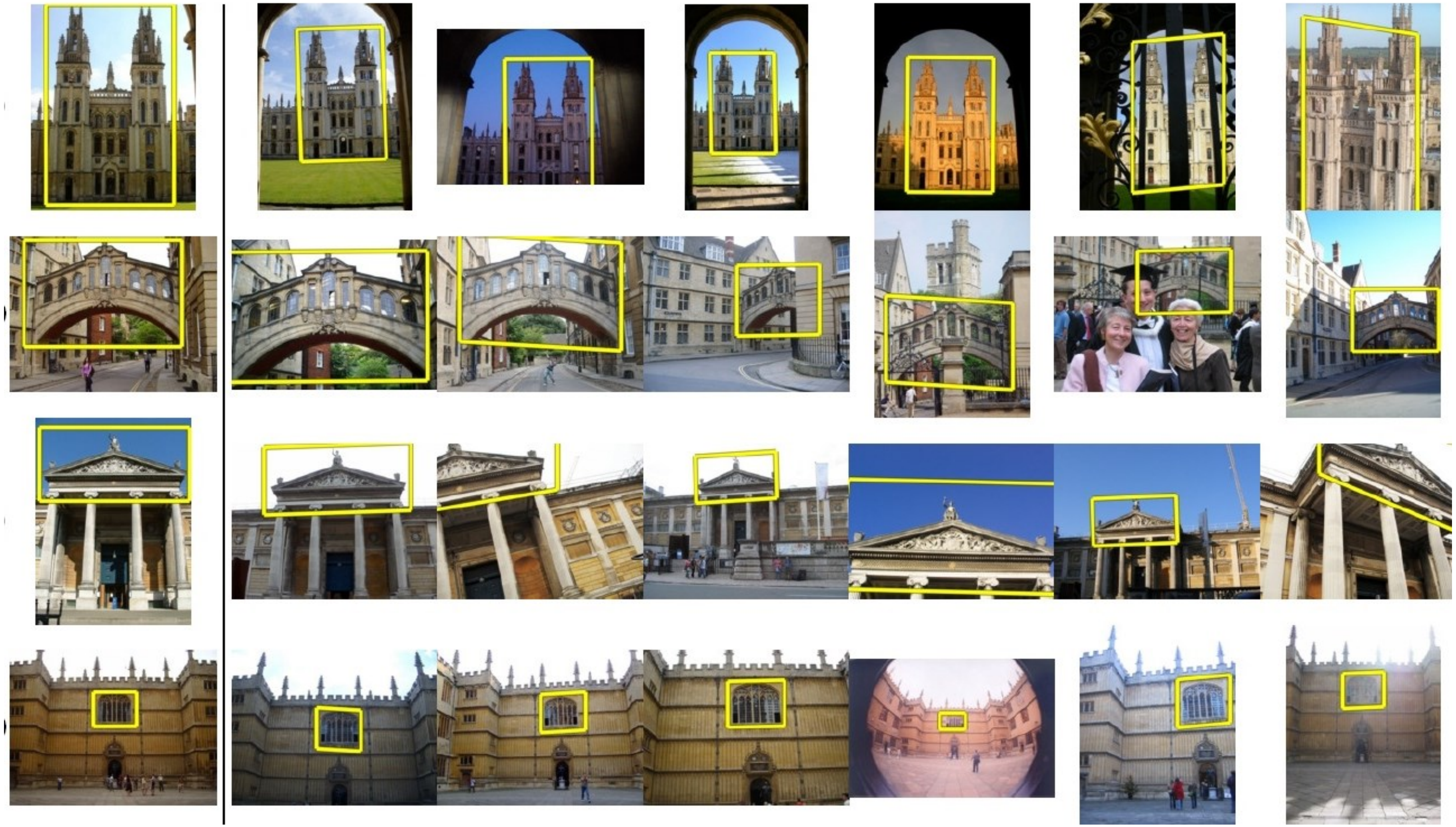
- **Robotics**:
  - Has the robot been to this place before?
    - Which images were taken around the same location?

- **Image retrieval**:
  - Have I seen this image before?
    - Which images in my database look similar to it?
      E.g., Google Reverse Image Search



Place Recognition/Image Retrieval

Query image Results on a database of 100 million images



How much is 100 million images?

If each sheet of paper was 0.1 mm thick…

MetLife
Kodak
EasyShare Digital Camera and Dock
Shoot.
Touch.
Share.
GRAY LINE
New York Sightseeing
New York Sightseein
PLANET HOLLYWOOD


Mount Everest (8,849 m)

Visual Place Recognition

- **Goal**: **query** an image in a database of $\boldsymbol{N}$ **images**
- **Complexity:** $\mathrm{O}(NF^2)$ feature comparisons (assumes each image has ***F*** features)
  - Example:
    - assume 1,000 SIFT features per image → $\mathrm{F} = 1{,}000$
    - assume $N = 100{,}000{,}000$
    - → NF^2= $100{,}000{,}000{,}000{,}000$ feature comparisons!
    - If we assume 10 microseconds per feature comparison → 1 image query would take **32 years**!

Solution: Use an index file! Complexity reduces to $\boldsymbol{O(F)}$

Fast visual search

How do we **query an image in a database of 100 million images in just 0.6 seconds**?

Sivic, Zisserman, *Video Google: A Text Retrieval Approach to Object Matching in Videos*, International Conference on Computer Vision (ICCV), 2003. PDF.
Nister, Stewenius, *Scalable Recognition with a Vocabulary Tree*, International Conference on Computer Vision and Pattern Recognition (CVPR), 2006. PDF.

Text Retrieval

- Image retrieval takes inspiration from **text retrieval**
- For text documents, an efficient way to find all **pages** in which a **word** occurs is to use an **index file**
- To **retrieve a given text query**, it is then sufficient to use a **voting scheme**

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ALPHABETICAL INDEX

Alphabetical Index

Text Retrieval Example

- Suppose that we have a **document with 10 pages** and we want to determine on which page this list of words appears:

"Zurich is a city of Switzerland"

- *"Zurich is a city of Switzerland"* is the **text query**
- Suppose that this is our index file:

Word	Page numbers
Zurich	3, 5, 7
City	1, 3, 5, 9
Switzerland	2, 3, 6, 8

Text Retrieval Example

- The solution is to use a **voting array** that has as many cells as the number of pages in the document
- We first set all the cell values to 0
- Then, we add 1 to each cell corresponding to the page numbers where the words of the query text appear according to the index file

Page number	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Cell value	0	0	0	0	0	0	0	0	0	0

Text Retrieval Example

- The solution is to use a **voting array** that has as many cells as the number of pages in the document
- We first set all the cell values to 0
- Then, we add 1 to each cell corresponding to the page numbers where the words of the query text appear according to the index file

”Zurich” {3, 5, 7}

Page number	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Cell value	0	0	1	0	1	0	1	0	0	0

Text Retrieval Example

- The solution is to use a **voting array** that has as many cells as the number of pages in the document
- We first set all the cell values to 0
- Then, we add 1 to each cell corresponding to the page numbers where the words of the query text appear according to the index file

”City” {1, 3, 5, 9}

Page number	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Cell value	1	0	2	0	2	0	1	0	1	0

Text Retrieval Example

- The solution is to use a **voting array** that has as many cells as the number of pages in the document
- We first set all the cell values to 0
- Then, we add 1 to each cell corresponding to the page numbers where the words of the query text appear according to the index file

"Switzerland" {2, 3, 6, 8}

Page number	1	2	3	4	5	6	7	8	9	10
Cell value	1	1	3	0	2	1	1	1	1	0

Bag of Words

Using the analogy from text retrieval, we need to:

- define what a "*visual word*" is and
- define a "*vocabulary*" of visual words

This approach is known as "Bag of Words" (BOW)

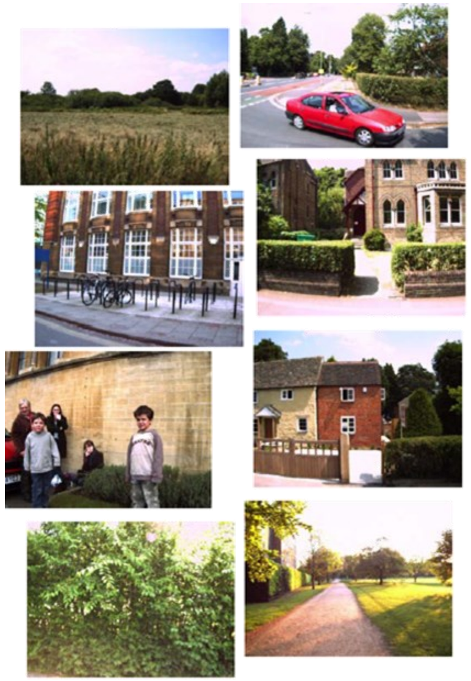
- Can a SIFT descriptor be used as a visual word? And a BRISK descriptor?
  - SIFT $\rightarrow 128 \times 4\ bytes\ float = 512\ bytes = 4096\ bits \rightarrow 2^{4096}$ possible SIFT descriptors!
  - BRISK-128 $\rightarrow 128 \text{ bits} = 2^{128}$ possible BRISK descriptors!
  - **Usually, 1 million visual words is enough**
  - **Idea**: **cluster SIFT descriptors into visual words**

How to extract Visual Words from descriptors

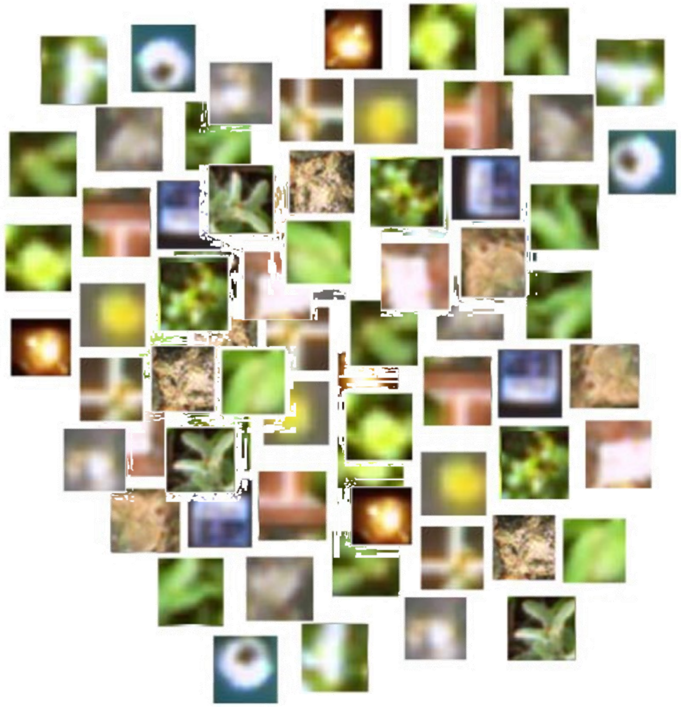
- **Collect a large enough dataset** that is representative of all possible images that are relevant to your application (e.g., for automotive place recognition, you may want to collect million of street images sampled around the world)
- Extract features and descriptors from each image and map them into the **descriptor space** (e.g., for SIFT, 128 dimensional descriptor space)
- **Cluster the descriptor space into K clusters**
- **The centroid of each cluster is a visual word**.
  - This means that a visual word is also a descriptor. It is computed by taking the arithmetic average (i.e., centroid) of all the descriptors within the same cluster:
    - e.g., for SIFT, each cluster contains SIFT features that are very similar to each other;
    - the visual word then is the arithmetic average all the SIFT descriptors in that cluster

Extracting Visual Words

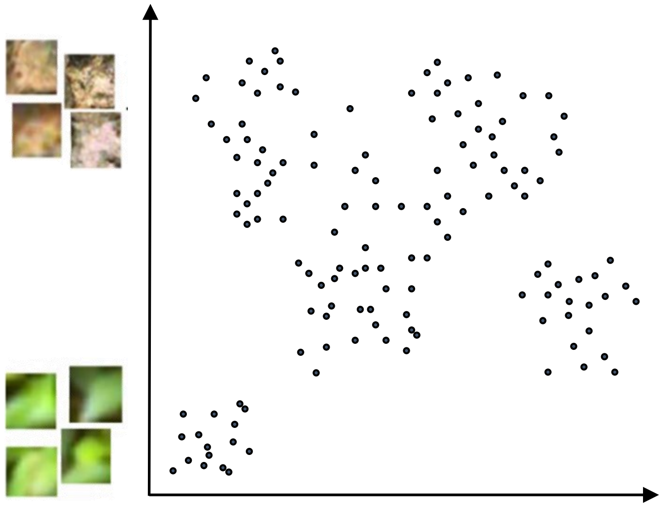
Image database
(e.g., 100 million images)



