TRECVID Automated and Interactive Search by NUS/ICT

Shi-Yong Neo, Yan-Tao Zheng, Hai-Kiat Goh, Tat-Seng Chua
School of Computing, National University of Singapore

Huanbo Luan, Juan Cao, Qiaoyan He, Sheng Tang, Yongdong Zhang
Institute of Computing Technology, Chinese Academy of Sci.

Overview

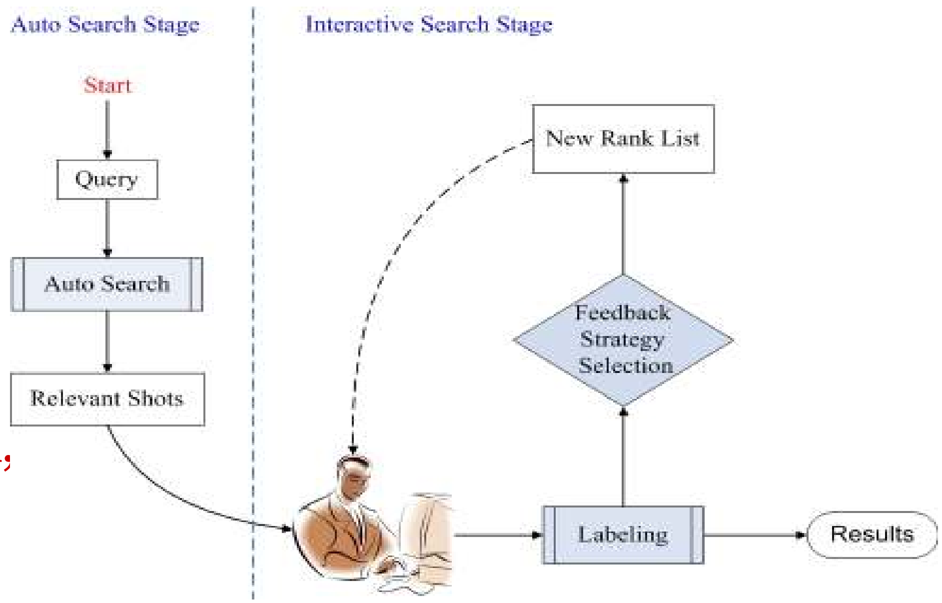
➢Performed two tasks: Automated search & Interactive search

➢Automated search:

- ➢process text and multimedia query
- ➢perform retrieval

➢Interactive search:

- ➢Perform flexible relevance feedback, active learning, locality inference
- ➢Use motion icons (m-icon)



Automated Search

Auto Search Overview

- Challenge: *ASR and MT are not good,*
- Solution: incorporate multi-modal features to complement text
  - Effective query analysis and retrieval using HLF, motion and visual features.
- Framework
  - Step 1: induce and extract query-information
    - *query-class, query-HLF from the text query;*
    - *Query motion & visual features from available example keyframes/shots*
  - Step 2: perform retrieval and ranking

Query Analysis

- Analyze queries to learn:
  - Query-class, Query-HLF, Query-image-feature and Query-shot-motion
- Query-class
  - Showed to be important functions by many prior works
  - Identified by heuristic rules using combination of noun, noun phrases, verbs, NE, etc
  - Function as a guide to fuse multi-modal features effectively.
  - Determined by a set of firing rules for each class:
  - We exploit {Scene, People, Object, Action, Unknown}.
    - *{Unknown} class is to accommodate the queries that do not belong to any of the first four classes.*
    - *Other classes cover 19 out of 24 queries*

Query Analysis: Query-HLF

- **Query-HLF** suggests possible HLFs that are important to the query in terms of visual requirements.
- Employ morphological analysis and selective expansion using WordNet on HLFs descriptions and query.
  - Stronger the match between HLF descriptions and query => the more important the HLF is to the query.
- Infer query-HLF from sample keyframes and shots
  - A sample image containing one of the HLFs could explicitly means that the particular HLF can be important.
- Combine inference from text query and video shots to obtain a better and more representative query-HLF for query.

