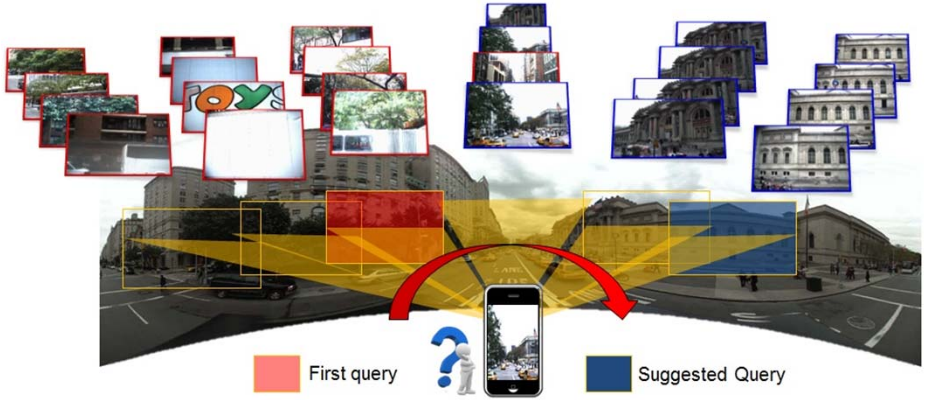


Active Query Sensing for Mobile Location Search

Felix. X. Yu, Rongrong Ji, Shih-Fu Chang

Digital Video and Multimedia Lab
Columbia University

November 29, 2011

digital video multimedia laboratary

Outline

- Motivation
- Problem Justification
- Active Query Sensing
  - Offline Salient View Learning
  - Online Active Query Sensing
- Evaluation
- User Interface
- Conclusion

Outline

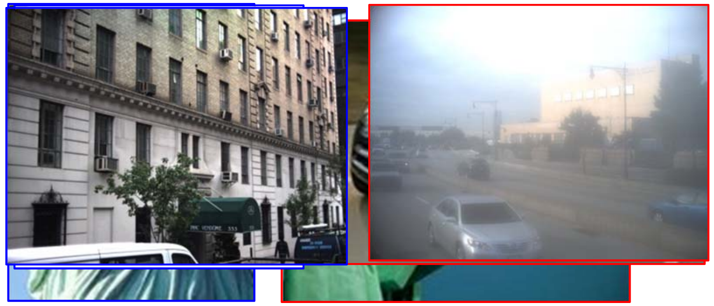
- Motivation
- Problem Justification
- Active Query Sensing
  - Offline Salient View Learning
  - Online Active Query Sensing
- Evaluation
- User Interface
- Conclusion

Motivation

- Mobile Visual Search
  - Search information about products, locations, or landmarks
  - By taking a photo of the target of interest using the mobile device
- Commercial Systems
  - Snaptell
  - Nokia point and find
  - Google goggles
  - Kooaba
- Research Prototypes
  - Nokia Stanford MVS system
  - PKU mobile landmark search
  - MIT sixth senses
  - MSRA Photo2Search prototype

Motivation

Performance of Mobile Visual Search Varies



- Search success depends on
  - How distinctive object classes are
  - View variation and object deformation
  - Quality of captured images
- Not every view of an object or location is distinctive enough as a successful query
  - Only 47% of the first query succeed in our location search endeavor on Manhattan 0.3m street view dataset
  - 0.4-0.7 *average precision* in the state-of-the-art location search systems ([Knopp 2010] [Girod 2011] etc.)

Motivation

How to guide the user to take the mobile query?

– Which view will be the best query?

- For example, in mobile location search:

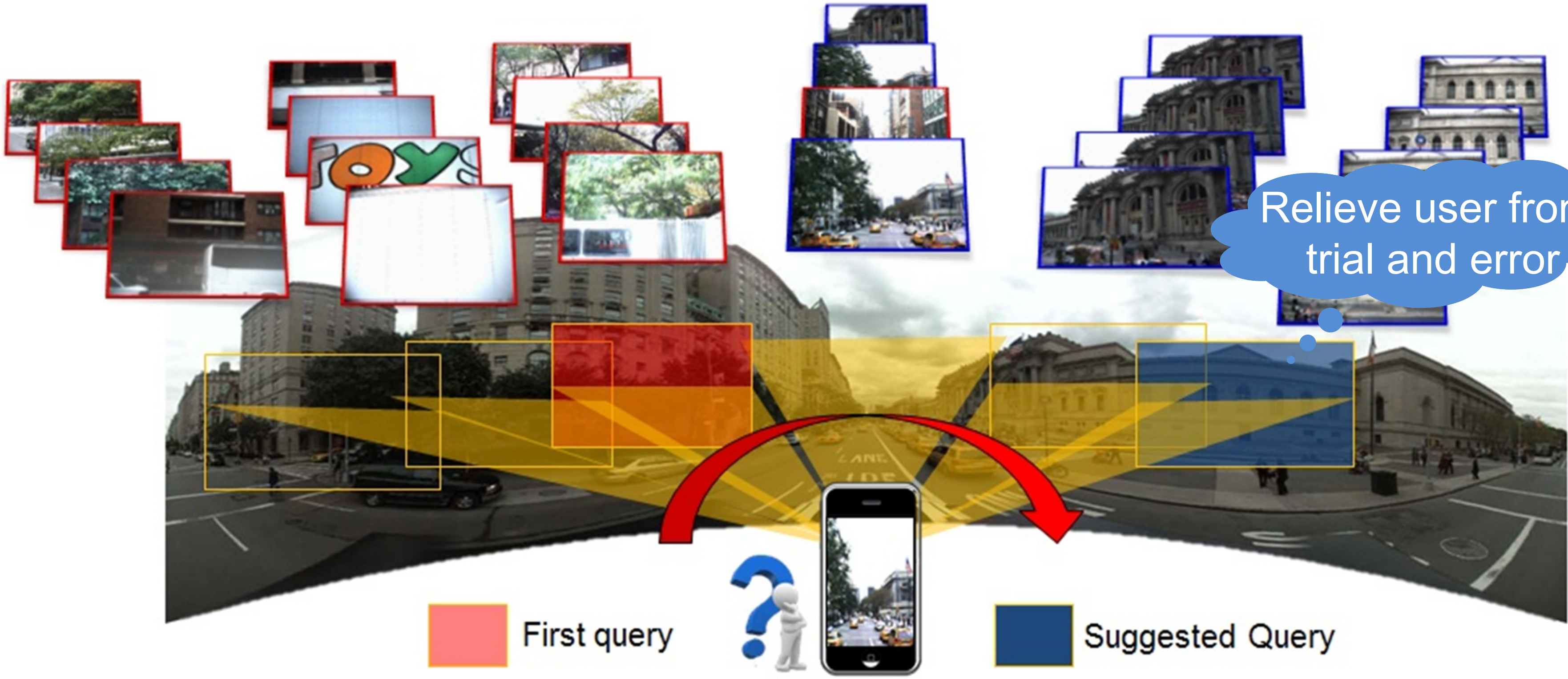
- Or in mobile product search:

– A General Yet Untouched Problem for searching locations, objects and landmarks.

