From Uncertain Photos to Certain Coverage: a Novel Photo Selection Approach to Mobile Crowdsensing

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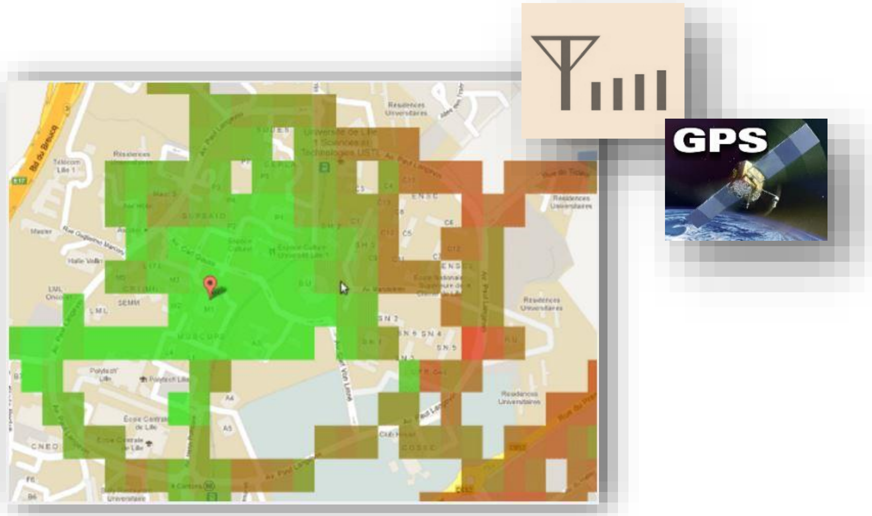
Background: From Physical to Cyber

- Mobile Crowdsensing (MCS), as a new sensing paradigm, bridges the gap between physical space and cyber space with sensors equipped on pervasive mobile devices.