Feature extraction
(~1,000 features per image)

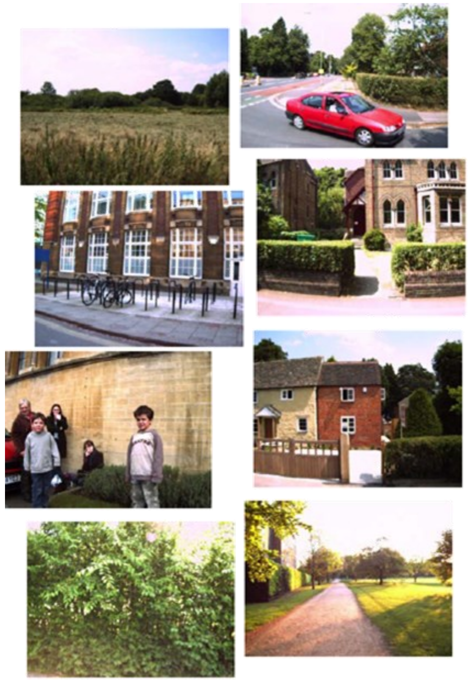


Map all features into the descriptor space
(~100 billion descriptors)

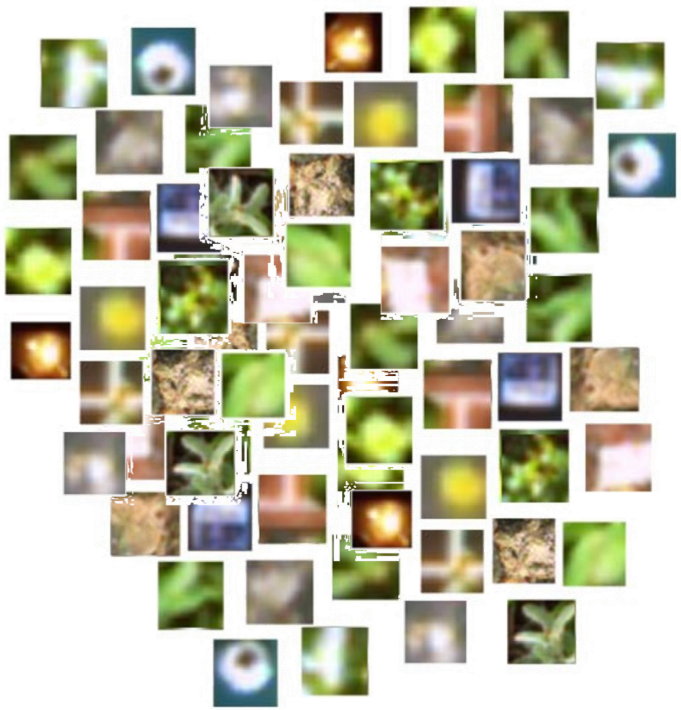


Extracting Visual Words

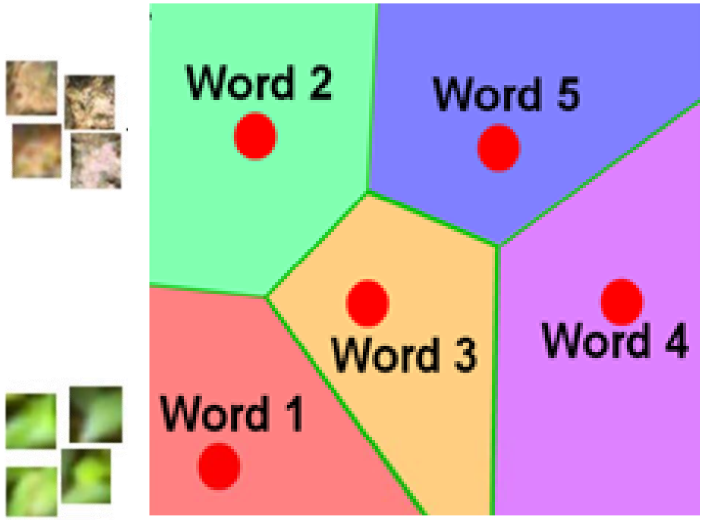
Image database
(e.g., 100 million images)



Feature extraction
(~1,000 features per image)

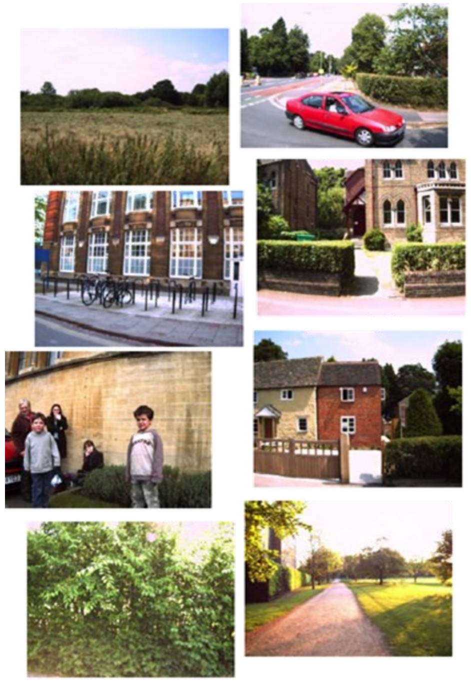


Feature clustering
(~1 million words)

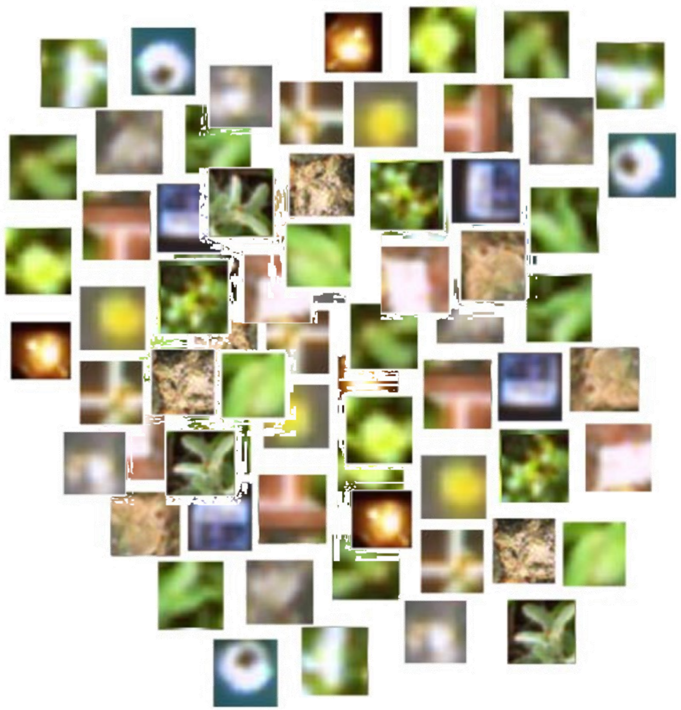


Extracting Visual Words

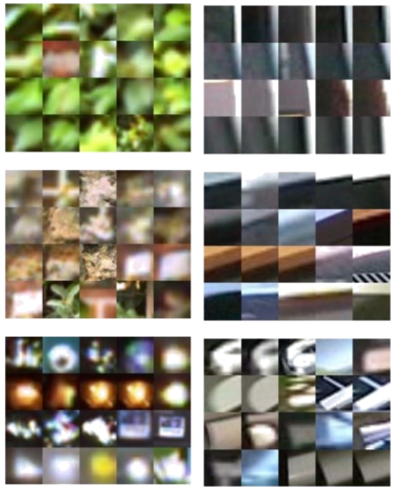
Image database
(e.g., 100 million images)



Feature extraction
(~1,000 features per image)



Feature clustering
(~1 million words)



Examples of features belonging to the same clusters (i.e., to the same visual word)

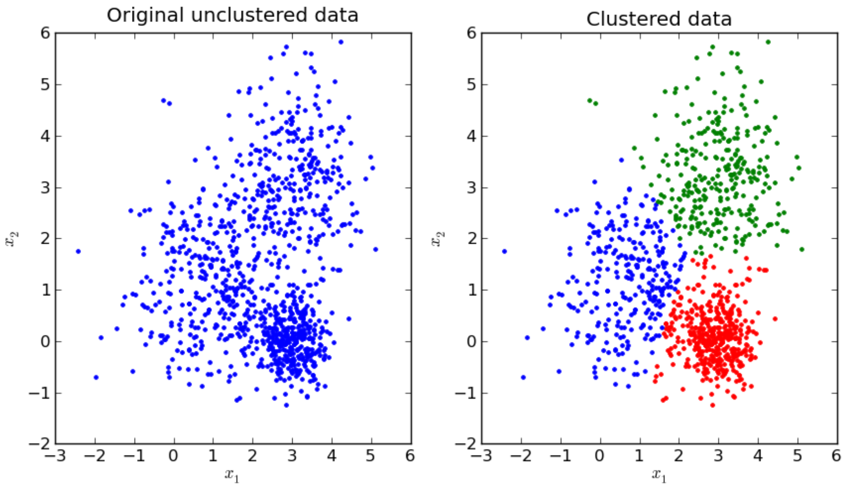
Extracting Visual Words and Updating the Vocabulary

- Extracting SIFT features from a VGA images takes ~20 ms on an i7 CPU
- This means that the **extraction of features from 100 million images would take ~23 days** without accounting for the time needed for clustering all these features
- However, notice that **this is ok since this process only needs to be done once**, when the database has been created.
- **If the database grows** as new images are collected, **new features can be extracted and the visual words can be updated accordingly**. This update process **does not need to run in real time**

How do we cluster the descriptor space?

- **k-means clustering** is an algorithm to partition n data points into k clusters in which each data point $\boldsymbol{x}$ belongs to the cluster $\boldsymbol{S_i}$ with center $\boldsymbol{m}_i$
- It minimizes the **sum of squared Euclidean distance** between points $\boldsymbol{x}$ and their nearest cluster centers $\boldsymbol{m}_i$

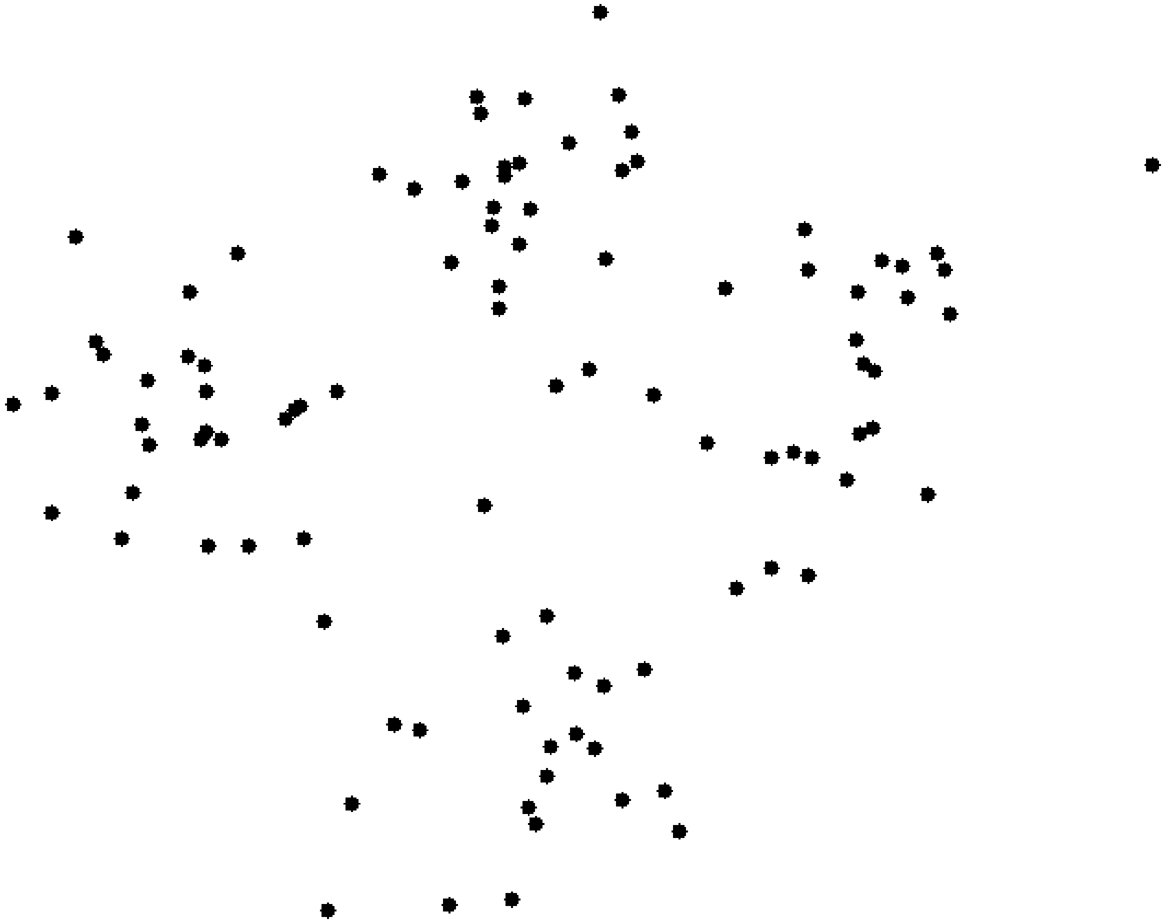
$$D(X, M) = \sum_{i=1}^{k} \sum_{x \in S_i} (x - m_i)^2$$