Motivation

- Possible Solutions
  - Solution I
    - User takes a video query by scanning the surrounding
    - Then the mobile end selec
      (views) to be sent to the

We focus on solution II, enabling users and machines to collaborate



Motivation

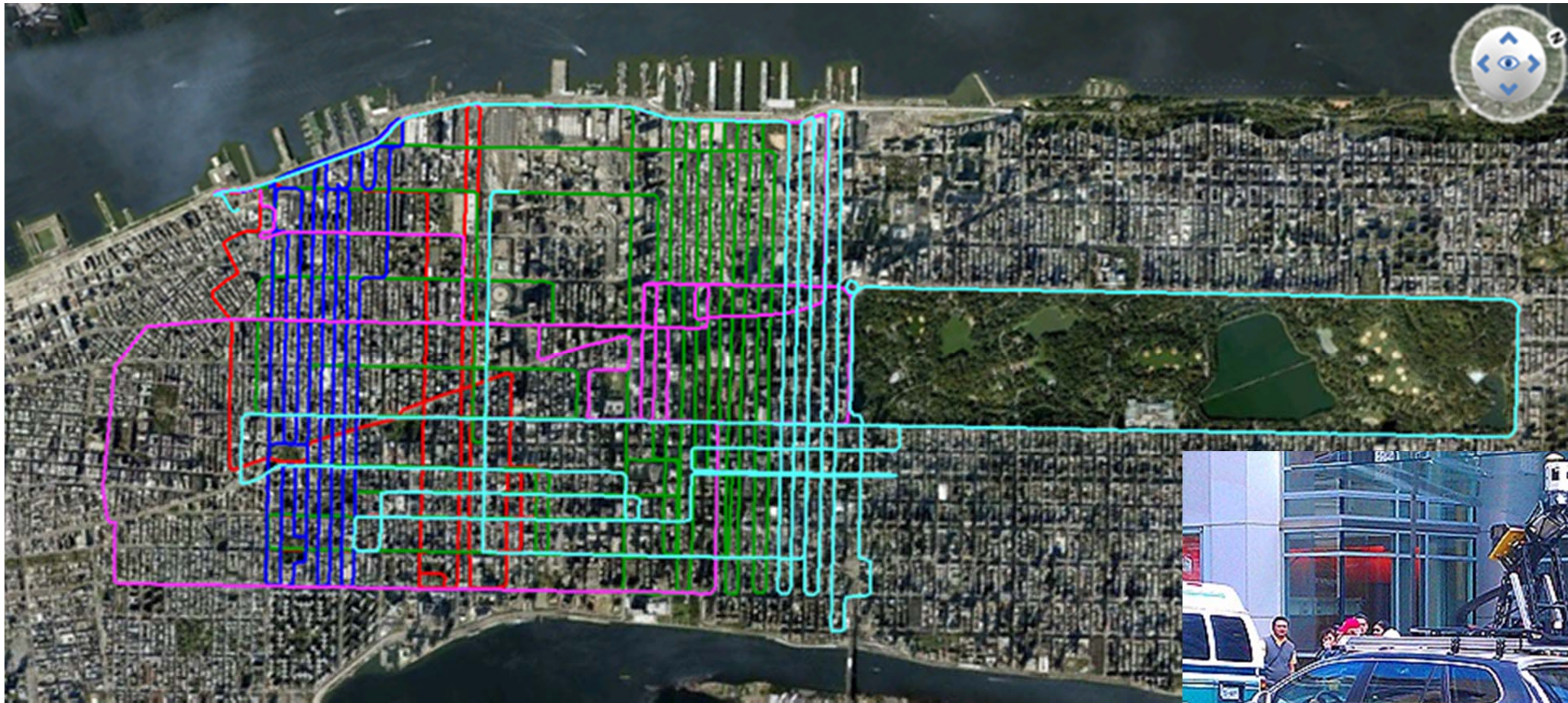
- Research Objective
  - Use mobile location search as a case study
    - We will develop a general framework that can be extended to mobile object retrieval and product search
  - Why not GPS?
    - GPS may not be reliable in the dense urban jungle areas
    - Visual based solutions can also be used to refine GPS solutions
    - Our research goal is general: a special case of multi-view mobile search

Outline

- Motivation
- Problem Justification
- Active Query Sensing
  - Offline Salient View Learning
  - Online Active Query Sensing
- Evaluation
- User Interface
- Conclusion

NAVTEQ 0.3M NYC Data Set

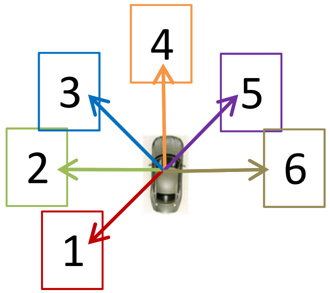
- 300,000 images of 50,000 locations in Manhattan
- Collected by the NAVTEQ street view imaging system



Geographical distribution

NAVTEQ 0.3M NYC Data Set

- Location Sampling
  - Locations are imaged at a four-meter interval on average
  - Six camera views for each location separated by 45º
- Visual Data Organization
  - Six views (images)
  - Also provide panorama (used for visualization in this work)

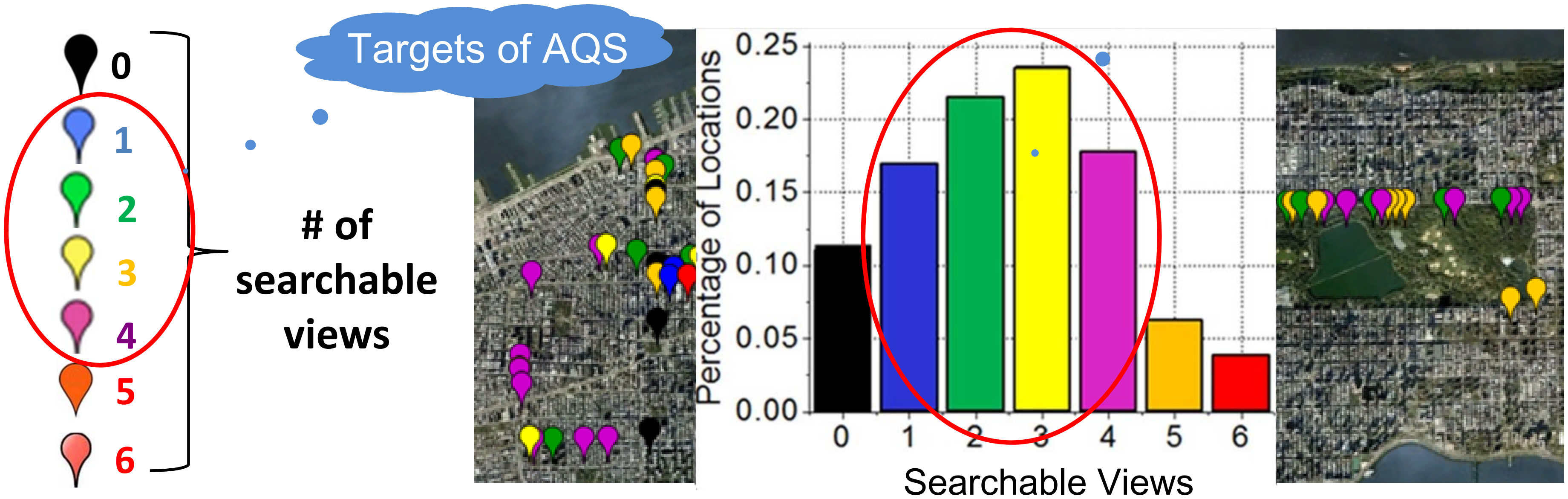


Problem Justification

- Our goal
  - Once the first query fail, how to take the best second query to correctly find his/her current correct loca