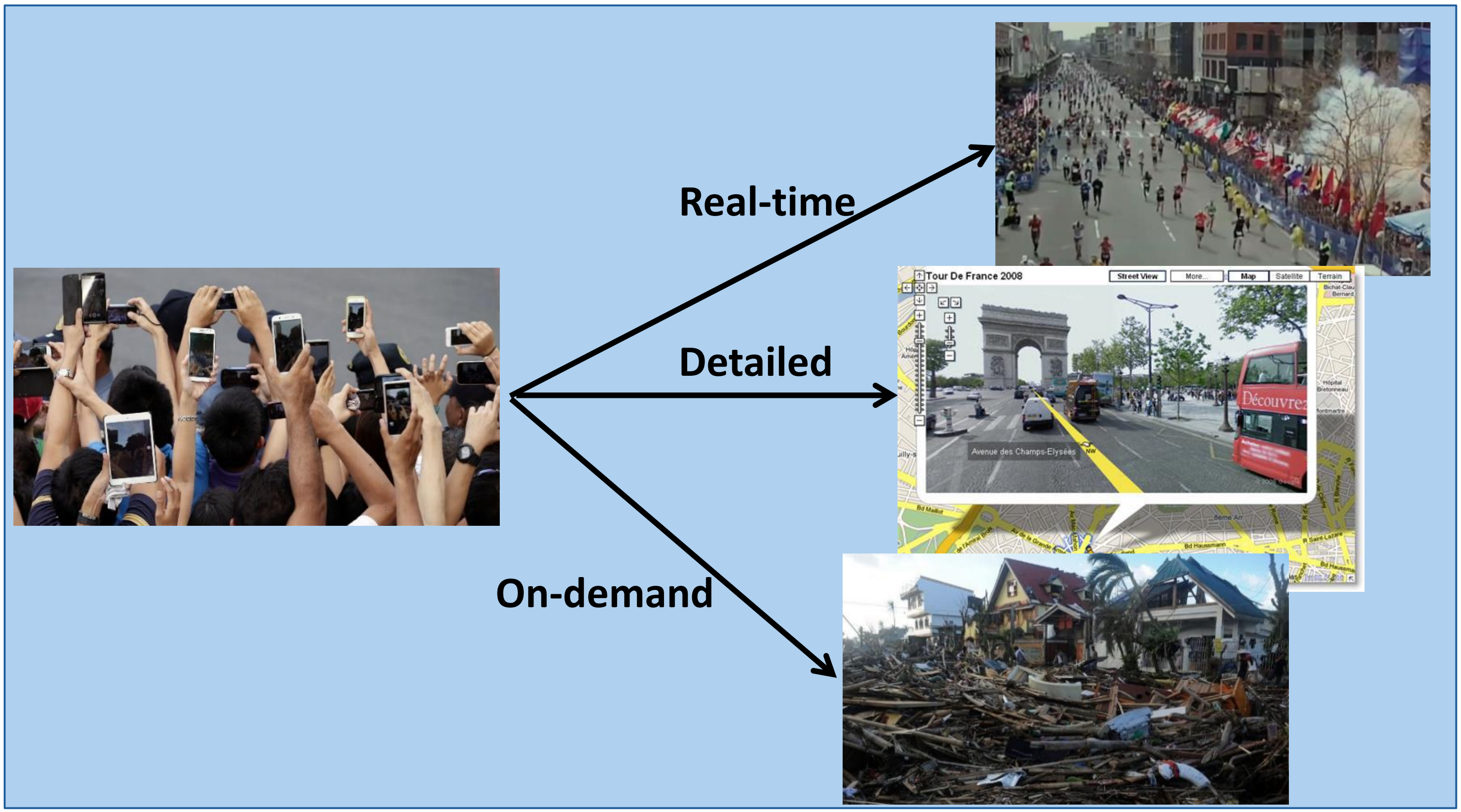


Network Measurement

Broken shared bikes reporting

Background: photo crowdsensing

- Photo crowdsensing visually senses the physical spaces based on cameras on mobile devices.



Background: photo crowdsensing

- A typical process
  - The requester gives a target physical area;
  - The MCS server campaigns a crowdsensing task;
  - Mobile participants report tons of photos to response.

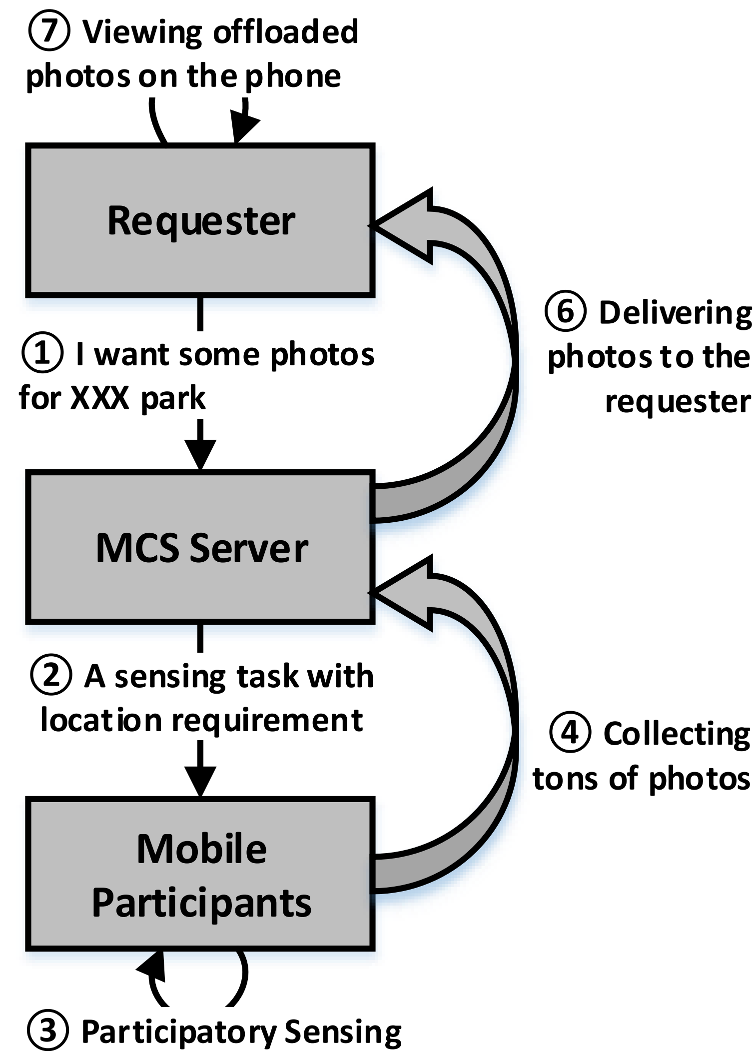


Photo selection and its challenges

- Offloading tons of collected photos and viewing them on his/her small smart phone screen are unacceptable and unrealistic.
- Photo selection should be performed during the crowdsensing task.