Algorithm:

- Randomly initialize k cluster centers
- Iterate until convergence:
  - Assign each data point $\boldsymbol{x}_j$ to the nearest center $\boldsymbol{m}_i$
  - Recompute each cluster center as the mean of all points assigned to it

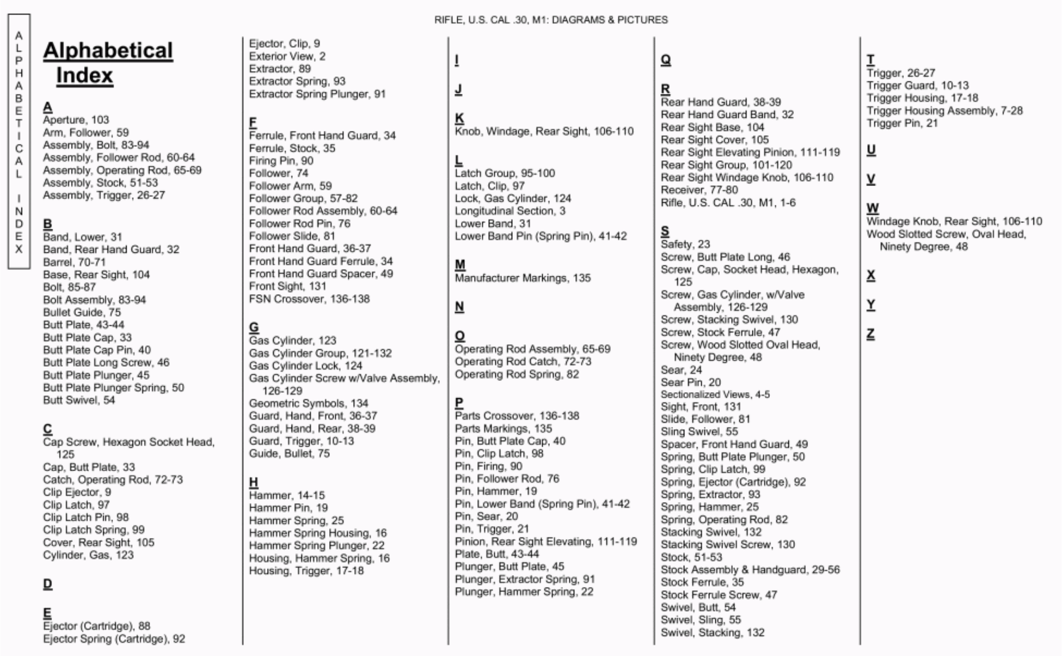
K-means demo



Source: http://shabal.in/visuals/kmeans/1.html

Building the Image Vocabulary

- The **Image Vocabulary** is a data structure that lists all extracted visual words
- Each visual word is assigned a unique identifier (an **integer number**)
- **Each visual word** in the image vocabulary **points to a list of images** (from the entire image database) in which that word appears
- If the database grows, the vocabulary is updated accordingly



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Alphabetical Index

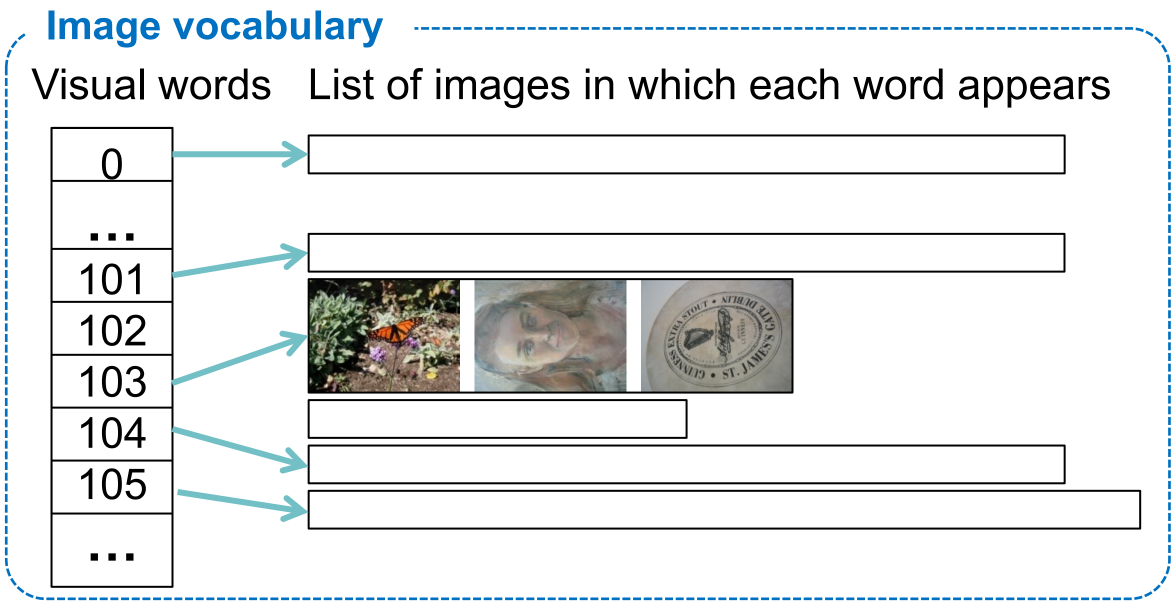


Image Retrieval

1. To query an image in the database, we must first extract features from the query image (this takes about 20 ms for ~1,000 SIFT features)

Query image Q

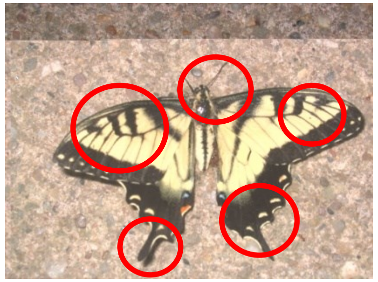
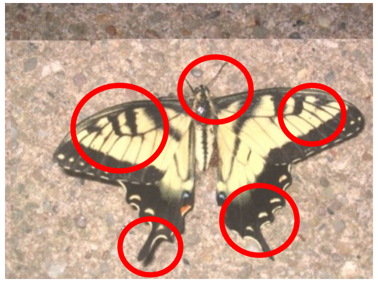


Image Retrieval

2. Then, we initialize the **voting array** to 0 (the voting array has as many cells as the number of images in the database).

Query image Q



Voting Array for Q

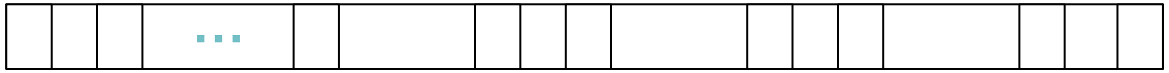


Image Retrieval

3. Then, we **look-up** each feature in the image vocabulary (basically, we look for the **closest visual word** in the vocabulary)