80% of locations have partial searchable views

- How much can AQS help
  - The percentage of locations that are partially searchable



Subsample 200 locations to “# of searchable views” using cropped Google street view

Outline

- Motivation
- Problem Justification
- Active Query Sensing
  - Offline Salient View Learning
  - Online Active Query Sensing
- Evaluation
- User Interface
- Conclusion

Active Query Sensing System

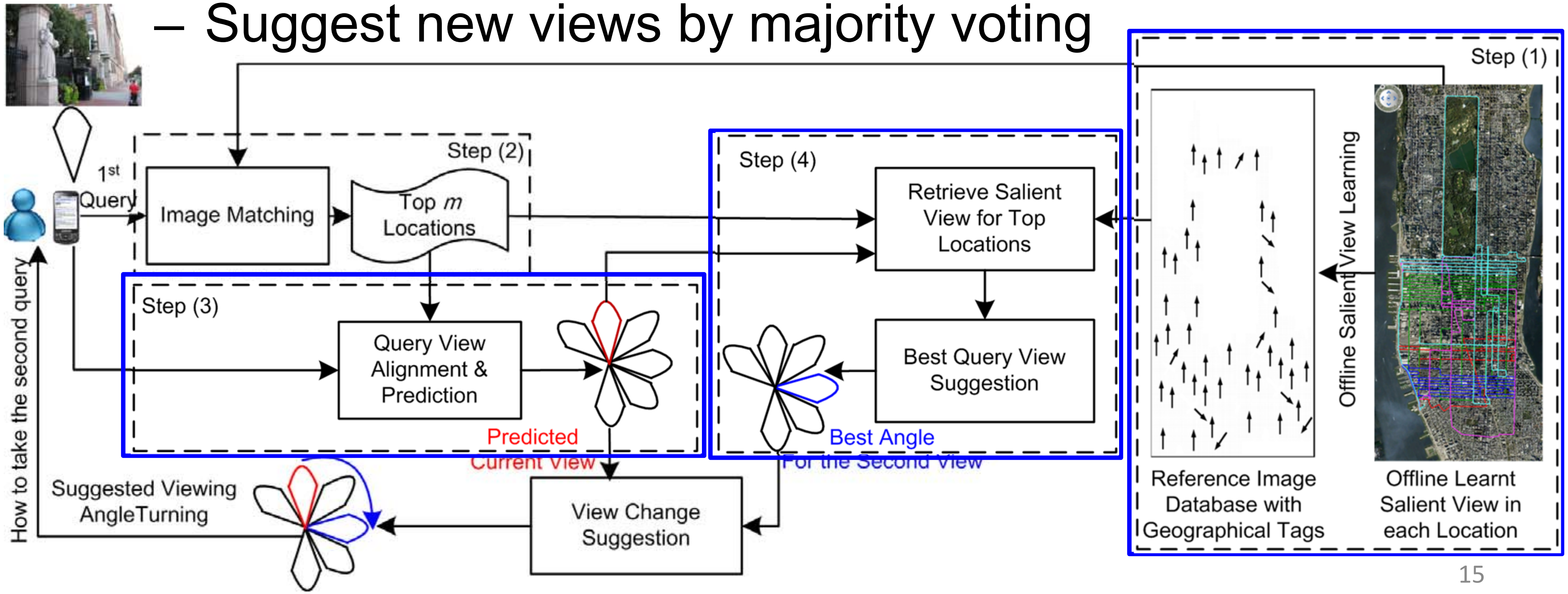
- Active Query Sensing Demo

(refer the demo video)

Active Query Sensing System

Basic Idea and Workflow

- Offline
  - Salient view learning for each reference location
- Online
  - Viewing angle prediction of the first query
  - Suggest new views by majority voting



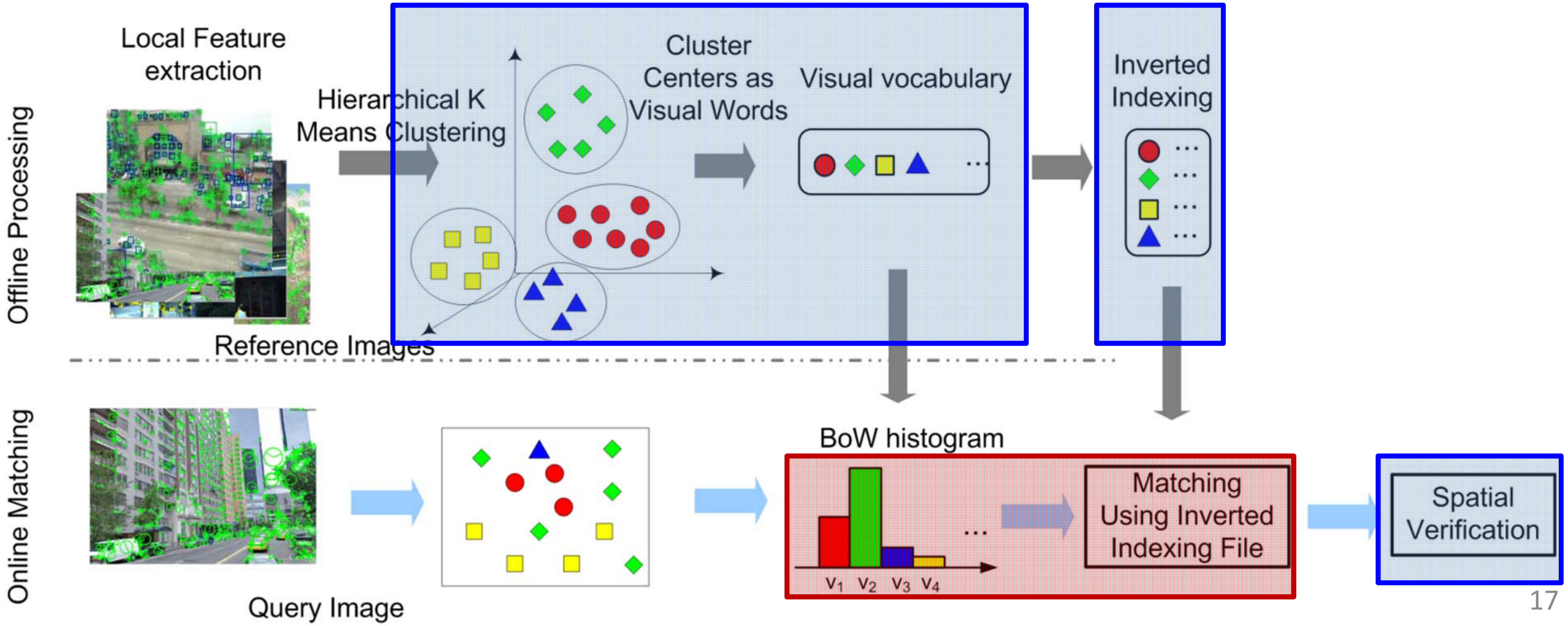
Outline

- Motivation
- Problem Justification
- Active Query Sensing
  - Offline Salient View Learning
  - Online Active Query Sensing
- Evaluation
- User Interface
- Conclusion