Query Analysis: Query-image-feature

- **Query-image-feature** (Q_{IMG}) corresponds to video features extracted from sample keyframes and video shots.
- Step 1: extract three visual features from all the sample keyframes
  - a 320-dimensional vector of edge histograms(***EH***) on 5 regions;
  - a 166-dimensional color histogram (***CH***) vector in HSV space;
  - a set of visual words (***VW***) constructed based on 128-dimensional SIFT vector
- Step 2: learn three nonparametric LDA models based on above three visual features (***CH***, ***EH***, ***VW***)
  - obtain the latent topic distribution of every shot.

Query Analysis: Query-motion features

- A number of query topics are highly associated with motions.
  - For example,
    - *Query "finding shots of train in motion" and "find shots in which a boat moves past" tend to present large horizontal translational global motions in the shot,*
    - *Query "find shots of a road taken from a moving vehicle through the front windshield" tends to present zoom-like diffusing global motions,*
- We use 2 descriptors for global motion patterns
  - 8-dimensinal vector of motion directions: up, down, left, right, up-left, up-right, down-left and down-right
  - 1D global motion intensity: still, median, etc
- The motion cues are extracted from motion vectors stored in p-frames in compressed domain
  - High efficiency: processing around 50-hour testing videos in approximately 40 hours.

Shot Level Retrieval

➢Fuse the ASR & MT text, Query-HLF, Query-image-feature and Query-shot-motion

$$Score(Q, Shot_j) = \beta_c \cdot Text(Q, words \mid words \in Shot_j) +$$

$$\gamma_c \cdot \sum_{HLF_m \in shot_j} \left[Conf(HLF_m) \times Sim\_Lex(Q_{HLF}, HLF_m) \right] +$$

$$\delta_c \cdot \max_{image_n Q_{IMG}} (image\_sim(image_n, shot_j)) +$$

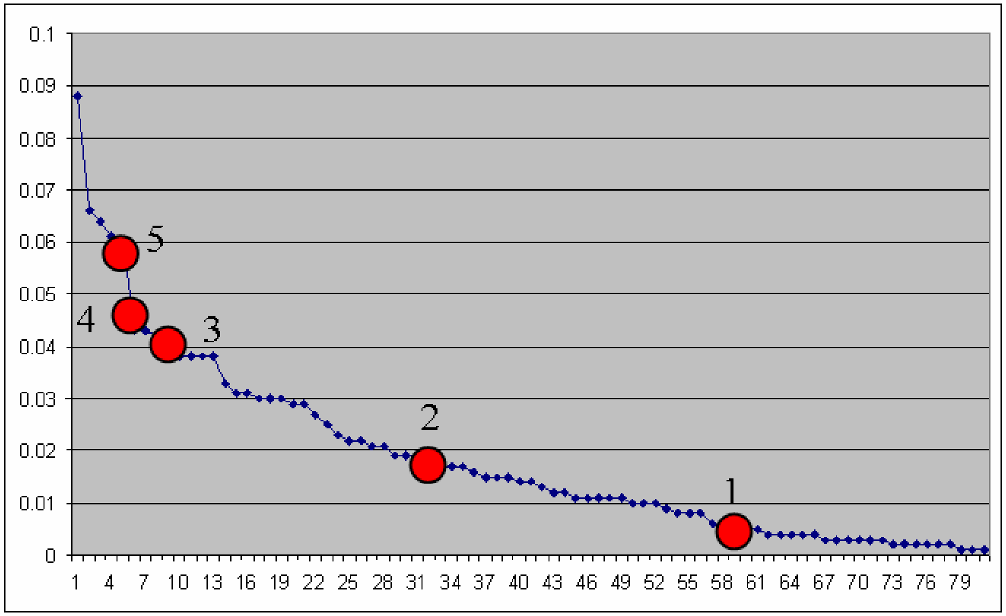
$$\chi_c \cdot \max_{image_n Q_{IMG}} (motion\_sim(image_n, shot_j))$$

Experimental Results

- Performed 5 runs to progressively evaluate effect of HLF, visual and motion features
  - *Run1:* *Required text baseline;
  - *Run2:* *Required visual baseline;
  - *Run3: Fusion without motion using only text query;*
  - *Run4: Fusion with motion using only text query;*
  - *Run5: Fusion with motion using multimedia query;*