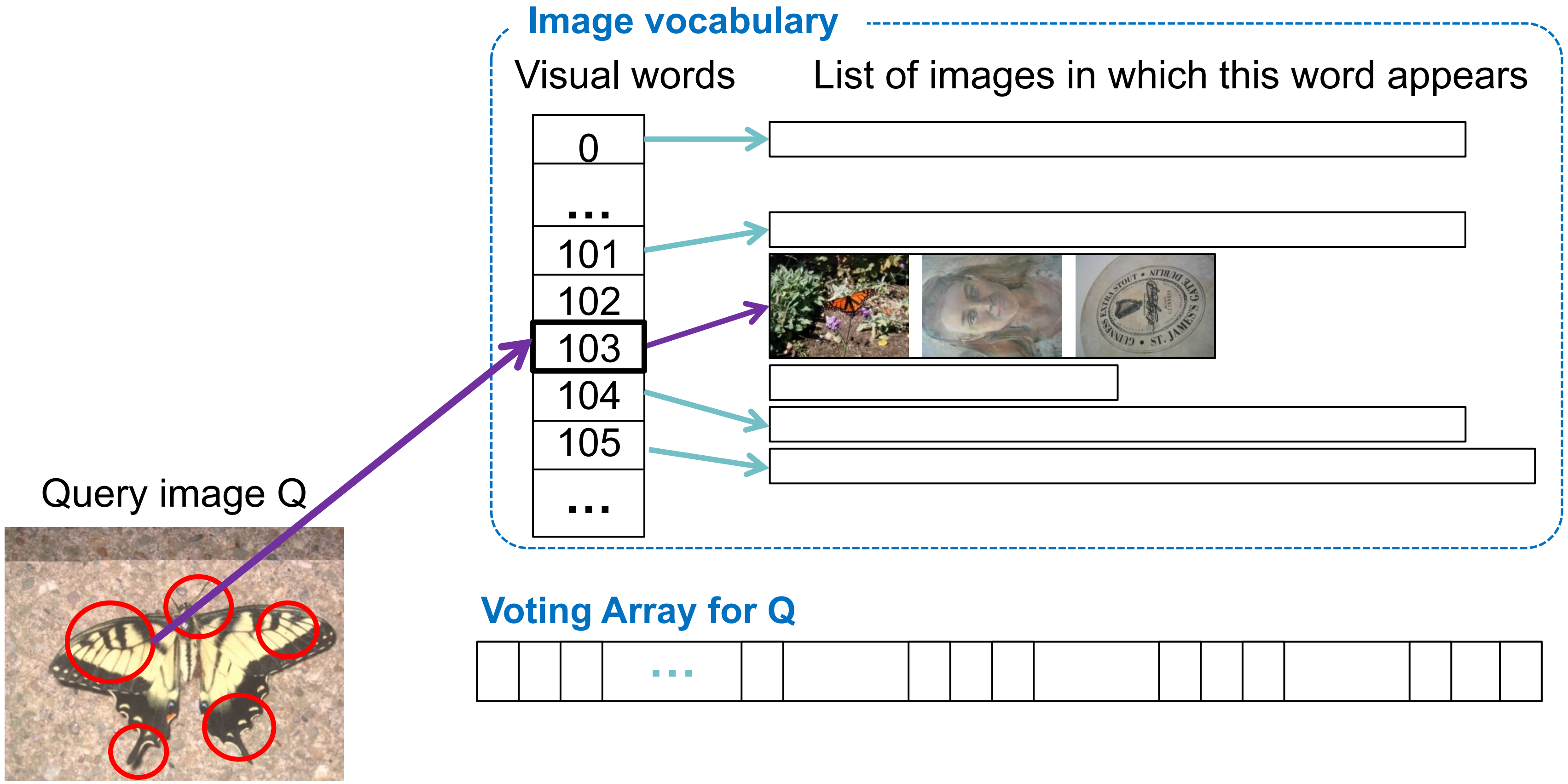
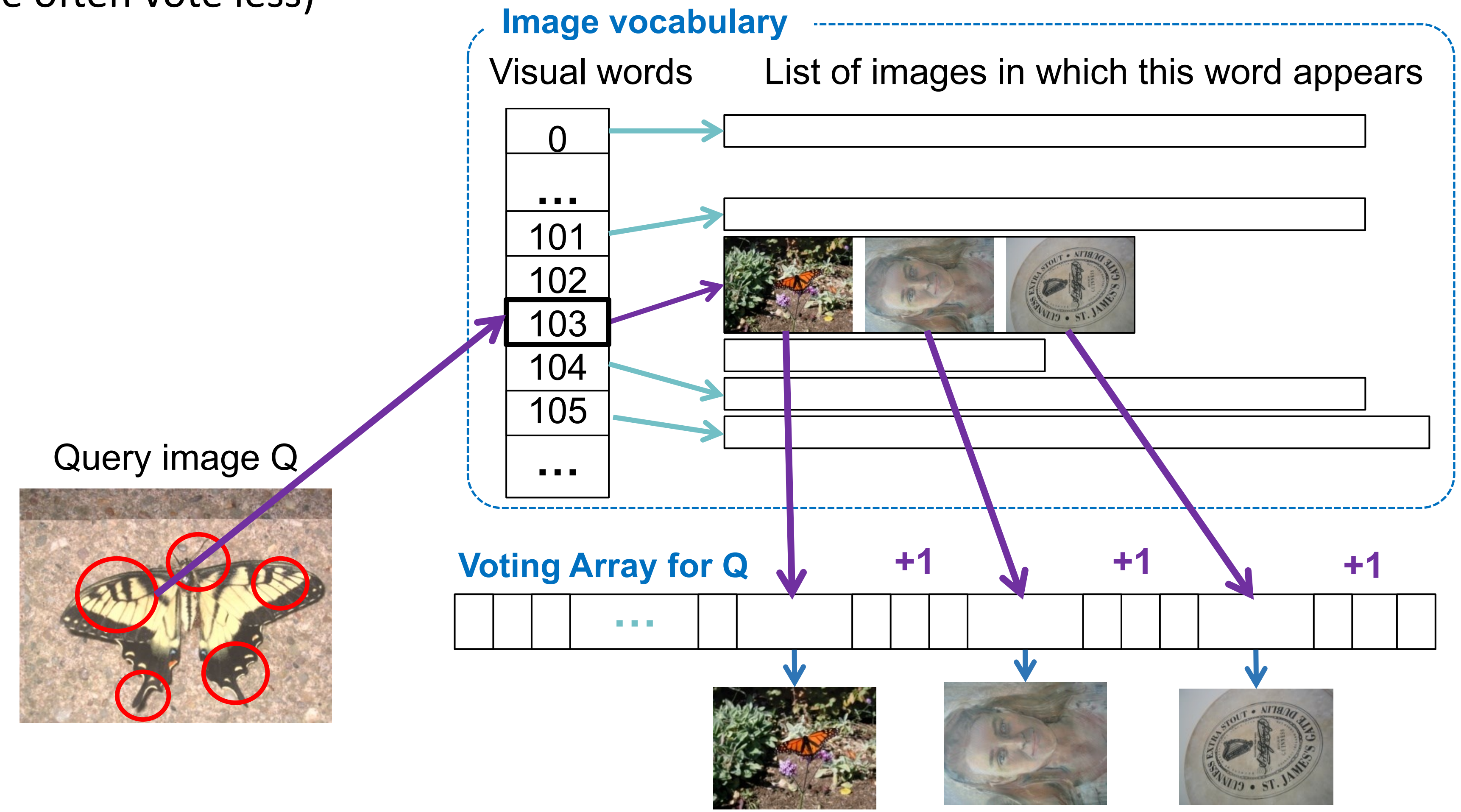
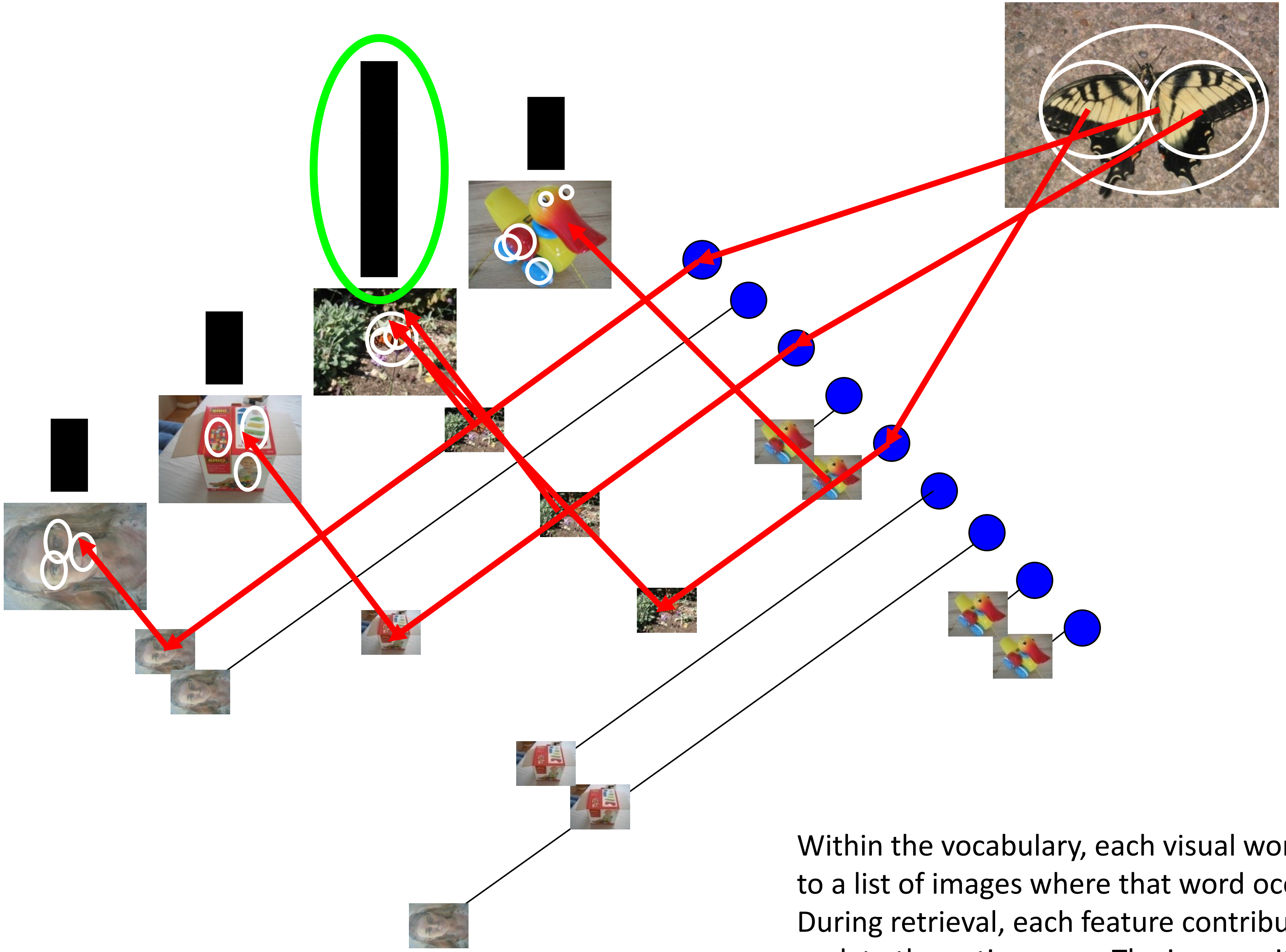


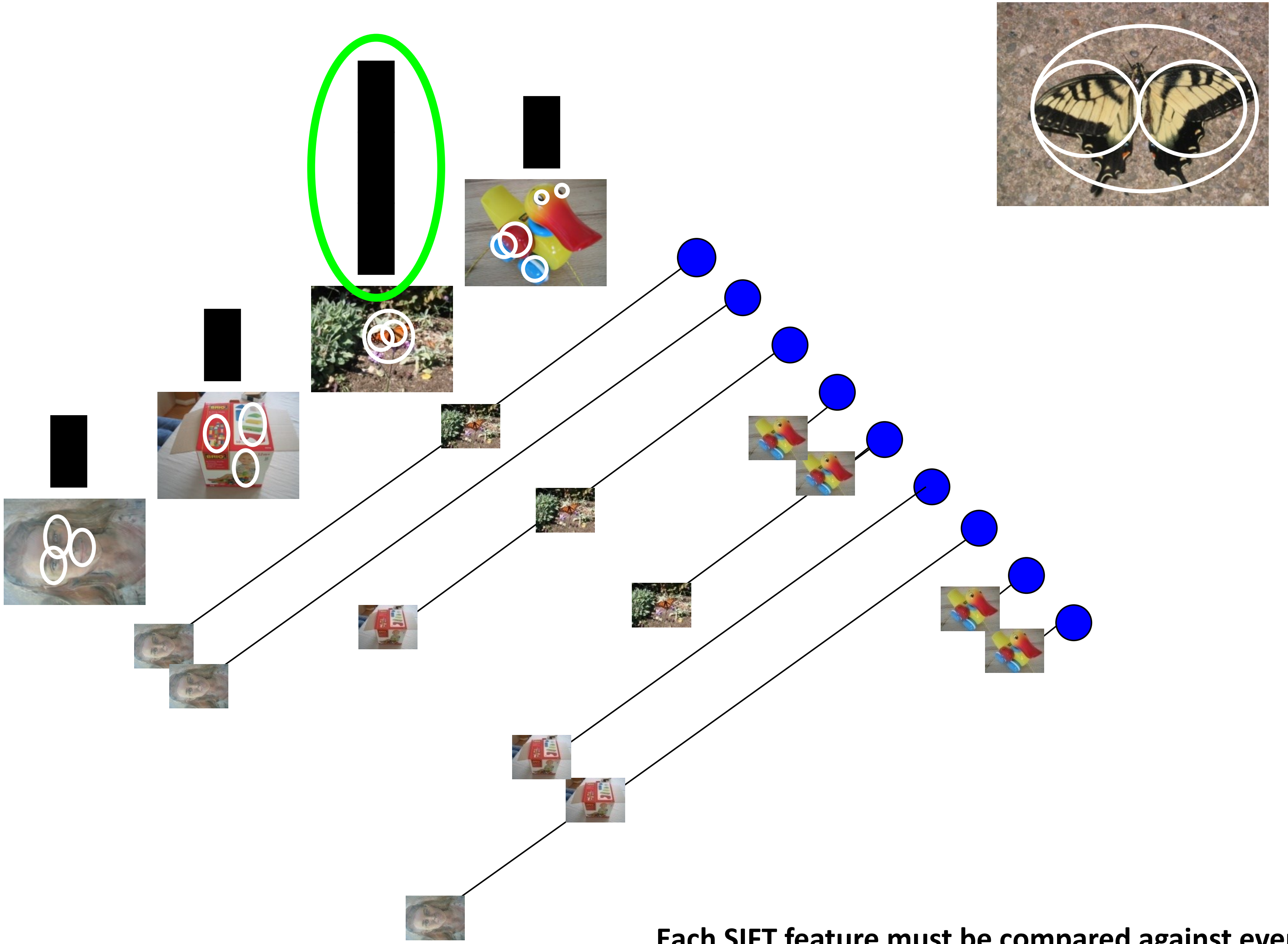
Image Retrieval

4. Finally, **each visual word votes for multiple images** as we saw for the case of text retrieval; however, the **voting is not uniform but is weighted by the inverse of the frequency of the word** (i.e., words that repeat more often vote less)





Within the vocabulary, each visual word points to a list of images where that word occurs. During retrieval, each feature contributes to update the voting array. The image with most votes is returned.



Each SIFT feature must be compared against every visual word

Issues

Every feature in the query image has to be compared against every visual words in the vocabulary:

- Example:
  - assume our query image has 1,000 features;
  - assume 1 million visual words → number of feature comparisons would be equal to **1 billion**!
  - If we assume 10 microseconds per feature comparison, then querying one image would take ~**3 hours**!