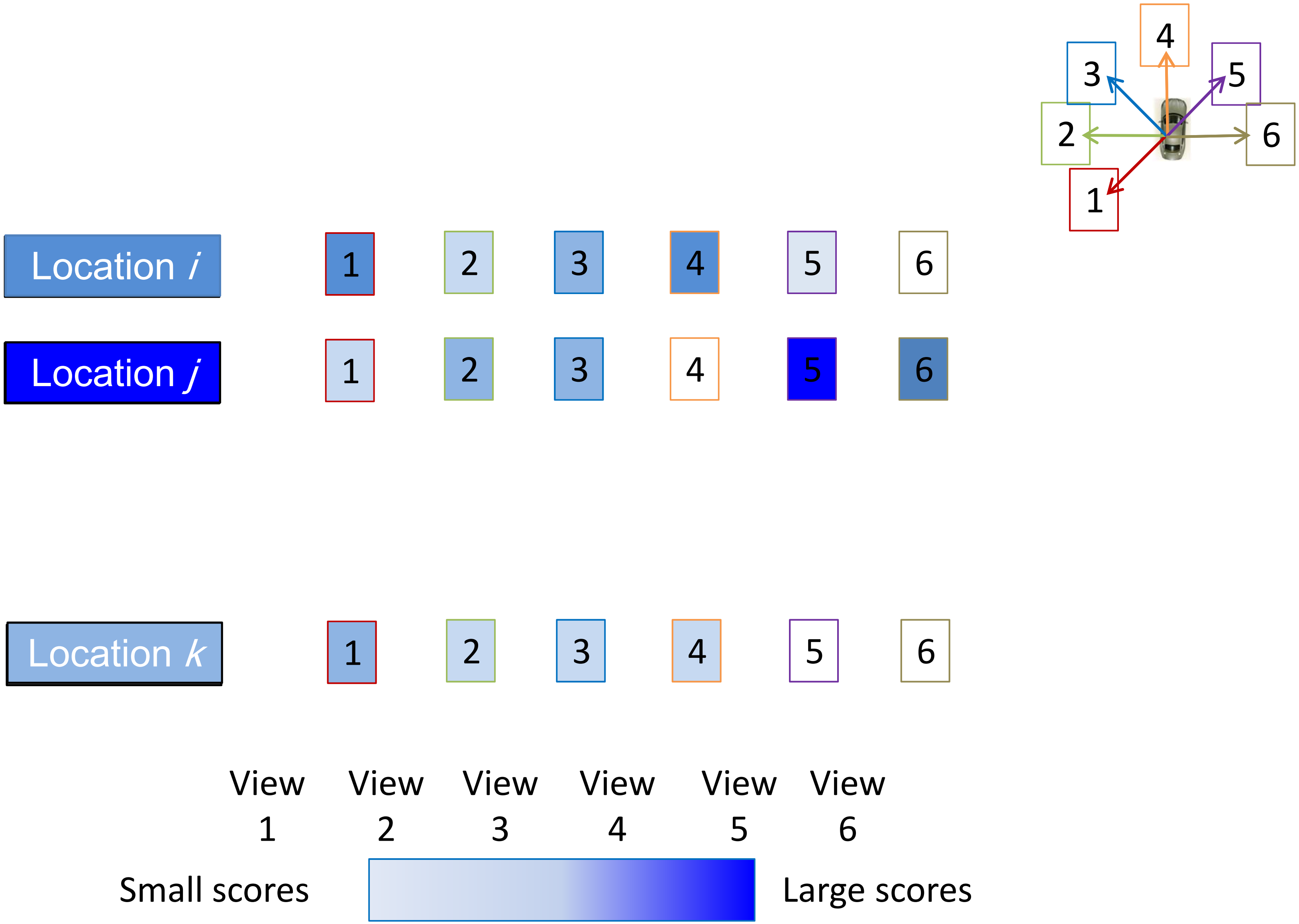
Million Scale Image Matching

Extend and modify from [Nister 06][Schindler 07]

- Offline
  - Codebook construction and BoW quantization
  - Inverted location/image indexing
- Online
  - Inverted indexing based search + spatial verification