Experimental Results

- Firstly, the worst performing run (Run1: MAP 0.004) comes from the text baseline.
  - ASR and MT text are not erroneous and thus less predictive than HLF and visual counterparts.
- The visual baseline (Run2: MAP 0.017) in contrast yields much better results.
- Improvements in Run3 and Run4 show that the use of HLF and motion features is effective.
- Run5 (0.061) delivers the highest MAP by multimedia queries



- Observations:
  - HLFs are one of most important features
  - Motion is effective in certain queries
  - Visual and motion features tend to complement text and HLF features
  - Query content from multimedia counterpart is more discriminating than text alone

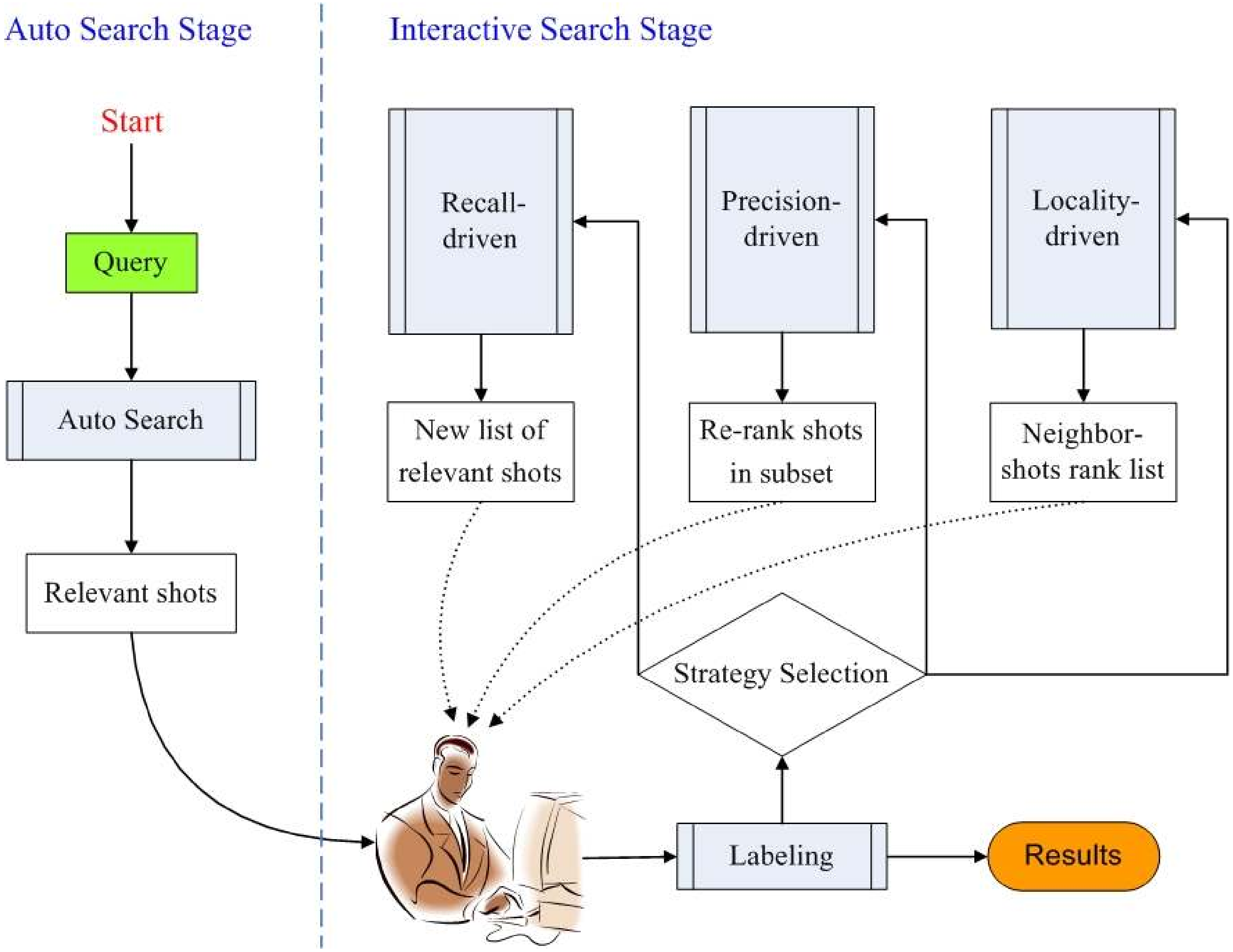
Interactive Search

Introduction

- Poor performance of fully auto search
- More intelligent system is demanded
- Solution: interactive search
  - Incorporate user's feedback to refine the results