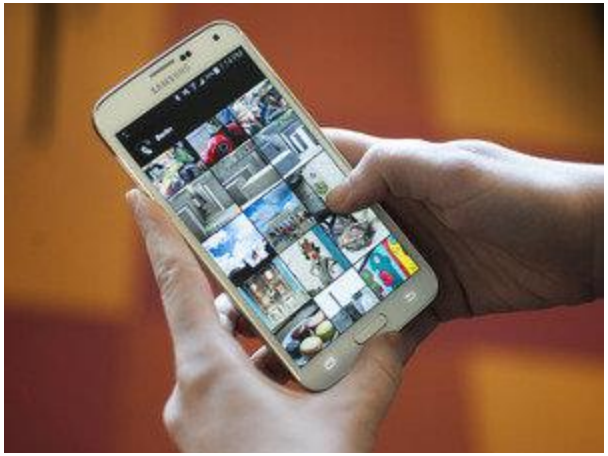


Photo selection and its challenges

- Traditional participants-to-server pre-selection of crowdsensing photos focuses on reducing the redundancy.
- Our photo selection process attempts to distill **a proper photo** subset to satisfy requesters' expectation in understanding the target.

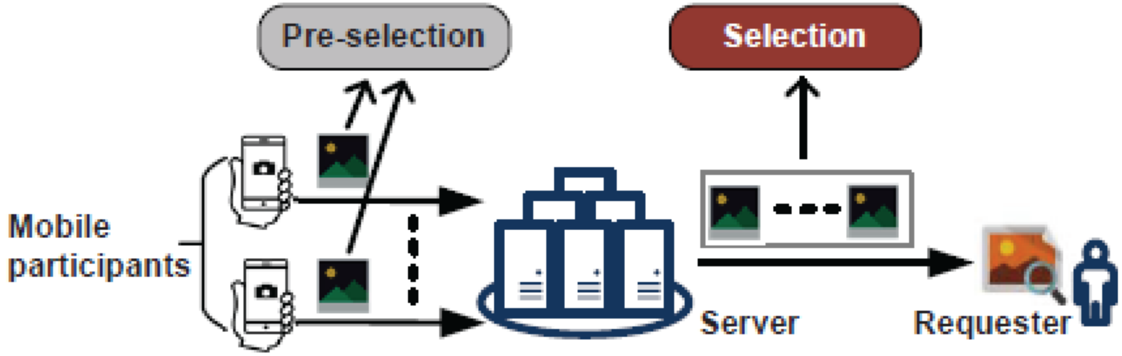


Photo selection and its challenges

- Define 'proper': Certain coverage
  - Photo coverage (Points of Interest (PoIs) of the target area)

$$C(\mathcal{I}) = -N_{cov}^{\mathcal{I}} \cdot \sum_{i=1}^{|PoIs|} \frac{|\mathcal{I} \cap PoI_i|}{|PoI_i|} \cdot \log_2\left(\frac{|\mathcal{I} \cap PoI_i|}{|PoI_i|}\right)$$

  - View quality (Clear and accurate view)

$$Q(\mathcal{I}) = 1 - \frac{N_{in}^{\mathcal{I}}}{|\mathcal{I}|}$$

  - Put them together

$$V(\mathcal{I}) = (\|C(\mathcal{I})\| + \|Q(\mathcal{I})\|)/2$$

Photo selection and its challenges

- Selecting a photo subset that captures as many Points of Interest (PoIs) uniformly with clear and accurate view (i.e., not a blocked, blurred, or wrong direction view)