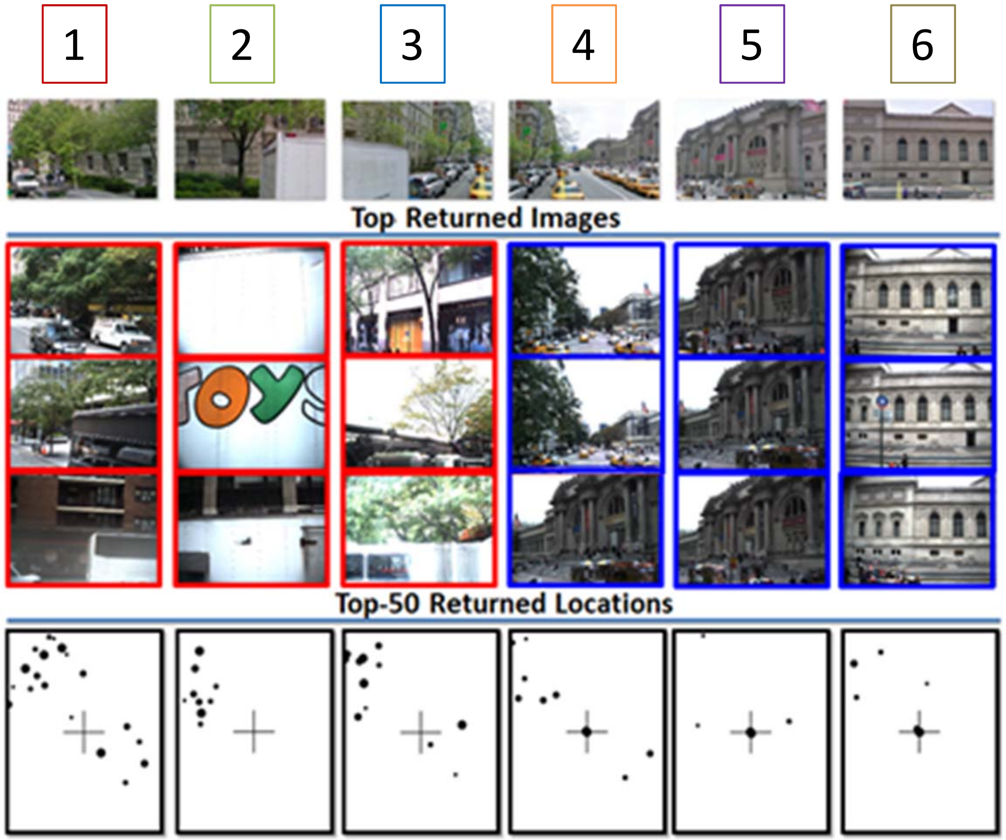


Location Score Calculation



Offline: Salient View Learning

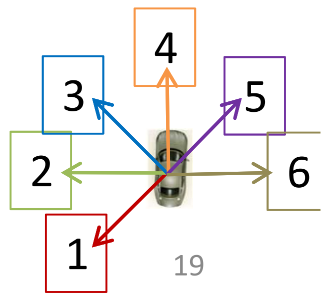
- Question
  - Among 6 views of a location, which is most informative?
- Definition
  - Salient view is the most discriminative view in a location



Six Views

Geographical scatter graph

Query over the salient view can lead to successful

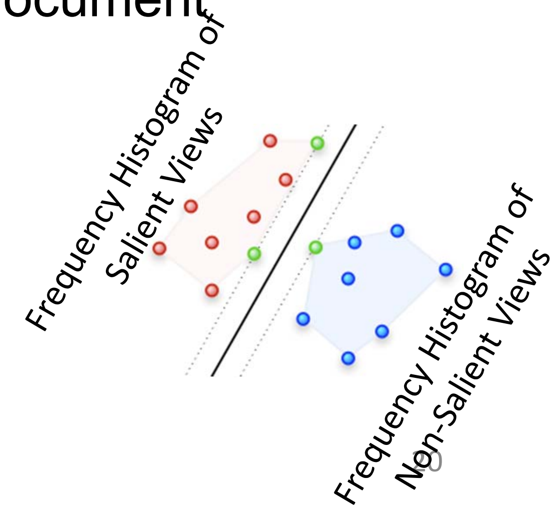


Offline Salient View Learning

- Solution I: Content-based prediction
  - Occurrence of attributes/content
    - Such as detecting discriminative objects in this image

  - Visual word discriminability distribution
    - Step I

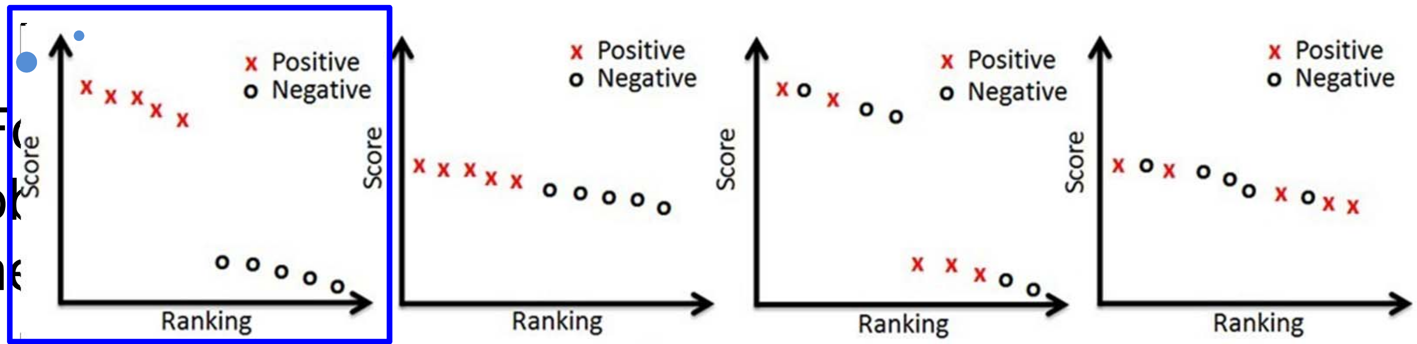
      - Measure the frequency of the discriminative words
        - Use term frequency and inverted document frequency
      - Build a TF-IDF frequency histogram
        - Example of discriminative words
    - Step II
      - Train SVM on to predict the saliency



Offline Salient View Learning

- Solution II: Self retrieval testing
  - Goal: Determine whether a view is salient
  - Approach: Using the reference image of each view to retrieve the corresponding location
    - Step I
      F
      o
      n
    - Step II

An ideal score distribution



$$Saliency = \frac{\sum_{i=1}^{N}\sum_{j=1}^{i} score(j)rel(j)/i}{\sum_{i=1}^{N}\sum_{j=1}^{i} score(j)\overline{rel}(j)/i},$$

(2 … nt r.

(1) N is the number of returned locations.

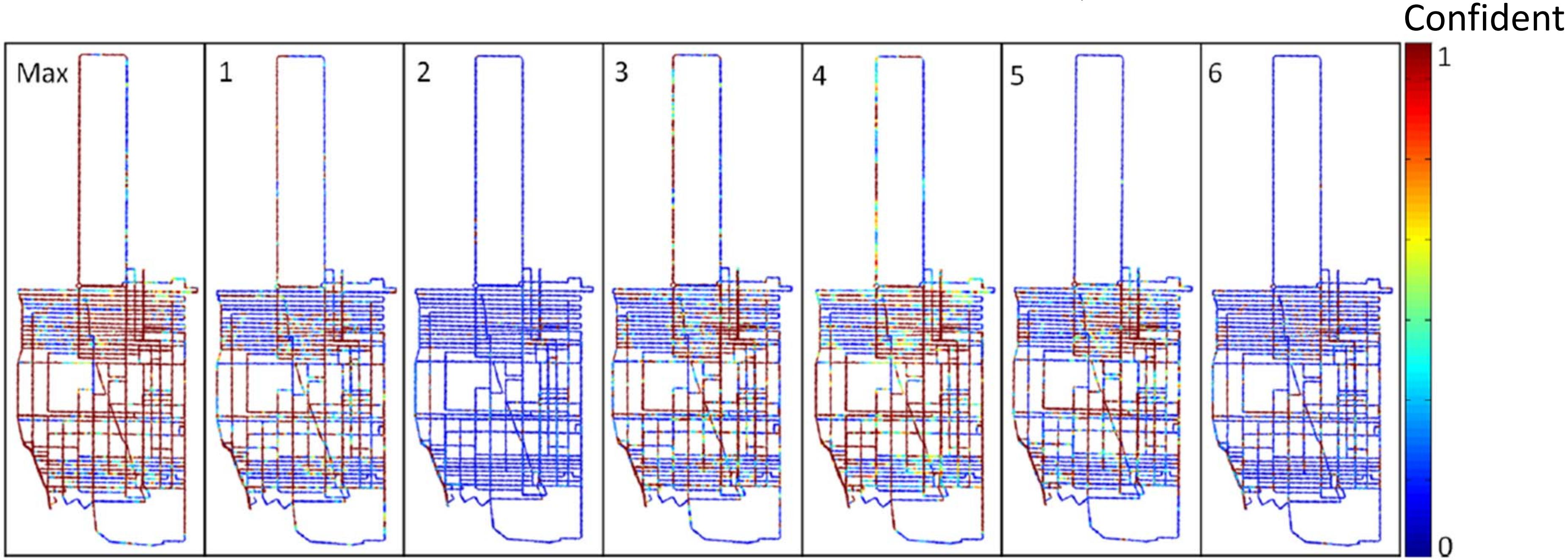
(2) $score(j)$ is the location matching score: the maximal score of its six views.