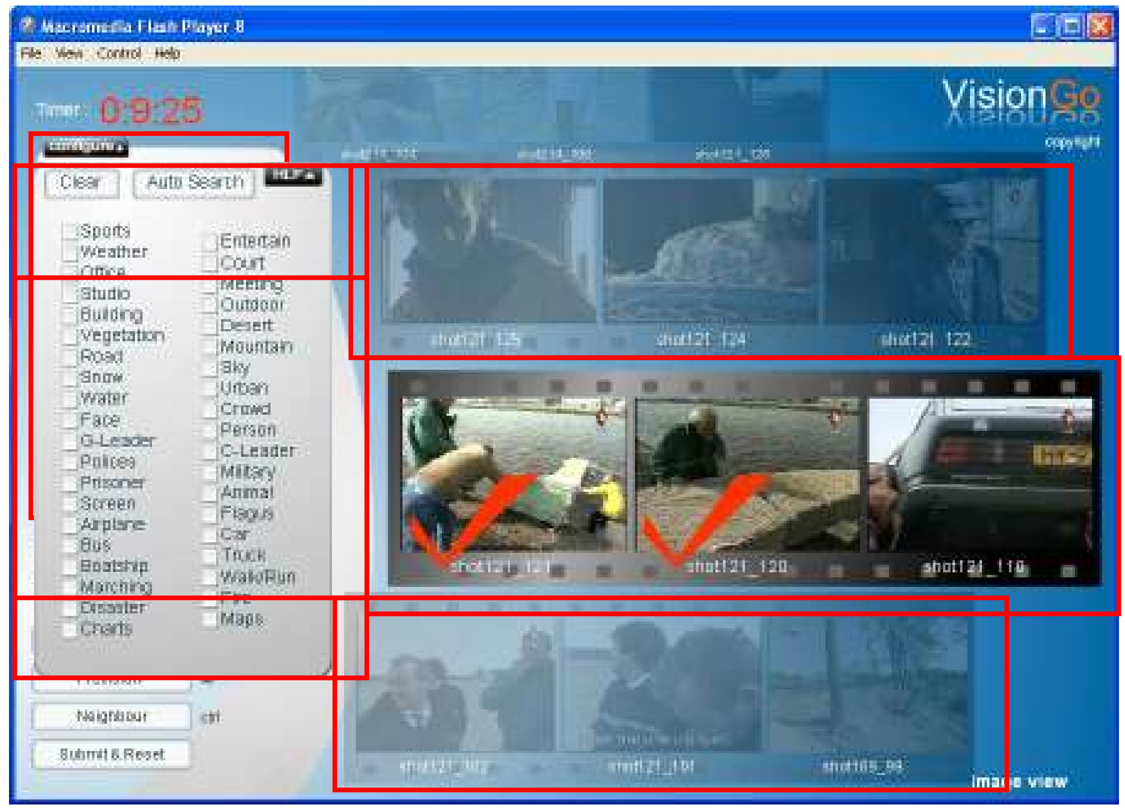
- Our emphases for interactive search:
  - Effective UI (User Interface)
    - *To maximize user's annotation speed*
  - Multiple feedback strategies
    - *To provide multiple refinement options to users*
  - Motion icons
    - *Design Moving Icons (M-icons) to give info on motion of the shots*