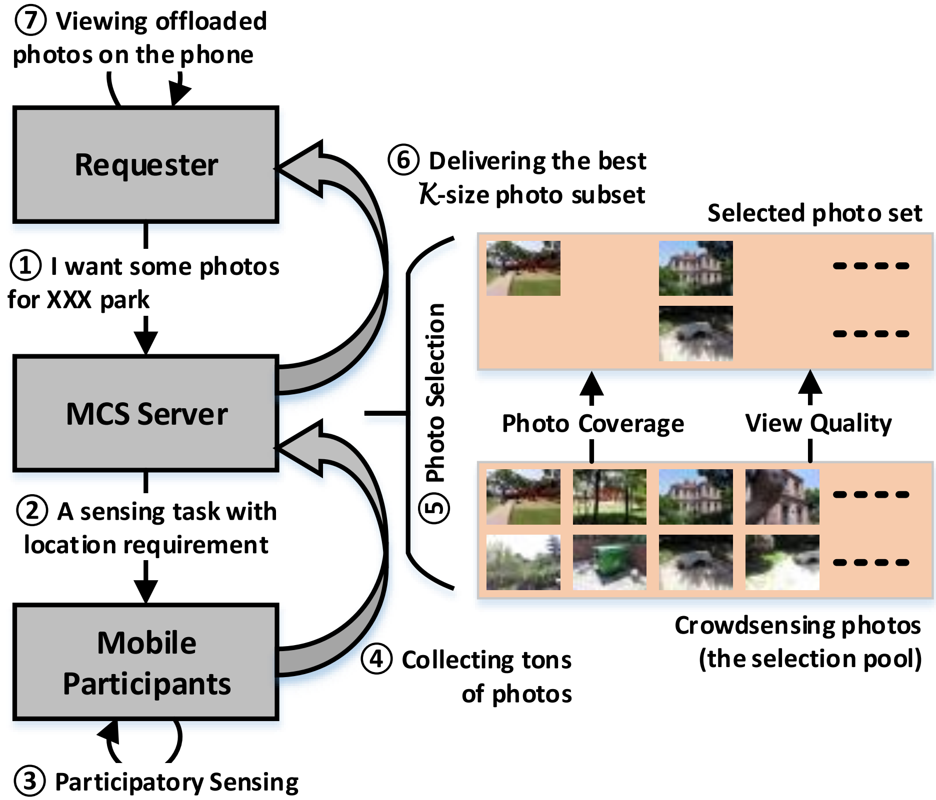


Photo selection and its challenges

- Uncertain photos
  - Shooting direction information is not available
    - Not recorded in the metadata of photos taken by built-in cameras of mobile phones
    - Don't know which photo captures which PoI.
  - The target area is usually uncharted
    - Unknown PoI distribution
    - No reference photos
    - Don't have a criteria for the view quality.

How to select a certain coverage photo set for the requester from the collected uncertain photos?

Our scheme: basic idea

- What do we have?
  - Photos with location tags;
- Basic idea:
  - **Photo coverage** is a geographic metric, so we try to measure it with the **locations**.
  - **View quality** is a metric for the visual content, so we try to measure it using the **visual features**.
  - Designing a **utility measure** of one photo subset's certain coverage by jointly exploiting locations and visual features.

Our scheme: utility measure

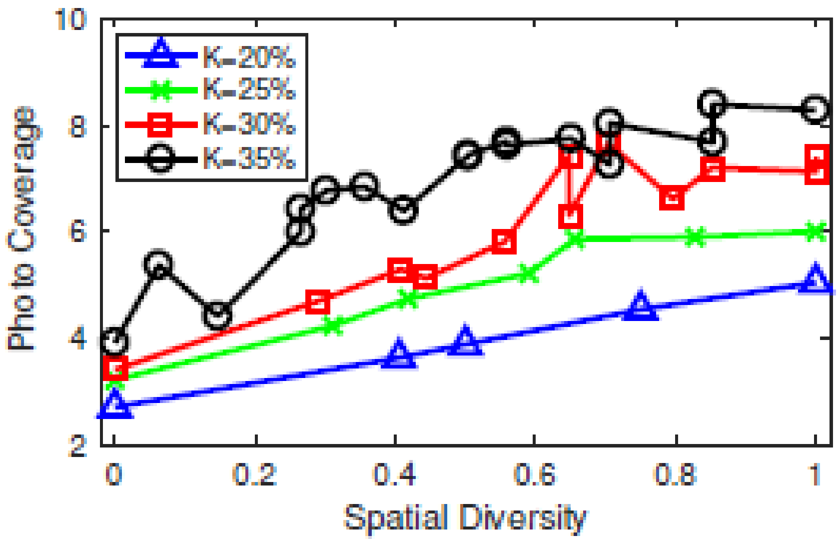
- Estimating photo coverage using <u>*spatial diversity*</u>
  - Definition: distribution entropy of photos' locations in a photo subset,

$$SD(\mathcal{I}) = -\sum_{i=1}^{n_h \cdot n_w} \frac{n_i}{|\mathcal{I}|} \cdot \log_2\left(\frac{n_i}{|\mathcal{I}|}\right), \ n_i \neq 0$$

  - For several uniformly distributed photos, they could either be visual summations of different PoIs or views from different aspects of one PoI.