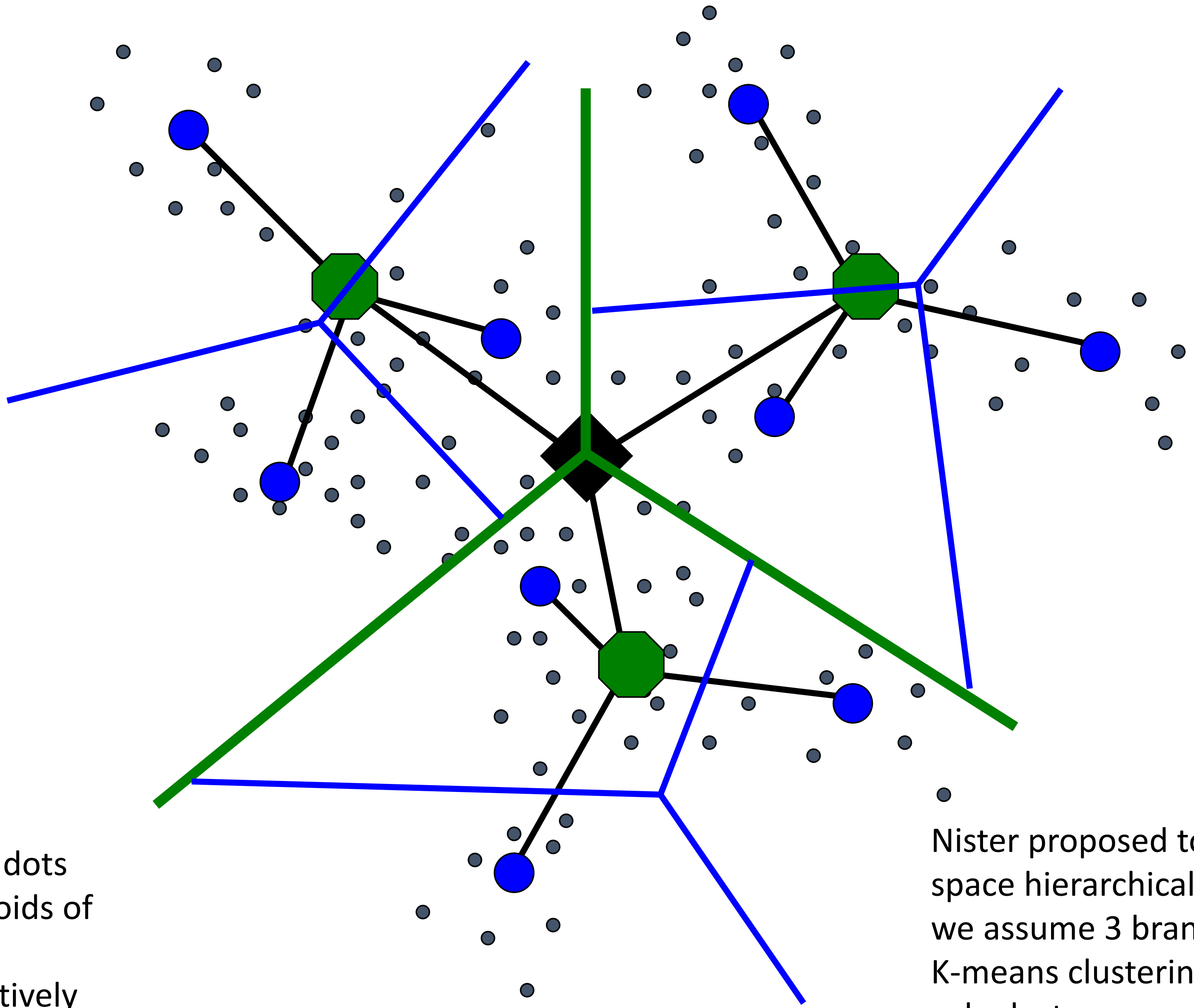
- How can we make the comparison cheaper?
  - Idea: use **hierarchical clustering**

Hierarchical Clustering

- David Nister proposed to cluster the feature space in a **coarse-to-fine manner** so that visual words could be represented as the **terminal vertices of a search tree**.
- As we will see, this significantly reduces the feature-to-word association, bringing image retrieval within the reach of resource-constrained mobile devices!

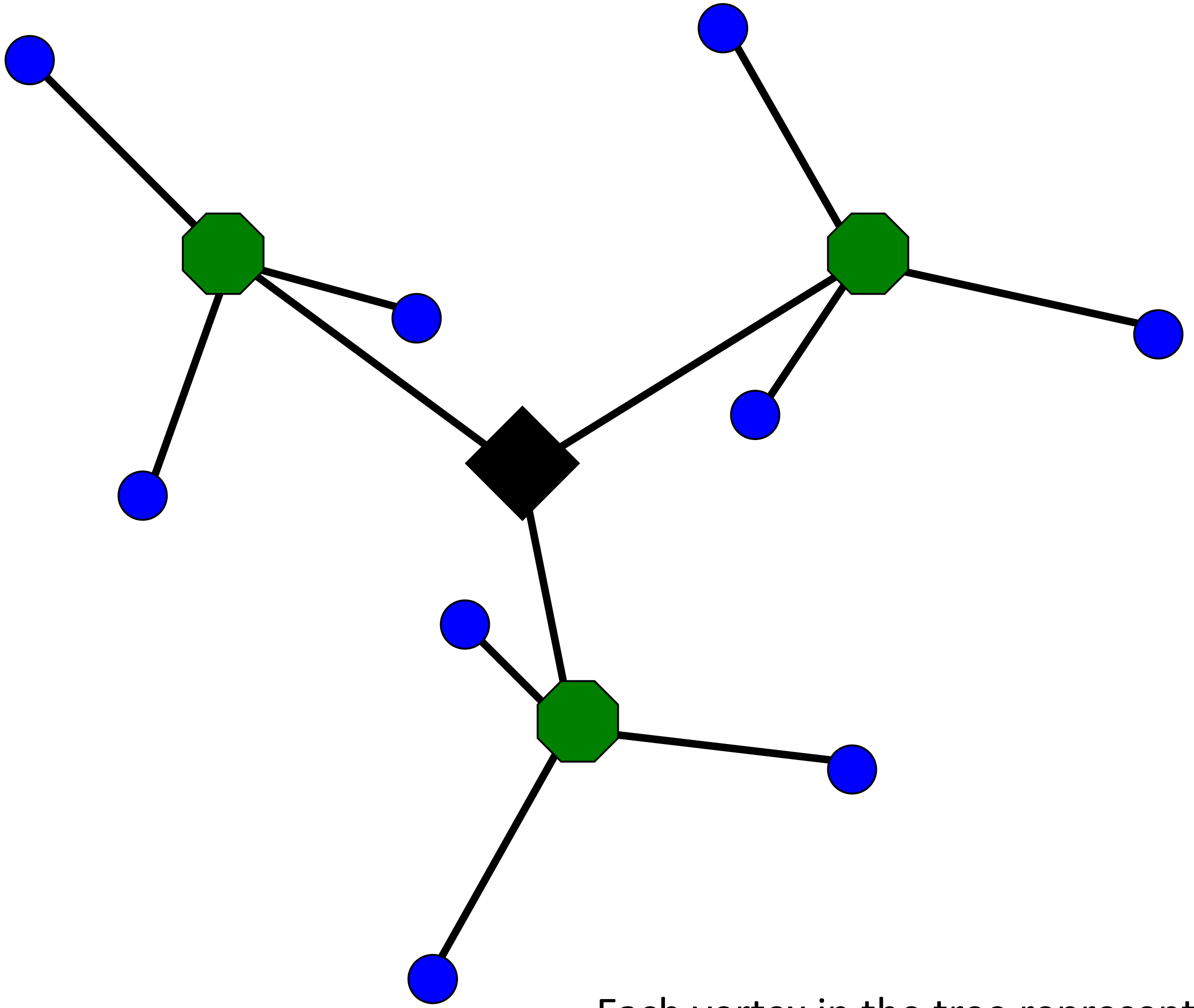
Nister, Stewenius, *Scalable Recognition with a Vocabulary Tree*, International Conference on Computer Vision and Pattern Recognition (CVPR), 2006. PDF.

Each dot represents a SIFT feature.
SIFT features have 128 dimensions!
For convenience, here we assume only
2 dimensions ☺

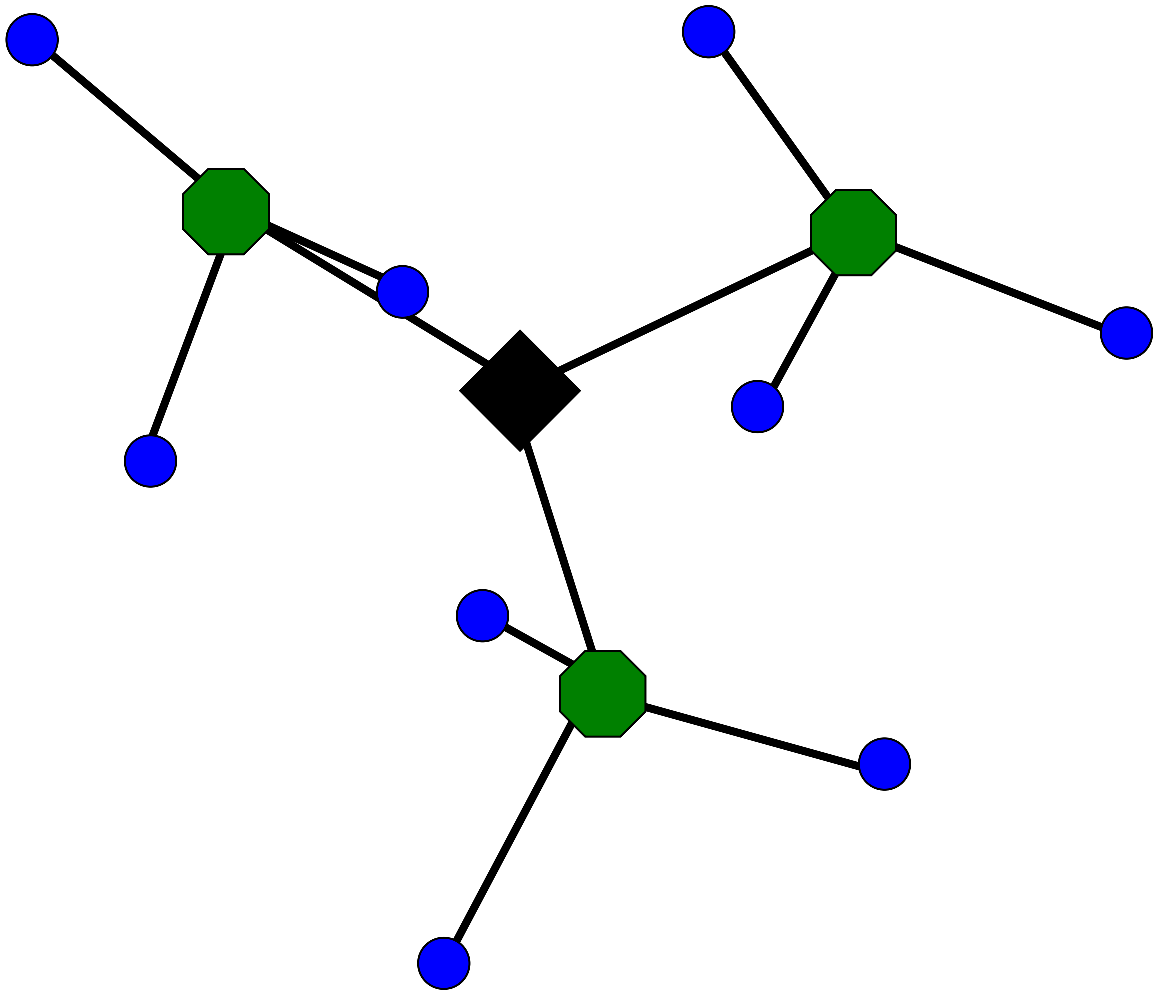


The green and blue dots represent the centroids of level 1 and level 2 sub-clusters, respectively

Nister proposed to cluster the feature space hierarchically. For example, here we assume 3 branches and 2 levels. K-means clustering is used to cluster each sub-cluster.



Each vertex in the tree represents a visual word.



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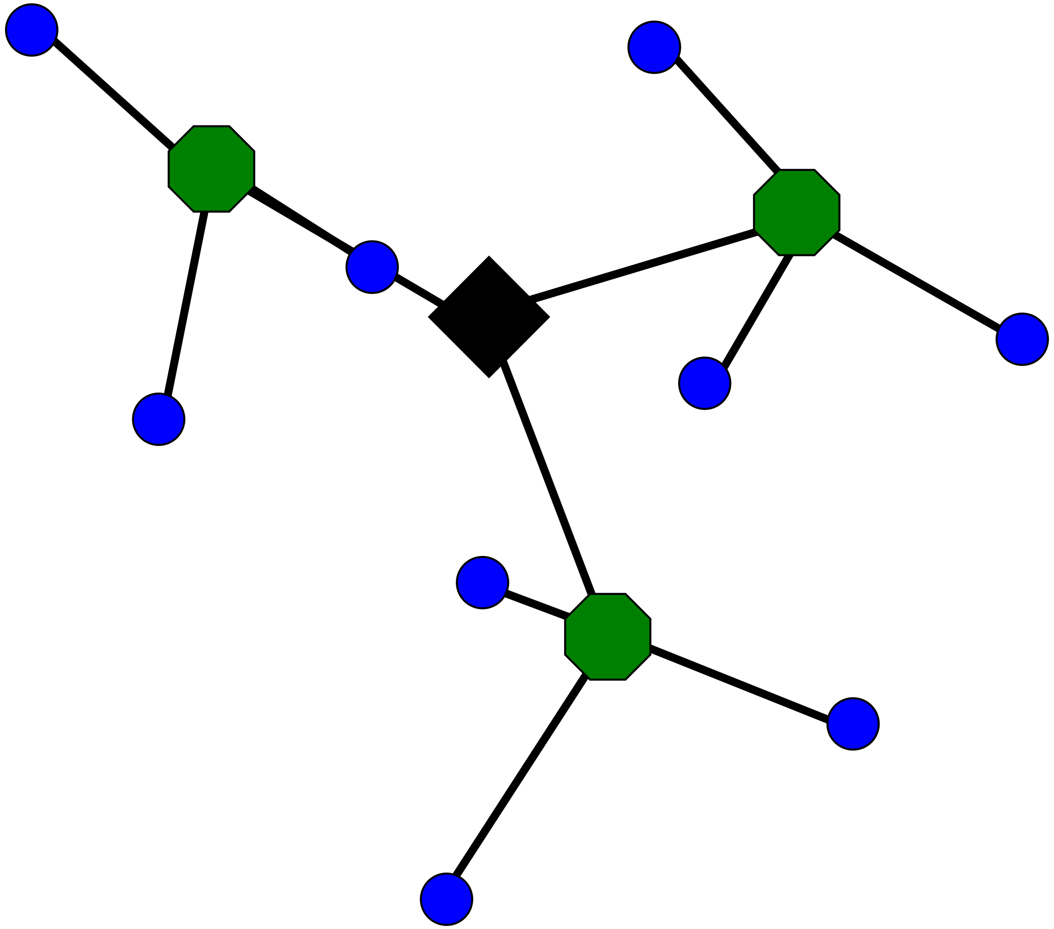