(3) $rel(j)$ is the relevance judgement of the jth returned location, 1:correct, 0:incorrect.

Saliency Measure

Can be also used to access the location difficulty

- We define the confidence of each location as proportional to its saliency (max of the six views)
- Useful for the user to determine when AQS is reliable



Geographical location confidence distribution

Outline

- Motivation
- Problem Justification
- Active Query Sensing
  - Offline Salient View Learning
  - Online Active Query Sensing
- Evaluation
- User Interface
- Conclusion

Online Active Query Sensing

Examples of “junk” images:

Examples of query images selected by user:

- Assumption
  - User is unlikely to take “junk image” with no hope for finding the true target.
  - The first query, even unsuccessful, can be used as “probe” to narrow down the solution space.

Online Active Query Sensing

- Formulation
  - Maximizing uncertainty reduction

$$\mathrm{v}_2 = \max_{v}\left(H(l|q_1) - H(l|q_1, v)\right)$$

- A subsequent query should
  - maximize the uncertainty reduction (information gain)
  - across candidate locations, narrowed down by the query already been taken
  - in terms of getting the best view

Online Active Query Sensing

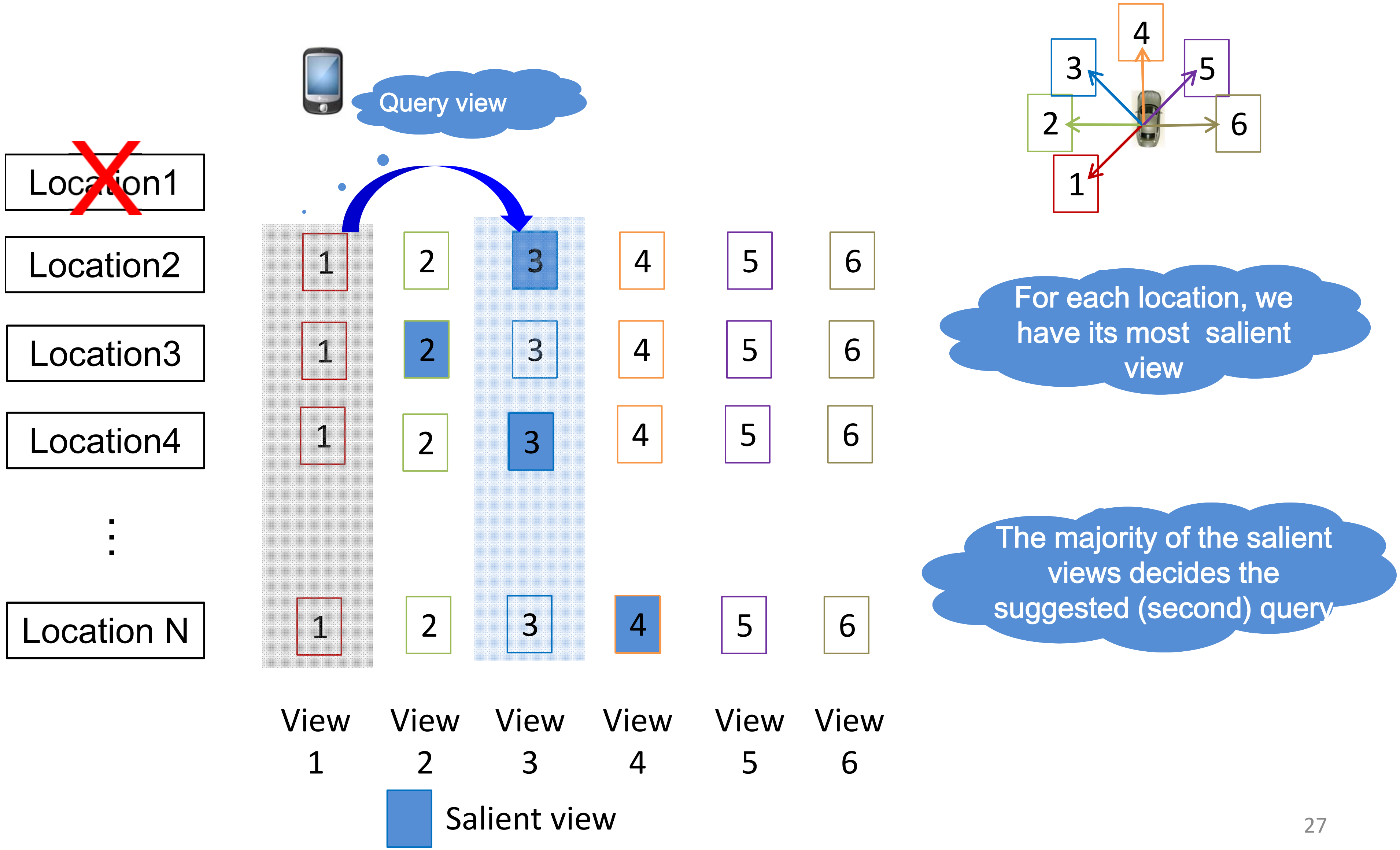
- In practice, we find maximizing uncertainty reduction can be well approximated by:

$$\max_v \sum_{l \in L_N} Saliency(l, v)$$

- L_N is the candidate locations narrowed down by the first query.

- In other words, AQS suggests the user to turn to the “most salient” view by a weighted sum or majority voting in terms of *Saliency*.

Online Active Query Sensing



What about current view unknown?