Our scheme: utility measure

- ⌘ The effectiveness of the *spatial diversity* model
  - Under four constraint conditions
  - Compare the prior spatial diversity and posterior photo coverage



Our scheme: utility measure

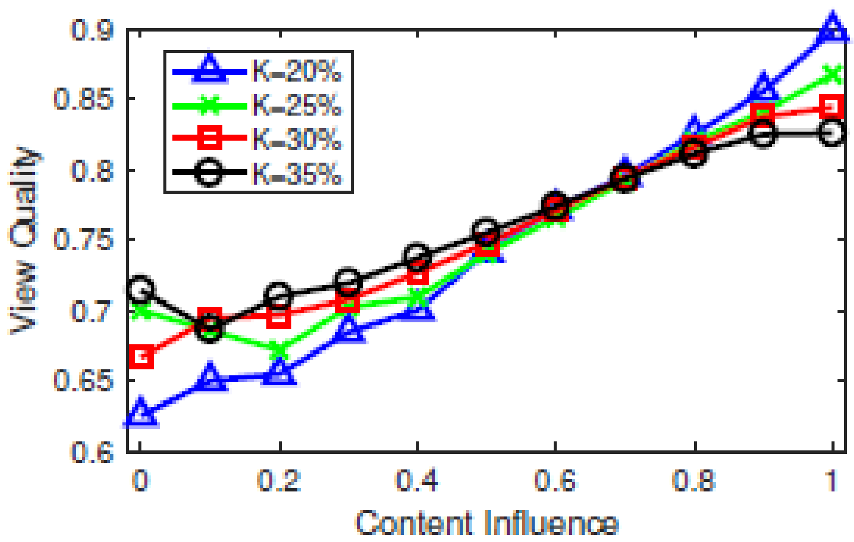
- Estimating view quality using *content influence*
  - Definition: visual correlation between a photo set and its complementary set,

$$CI(\mathcal{I}) = \sum_{p_i \in \mathcal{I}} INF_i^{\mathcal{D}\text{-}\mathcal{I}} \text{, where } INF_i^{\mathcal{A}} = \sum_{p_j \in \mathcal{A}} S(p_i, p_j)$$

  - Useful photos regarding one PoI usually share more similarity with each other, while photos with low view quality are supposed to have their own defects, thus distinct on their content.

Our scheme: utility measure

- The effectiveness of the *content influence* model
  - Under four constraint conditions
  - Compare the prior content influence and posterior view quality

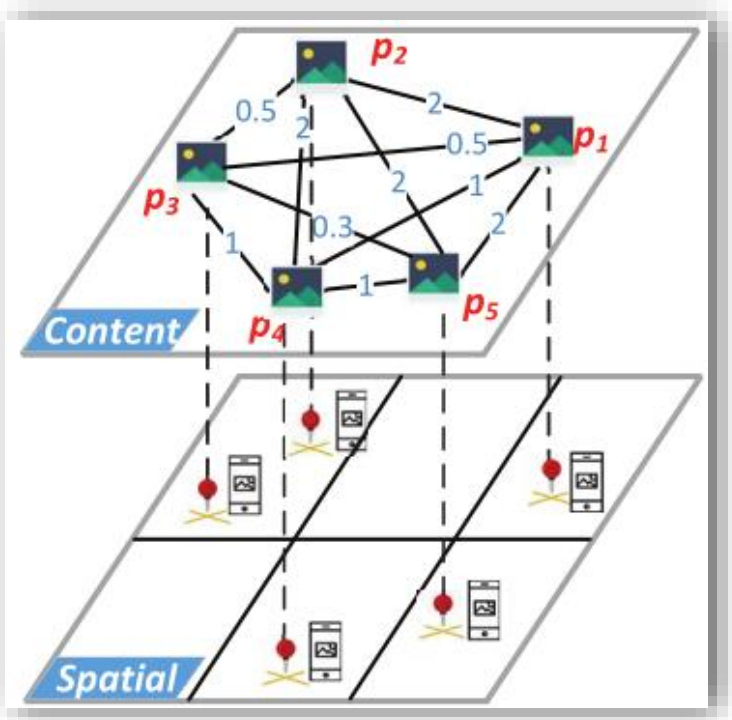


Our scheme: utility measure

- Utility for a photo subset's certain coverage level

$$U(\mathcal{I})=(1\text{-}\alpha)\cdot\|SD(\mathcal{I})\|+\alpha\cdot\|CI(\mathcal{I})\|+|\mathcal{I}|$$