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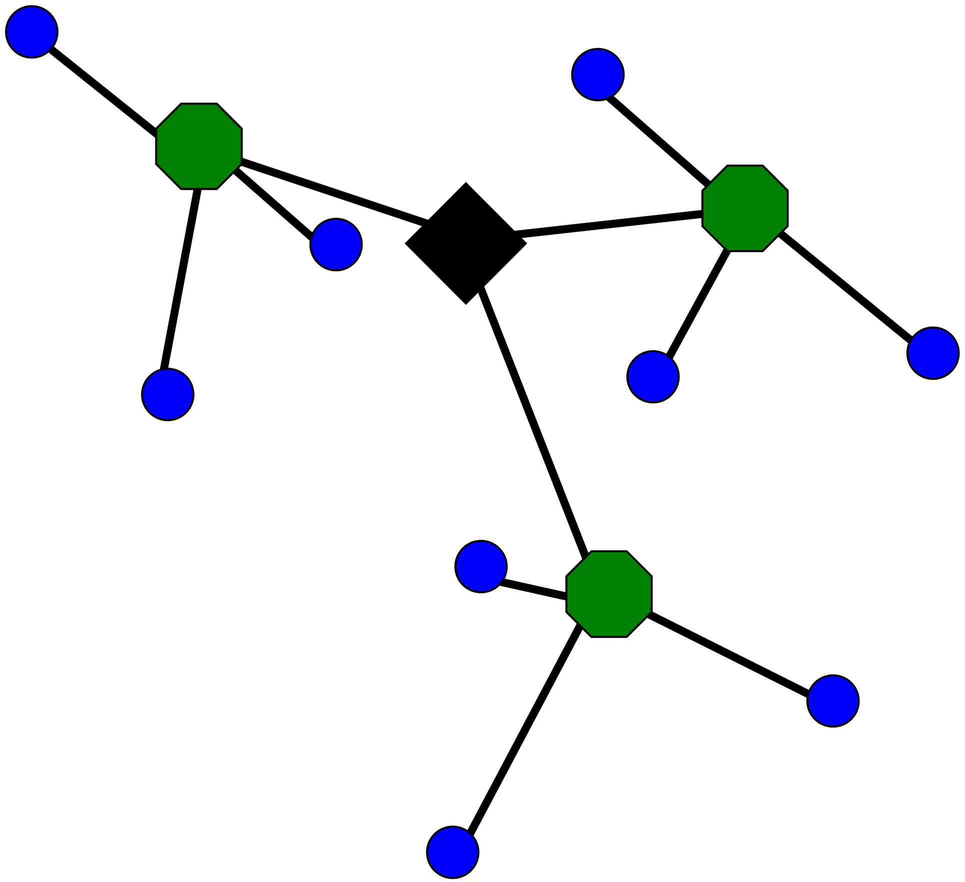

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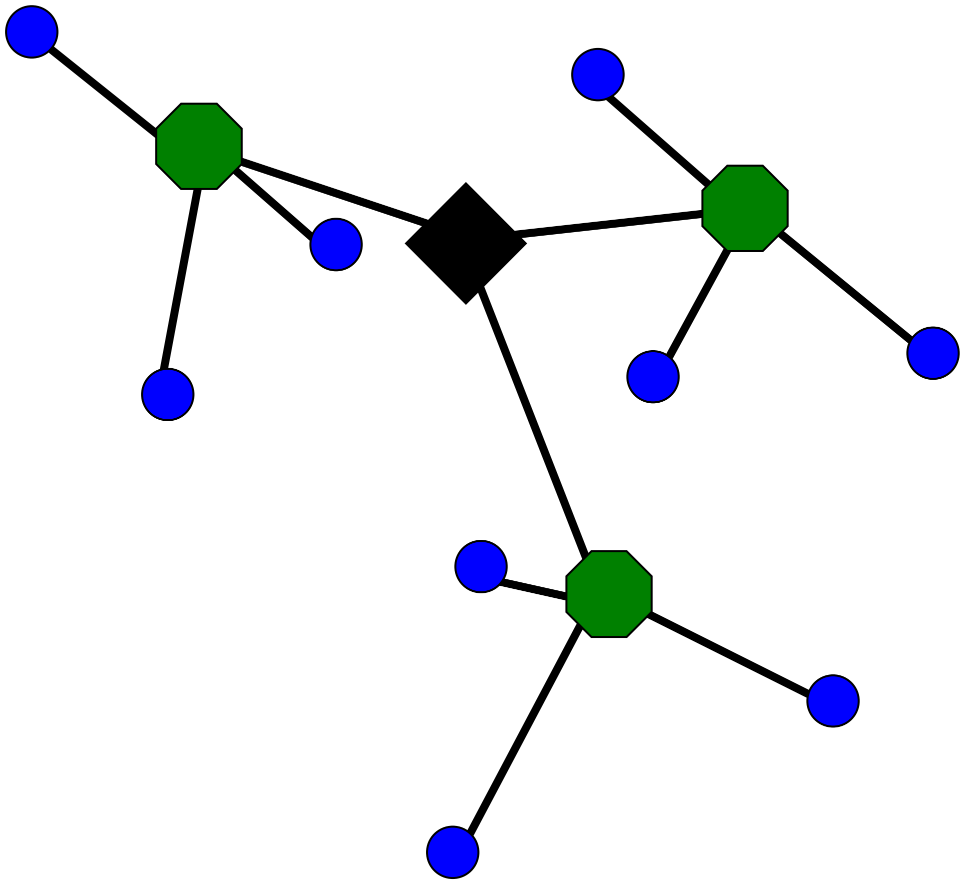

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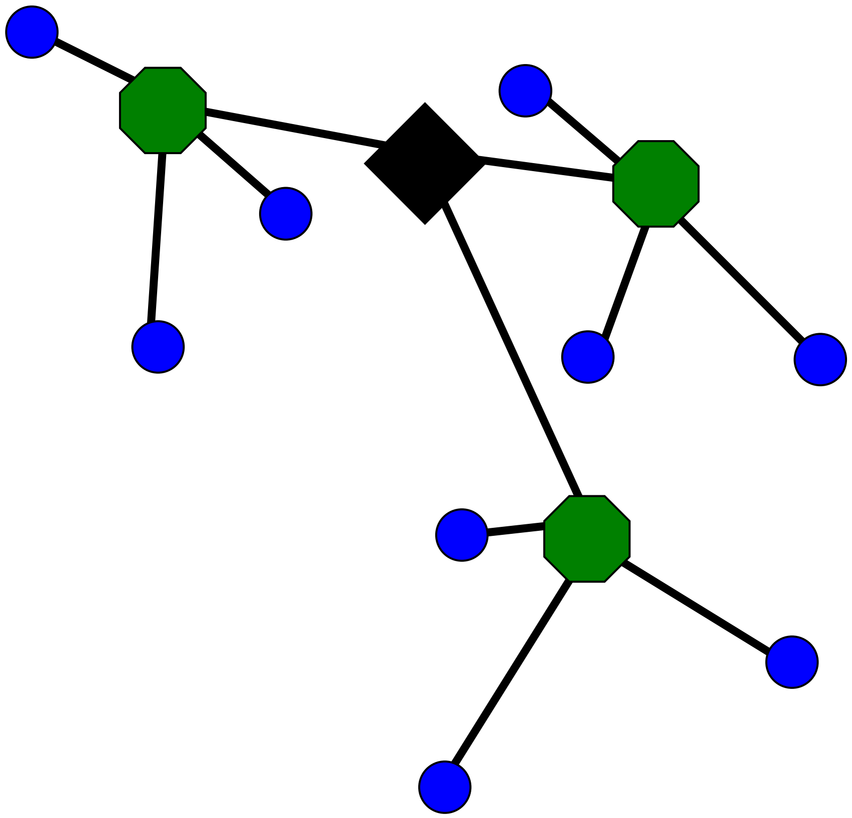

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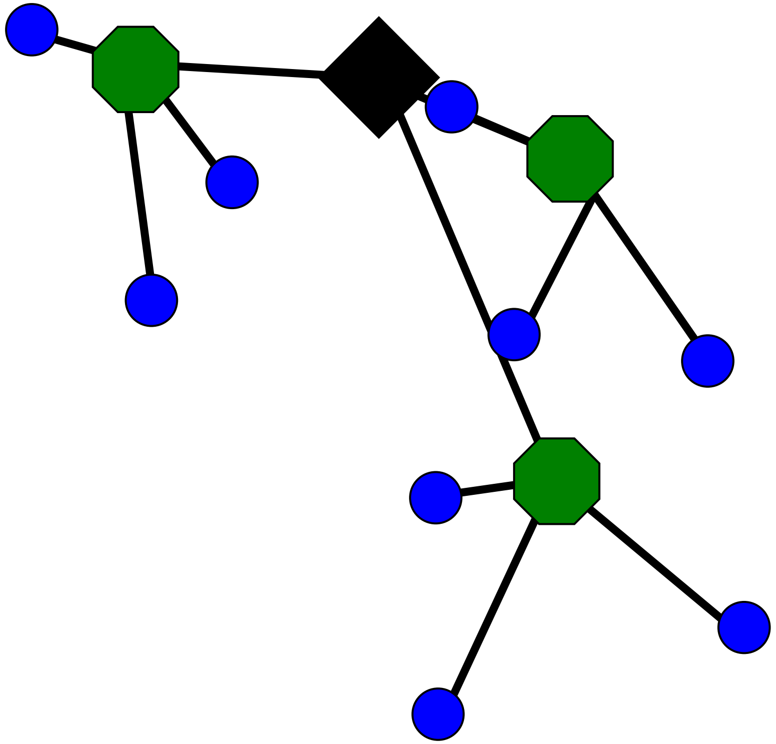

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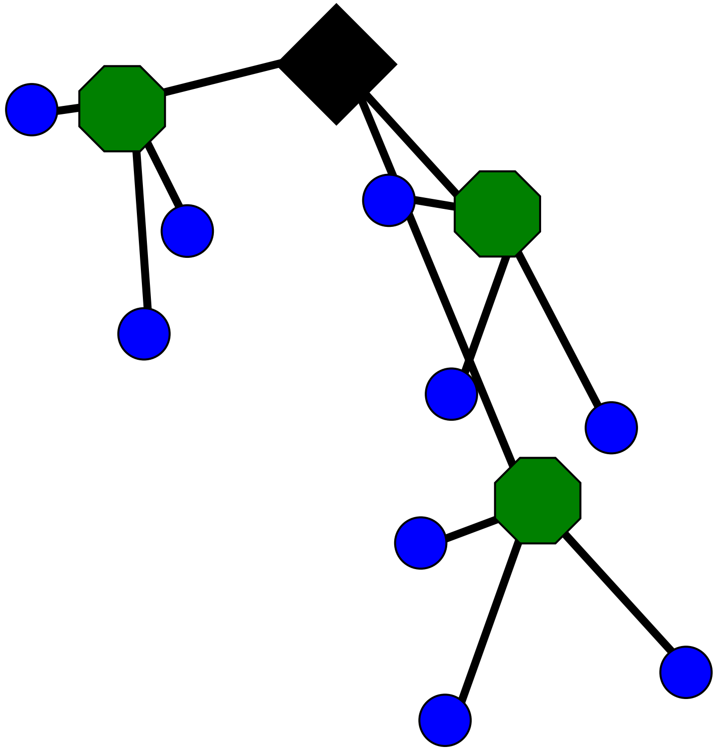