- Step I: Predict the view angle of the first query

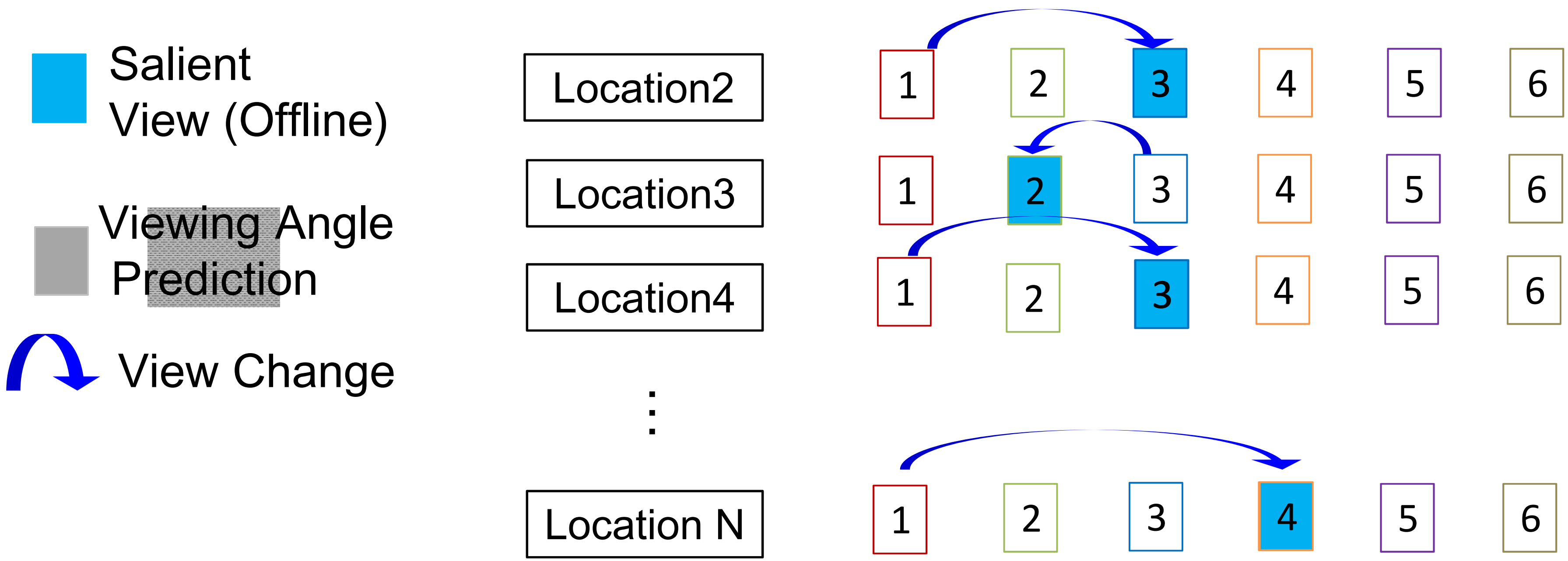
Offline Training: Train view prediction classifiers offline

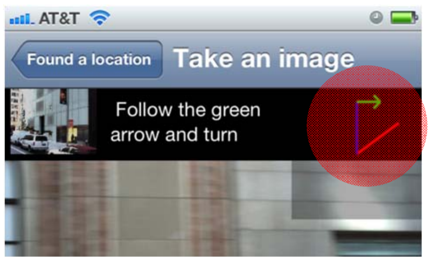
Online Prediction: View alignment based on the image matching

Our solution is to combine them both

What about current view unknown?

- Step II: Majority voting in terms of view change





Turn 90 degrees to the right

Outline

- Motivation
- Problem Justification
- Active Query Sensing
  - Offline Salient View Learning
  - Online Active Query Sensing
- Evaluation
- User Interface
- Conclusion

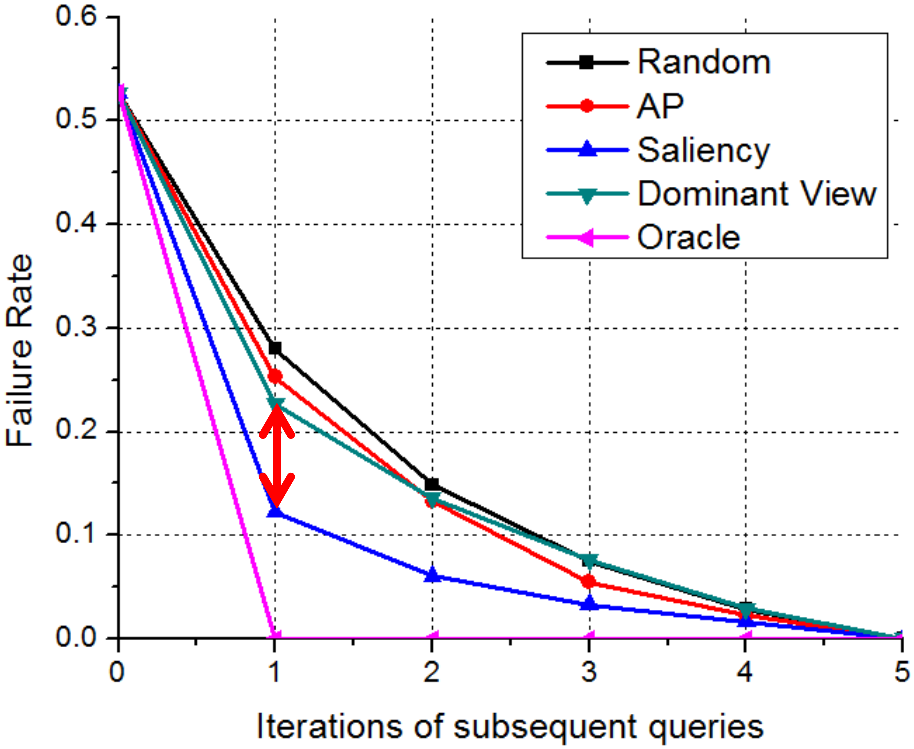
Query Set for Evaluation

- Manually cropped queries from Google Street View
  - 226 random locations
  - For each location: six query images are cropped from viewing angles similar to the view orientations used in the database
- A returned reference location is considered relevant
  - if it has visual overlapped view with the query image

Evaluation

- Baseline
  - Random view suggestion
  - Dominant view suggestion
    - Always change to front view
- Salient view selection
  - AP based
  - Saliency based
- Oracle view suggestion
  - Always suggest the ideal view

- Overall Performance



Failure rates over successive query iterations.