- A five photos use case



Our scheme: utility-based photo selection

- Finding the photo subset with the best utility is **NP-hard**.
  - Can be reduced from the traditional *Max Cut* problem.

- Leveraging the greedy strategy to obtain an approximate solution with **(1-1/e) approximation ratio**.
  - The utility measure we build is monotone and submodular.

Evaluation

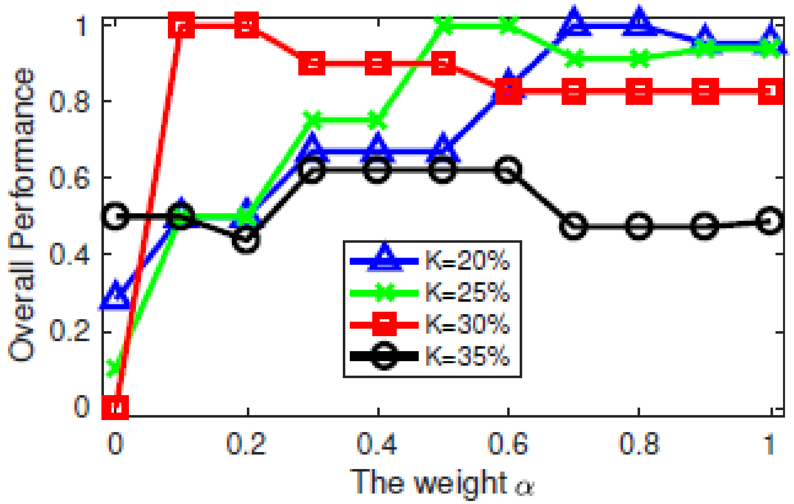
- Real world datasets
  - RESORT: Collected around a building in Juzizhou Park.
  - PARK: Captured in the technology park of the campus.

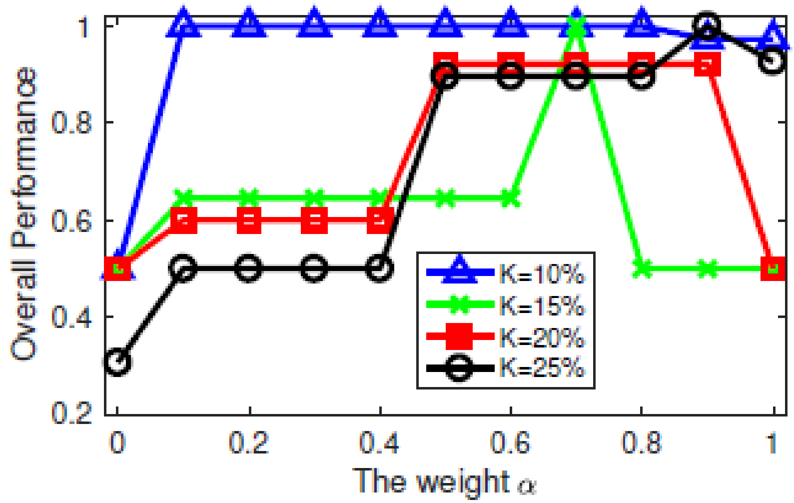
(a) Sensing area in a resort. (b) Sensing area in the university

Evaluation

⌘ Impact of weight alpha on the selection's certain coverage performance for both datasets