Overall Framework



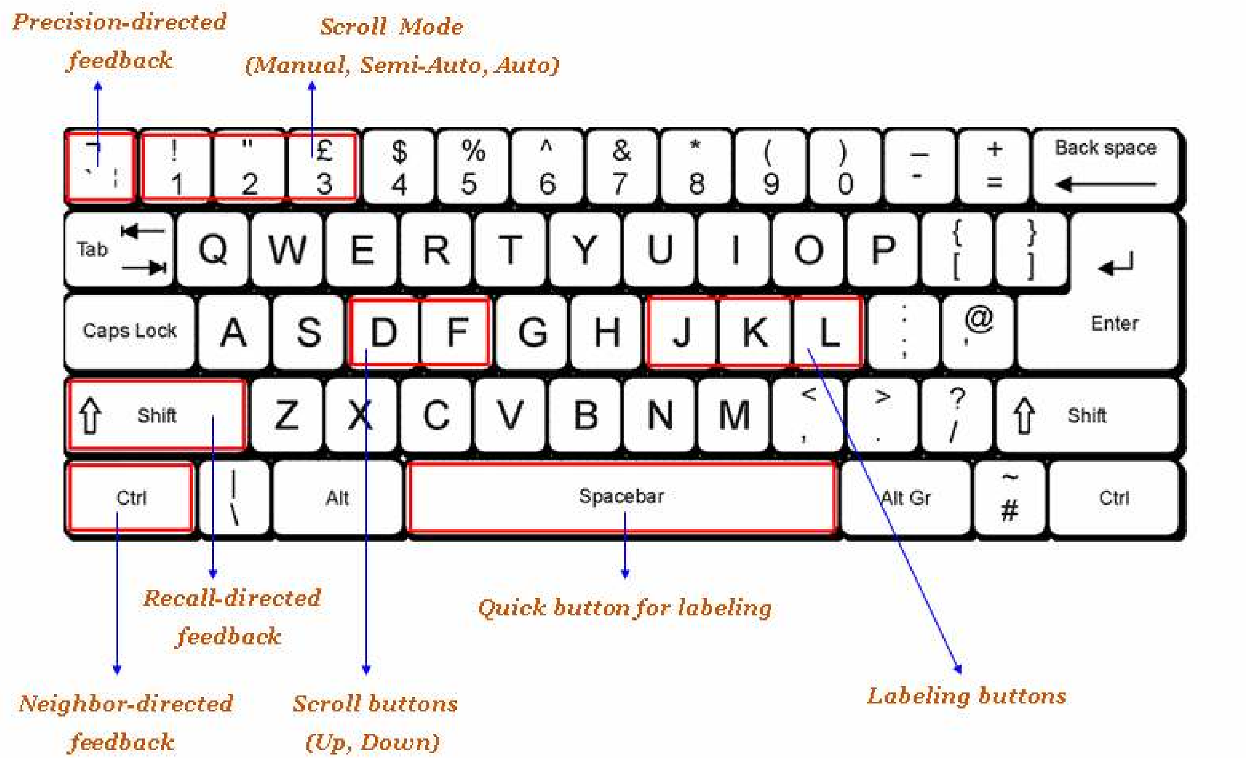
Intuitive User Interface

- UI Design Basis
  - Fast perception
    - *display 3 shots in each row*
    - *optimum for keystroke action*
  - Quick previews of previous & subsequent rank shots
  - Flexible annotation modes
    - *manual, semi-auto, auto*
    - *control flow of shot browsing*
  - Query by HLF
  - Retrieval Statistics
  - Self-contained, seperated from backend server and Web-enabled
    - *UI developed by Macromedia flash*



Intuitive User Interface

- UI Design Basis
  - Fast annotation
    - *keystroke actions, labeling by clicking on keyboard buttons*



- Efficiency
  - Approximate 3,500 shots based on motion icons in 15 mins
  - Approximate 5,000 shots based on static icons in 15 mins

Multiple Feedback Strategies I

- Strategy 1: Recall-directed feedback
  - Aim: maximize recall performance
  - Extract useful text token and HLF from labeled relevant shots for query expansion
  - Features: text and HLF
- Strategy 2: Precision-directed feedback
  - Aim: improve precision of retrieved shots by refining classifier
  - Adaptive sampling strategy for active learning based on SVM
  - Multimodal features: visual, HLF, motion
  - Real time training and classification

Multiple Feedback Strategies II

- Strategy 3: Semantic coherence (neighborhood inference)
  - Temporal locality-driven: return neighboring shots of the positive
  - Documentary videos possess high temporal coherency of same topic
  - Neighboring shots tend to be relevant
  - Select neighbors by sliding window
  - Example: *find shots of street market*

Shot123_123

Shot123_124

Shot123_125

Shot123_126

Shot123_127

Why Multiple Feedback Strategies?