Examples

First query

AQS suggested query

First query

AQS suggested query

Outline

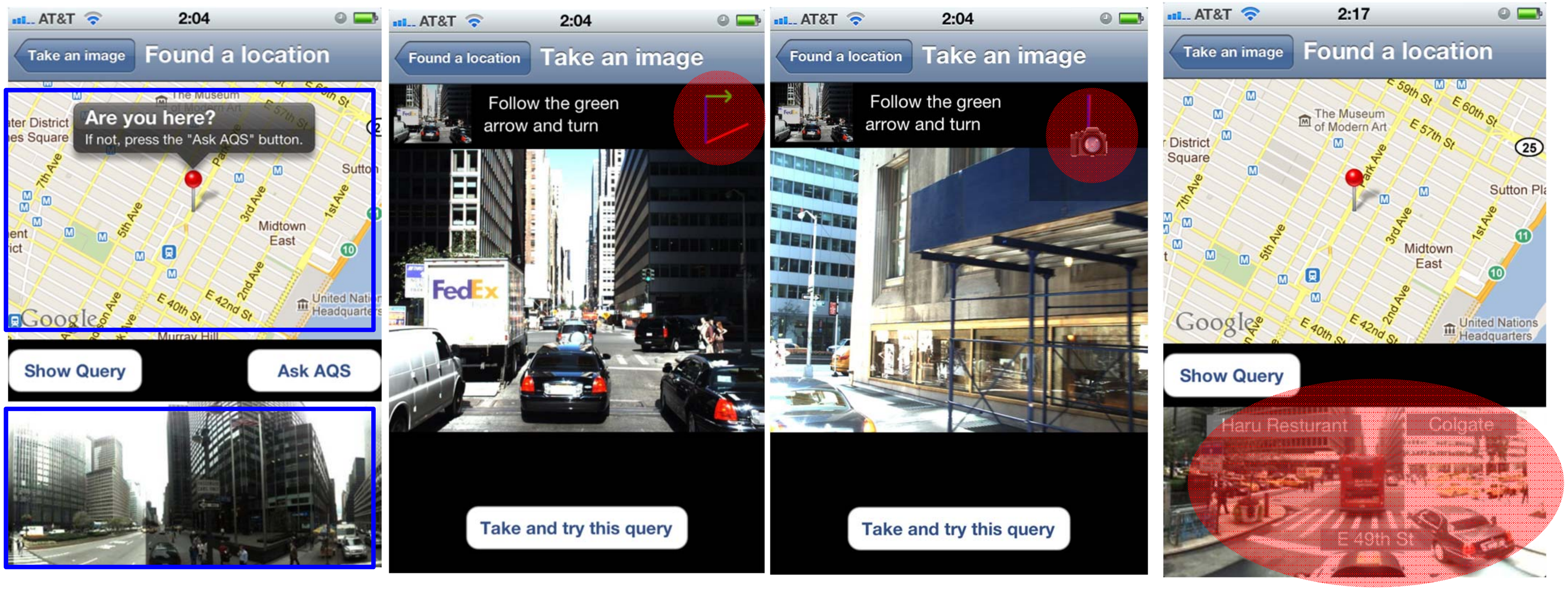
- Motivation
- Problem Justification
- Active Query Sensing
  - Offline Salient View Learning
  - Online Active Query Sensing
- Evaluation
- User Interface
- Conclusion

User Interface

- We have developed an iPhone application of the proposed AQS system
  - The client communicate with the server through wireless network
- Time
  - Visual matching requires <1s
  - Query sensing suggestion is almost in real time
  - Query delivery latency depends on wireless link

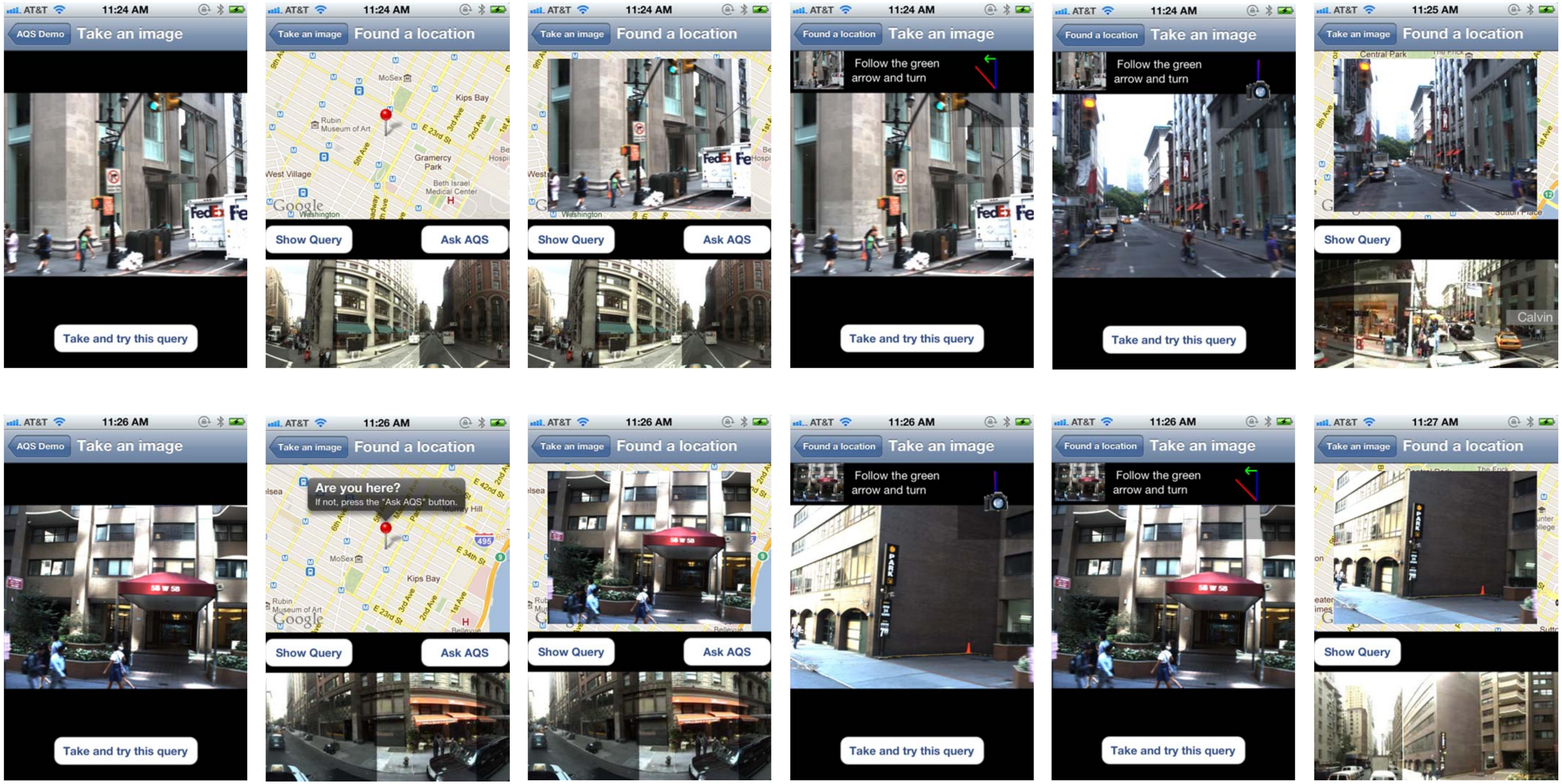
User Interface

- How does the user know the first query is incorrect
  - Panorama
  - Geographical map context
- How to guide the user to take the second query
  - Compass, camera icon
- Point of interest



AQS Examples

First Query	First Result	Ask AQS	Taking Second Query	Second Result



Outline

- Motivation
- Problem Justification
- Active Query Sensing
  - Offline Salient View Learning
  - Online Active Query Sensing
- Evaluation
- User Interface
- Conclusion

Conclusion

- We have designed the AQS system to
  - Intelligently guide user to take the second query without repetitive trial and error
  - Reduce the error rate from 53% to 12%
- The proposed approach is general. It can be extended to multi-view object search
  - If the database has multiple views of products, AQS can be used to suggest best view for searching

- We have demo about AQS on Thursday Morning Demo Session

Thank you

Any QuestionS?

We would like to also thank NAVTEQ for providing the NYC image data set, Dr. Xin Chen and Dr. Jeff Bach for their generous help.