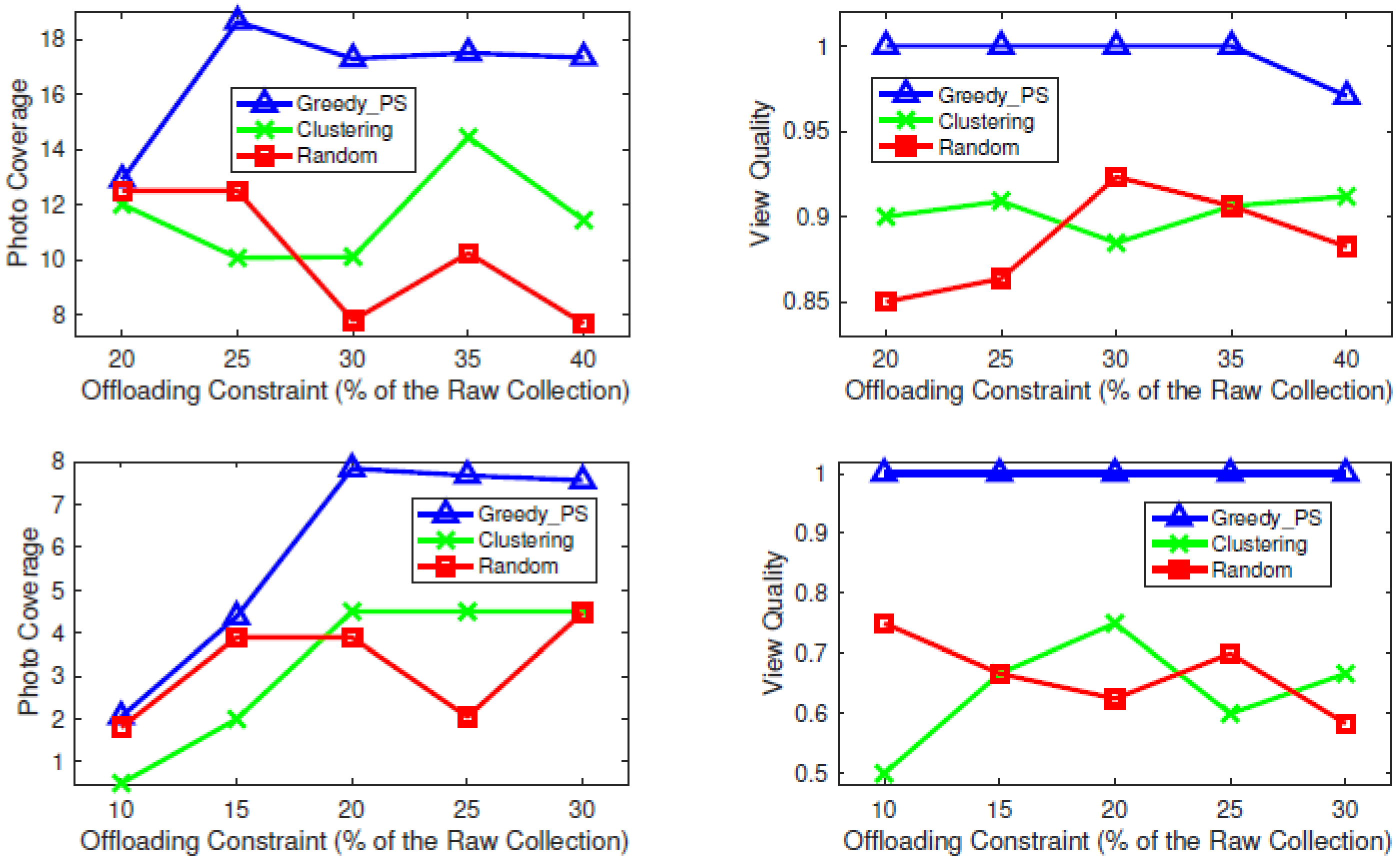
$$U(\mathcal{I})=(1\text{-}\alpha)\cdot\|SD(\mathcal{I})\|+\alpha\cdot\|CI(\mathcal{I})\|+|\mathcal{I}|$$





Evaluation

⌘ Performance on photo coverage and view quality for both datasets



Thank you

Q & A

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Backup

- About visual similarities
  - We calculate the similarities by matching the features of two photos.
  - In this work, we use the SIFT features of photos for similarity computation.
  - We also tests feature SURF, it is faster and can be used in cases with time constraint.

Backup

- About the datasets
  - Collected by two Huawei Mate 7 phones with Android 6.

Dataset	# PoIs	# photos	Ratio of inaccurate photos
RESORT	7	43	19%
PARK	5	20	35%

- We have recently collected 3 other datasets, each with around 50 photos. Based on the new collections, we have extended the experiments.