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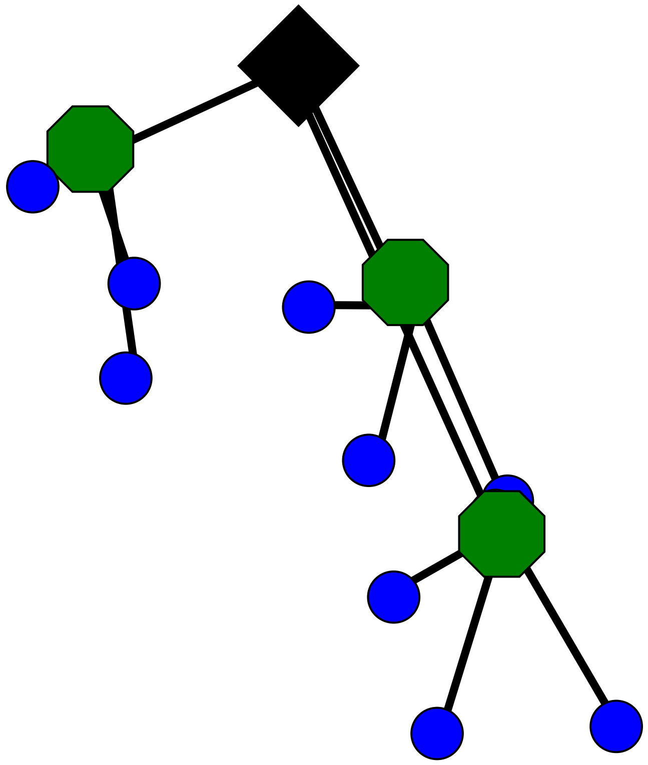

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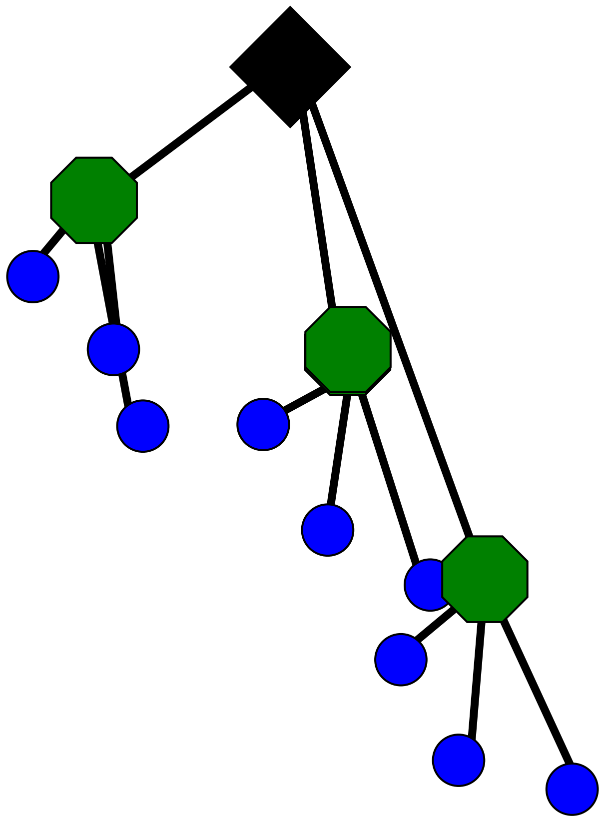

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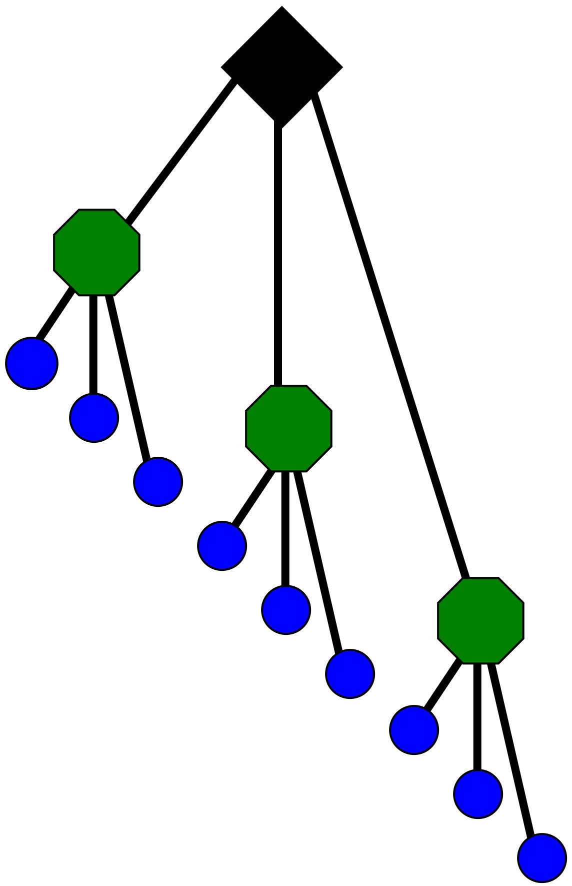

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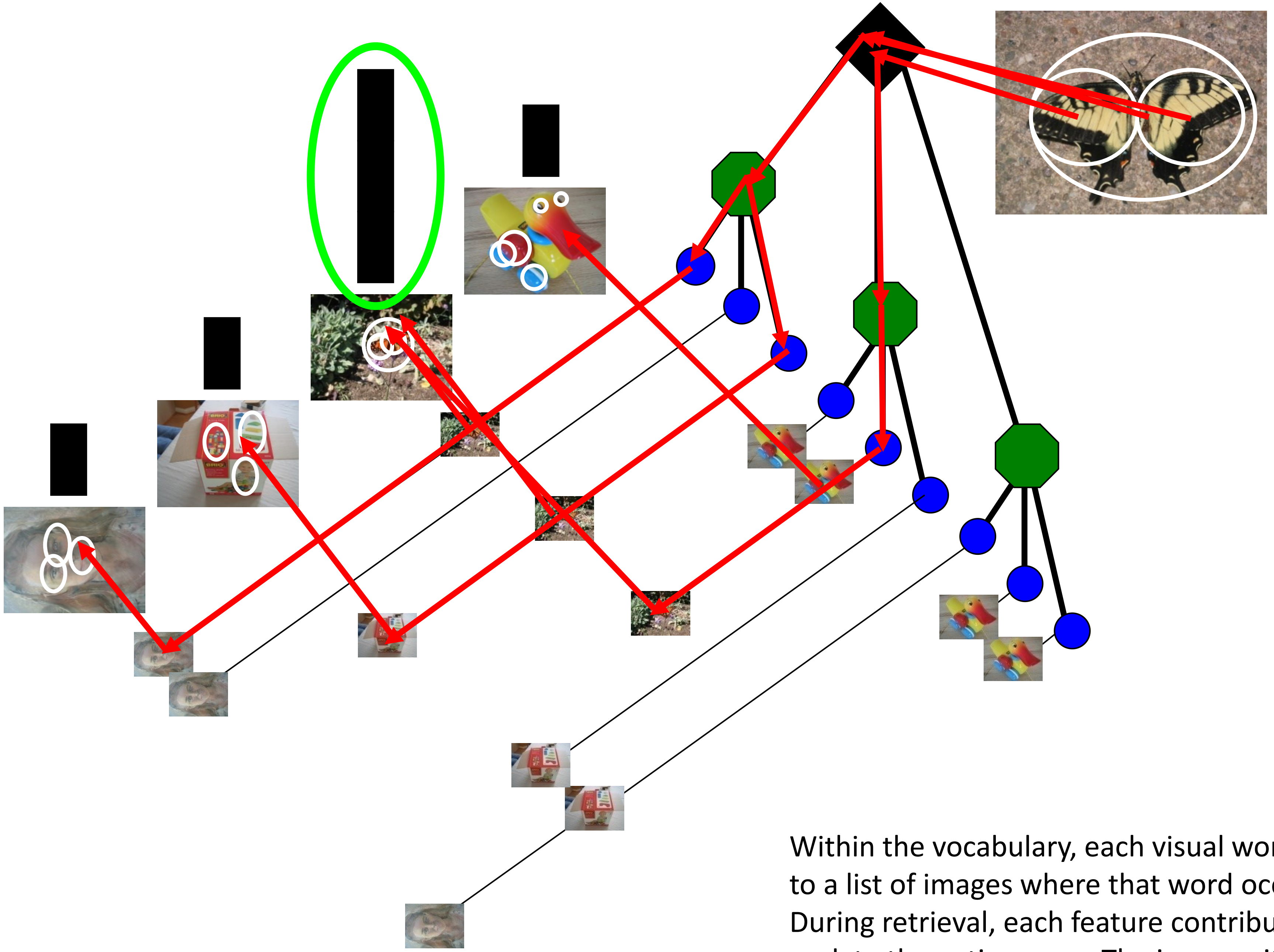

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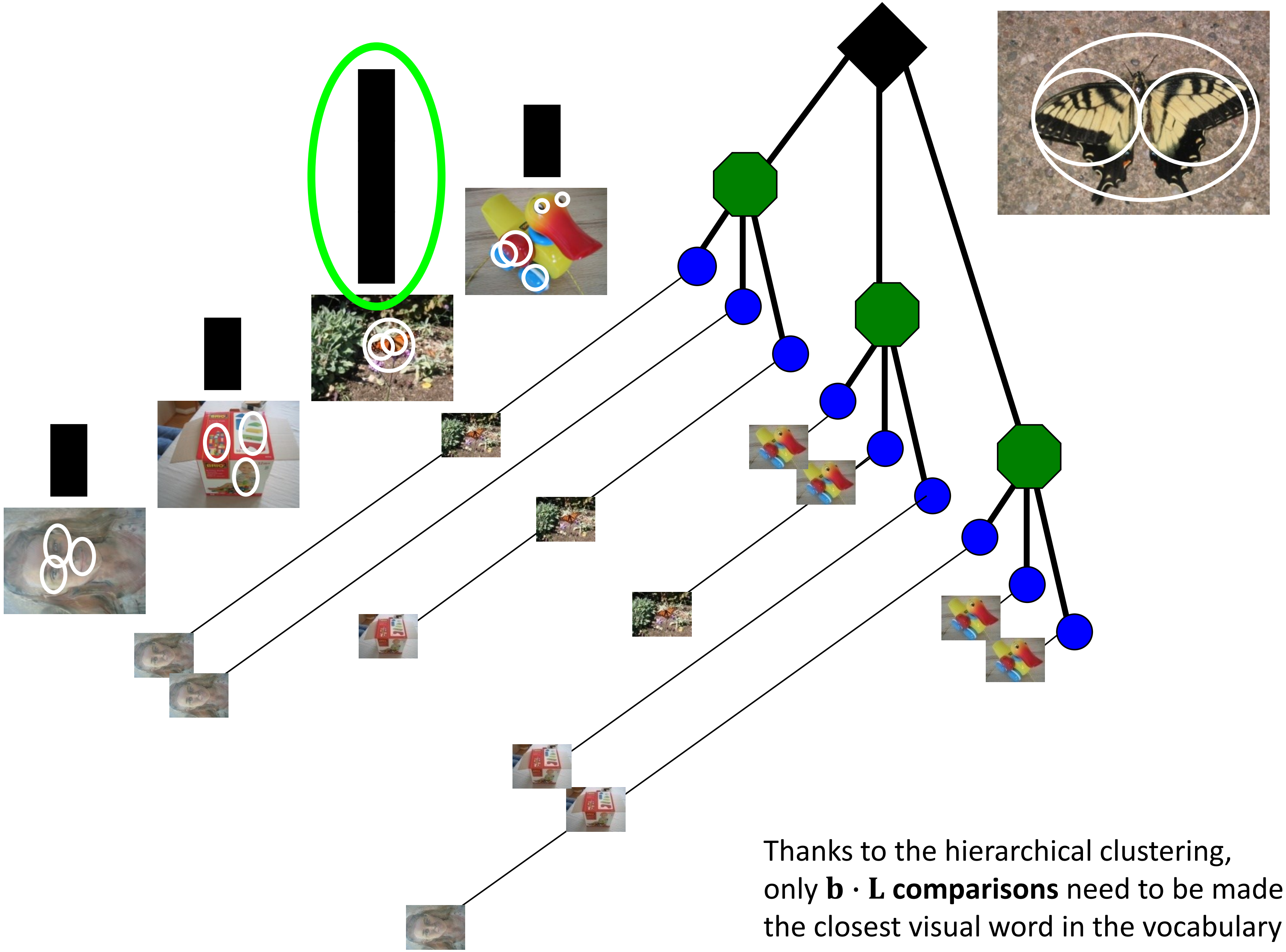


Thanks to the hierarchical clustering,
only **b · L comparisons** need to be made to find the closest visual word in the vocabulary!
b is the **number of branches** while
L is the **number of levels** of the tree.