- More options for users
  - More robustness in feedback
- More flexibility for cross-domain annotation
  - For news corpus (TRECV06), recall-driven feedback is effective
    - *ASR text is richly available*
  - For documentary corpus (TRECV07), neighborhood inference works well
    - *Documentary video tends to be of high temporal coherence.*

Motion Icons

- Motivation
  - Many queries are associated with objects in motion in the video.
  - Static keyframes contain deficient information about video content
- Our Approach
  - Construct a summarized clip comprising a sequence of keyframes which can show moving picture information.
  - Motion icon possesses more comprehensive info. than static keyframe
  - Users can have a clearer idea of shot content and identify relevant shots with better confidence

Motion Icons

➢Example 1: *find shots of train in motion*

keyframe

M-icon

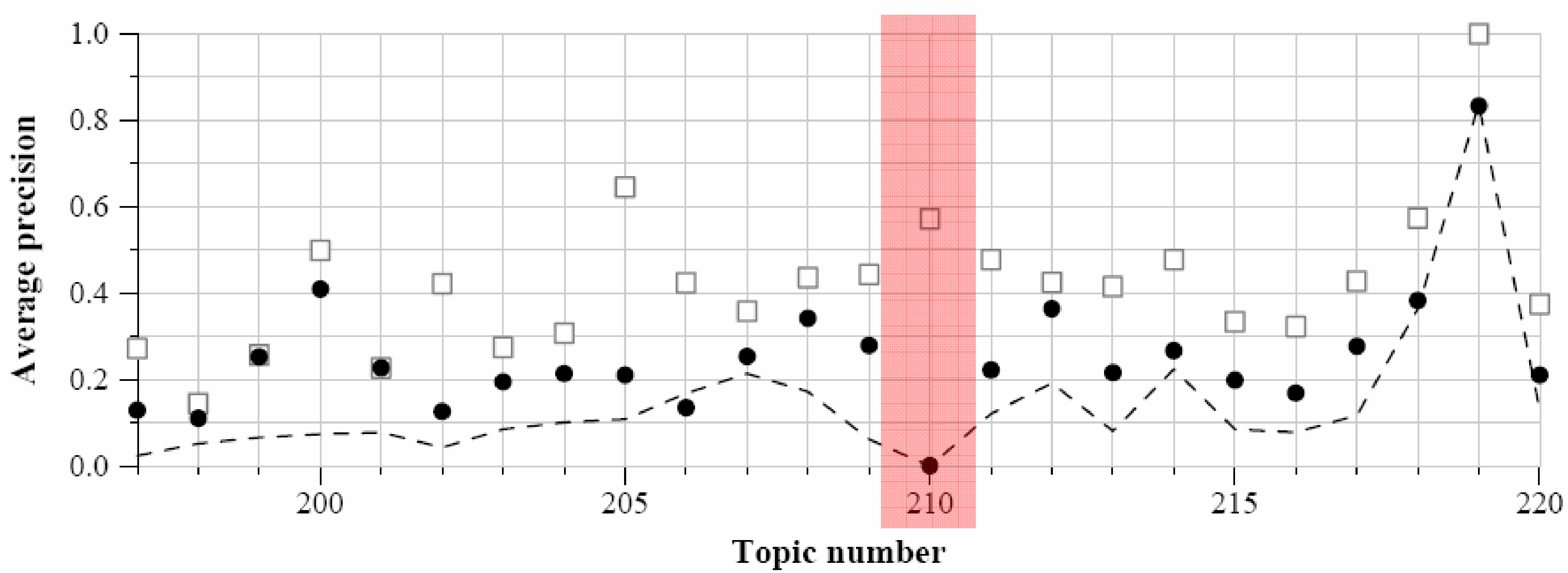
➢Example 2: *find shots of a canal, river, or stream with some of both banks visible*

keyframe

M-icon

Experiments

- We submitted one run of interactive search
- MAP of 0.251 and 5th best performing run
- 2 topics achieves highest MAP and 18 out of 20 topics are above median
- 1 query ("Find shots of people and dogs walking") has no relevant shots found, which lowers overall MAP badly.



Conclusion and Future Work

- Focus of Interactive Search
  - Efficient UI
  - Multiple Feedback Strategies
  - M-icon
- Future Work
  - Can we extend our system to non-expert users?
  - *Challenges:* When to do feedback, which strategy to choose?
  - *Solution:* Recommendation mechanism
    - *Analyze experts behavior pattern based on activity log*
    - *Annotation statistics of non-expert users*

Thank You

Q & A