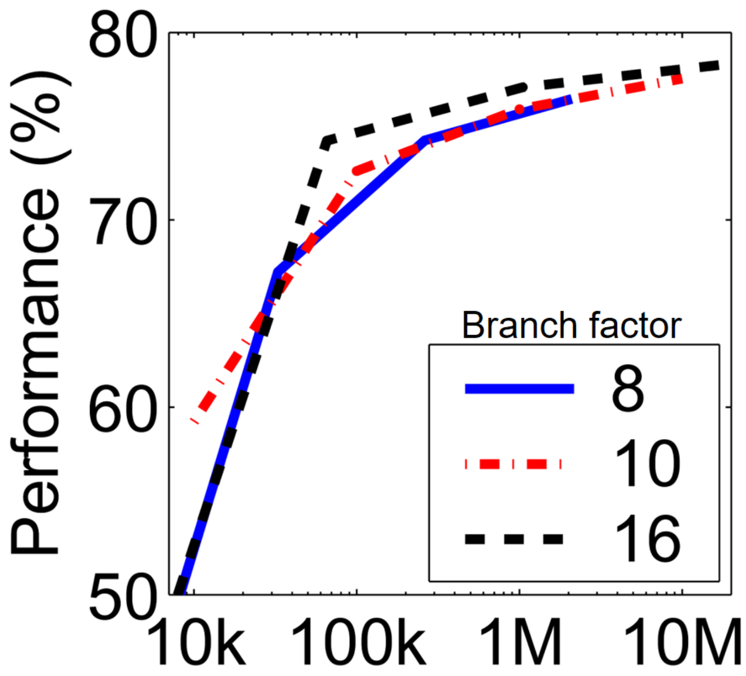
Example

Querying an image in a database of **100 million images**

- assume a query image with $\mathrm{F} = 1{,}000$ features
- assume a tree structure with $\mathrm{b} = 10$ branches per level and $\mathrm{L} = 6$ levels (i.e., $b^L = 1{,}000{,}000$ visual words)
- Then, the **number of feature comparisons** $= \mathbf{F} \cdot \mathbf{b} \cdot \mathbf{L} = 1{,}000 \cdot 10 \cdot 6 = 60{,}000$ **instead of** $\mathbf{F} \cdot \boldsymbol{b}^{\boldsymbol{L}} = 1 \text{ billion}$ comparisons (which was the case without hierarchical clustering)
- If we assume 10 microseconds per feature comparison
  → 1 image query would take **0.6 seconds**!

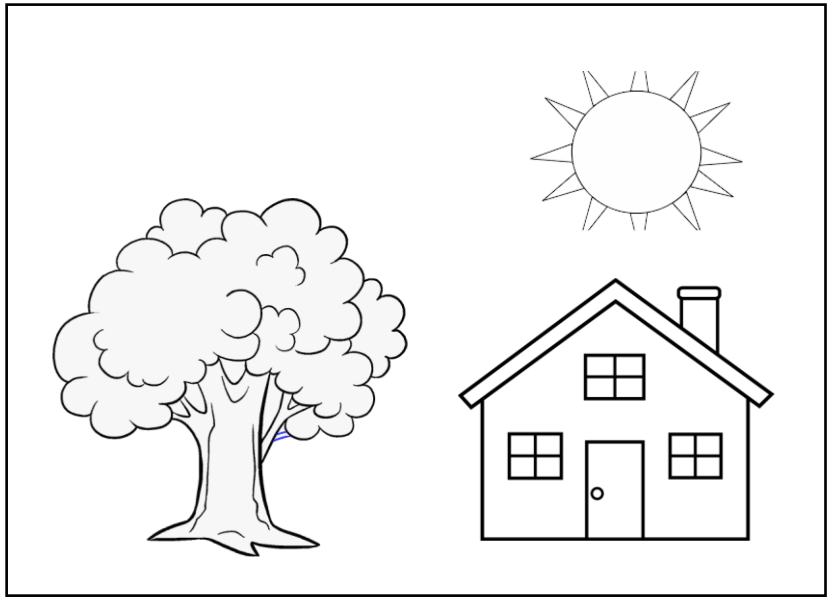
How many visual words, branches, and levels?

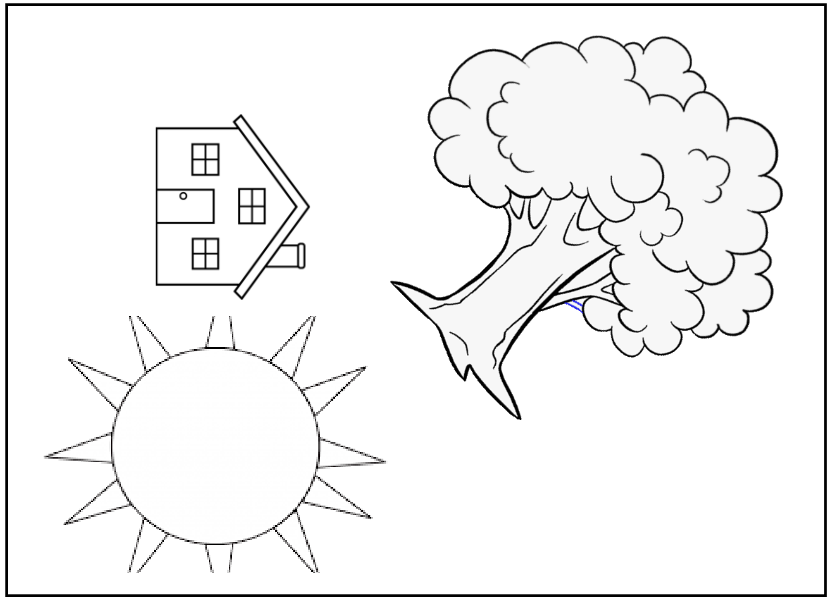
- **More words is better**, but **1 million words are used in practice**
- Also, **10 branches and 6 depth levels are practically used** (e.g., ORB-SLAM)



Question

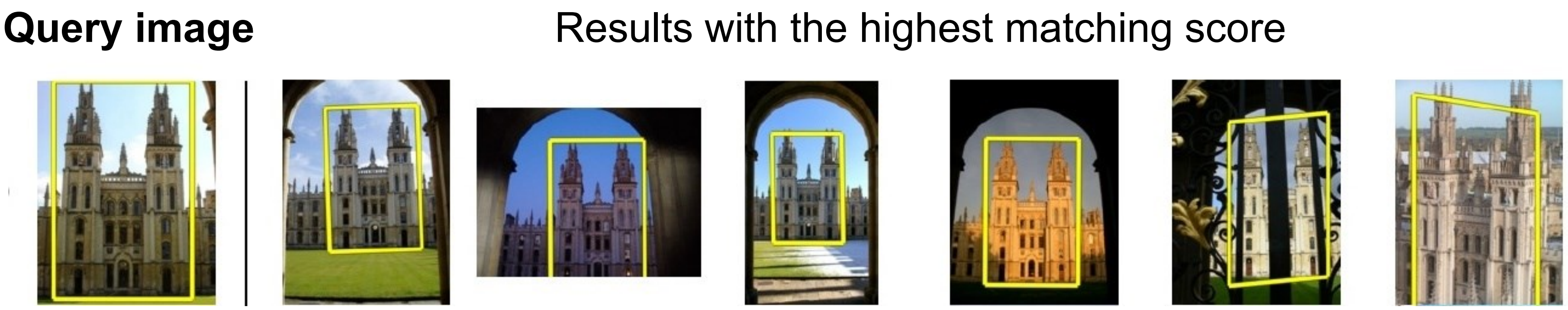
Imagine to query two images with the same features shuffled around. Will the scores returned by Bag of Words be different?





Geometric Verification

- Bag of Words discards the spatial relationships between features
- Bag of Words returns a list of images with score above a given threshold. How do we pick the image that was taken **closer** to the query image?



- Solution: Test each returned image for geometric consistency against the query image (e.g. using 5- or 8-point RANSAC) and pick the image with **the smallest reprojection error and largest number of inliers**

Open Challenges

When does place recognition fail and how would you address them?

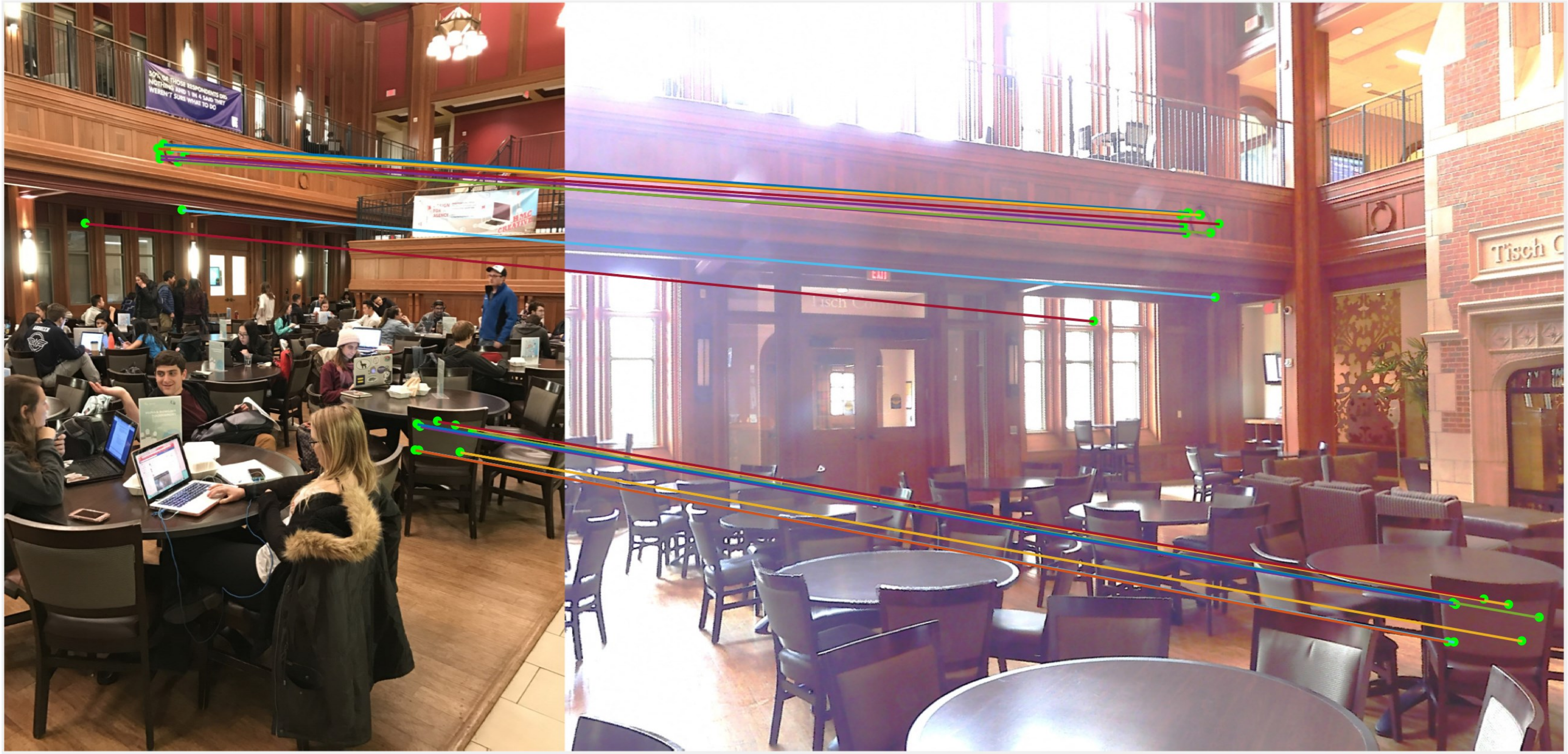
Open Challenges: Seasonal Changes

Different images of the same place at different times of the year

Open Challenges: Ambiguities

[Dusmanu, Rocco, Pajdla, Pollefeys, Sivic, Torii, Sattler, D2-Net: A Trainable CNN for Joint Detection and Description of Local Features, CVPR 2019]

Open Challenges: Ambiguities



[Dusmanu, Rocco, Pajdla, Pollefeys, Sivic, Torii, Sattler, D2-Net: A Trainable CNN for Joint Detection and Description of Local Features, CVPR 2019]

Open Challenges: Night vs. Day

[Porav, Maddern, Newman, Adversarial Training for Adverse Conditions: Robust Metric Localisation using Appearance Transfer, ICRA 2018]

Things to remember

- K-means clustering
- Bag of Words approach
  - What is visual word
  - What is a visual vocabulary
  - How do we query an image

Readings

- Sivic, Zisserman, *Video Google: A Text Retrieval Approach to Object Matching in Videos*, International Conference on Computer Vision (ICCV), 2003. PDF.
- Nister, Stewenius, *Scalable Recognition with a Vocabulary Tree*, International Conference on Computer Vision and Pattern Recognition (CVPR), 2006. PDF.