Album-Oriented Face Recognition For Online Social Networks

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Presenter: Baoyuan Liu April 23, 2013



People Like to Photograph Events







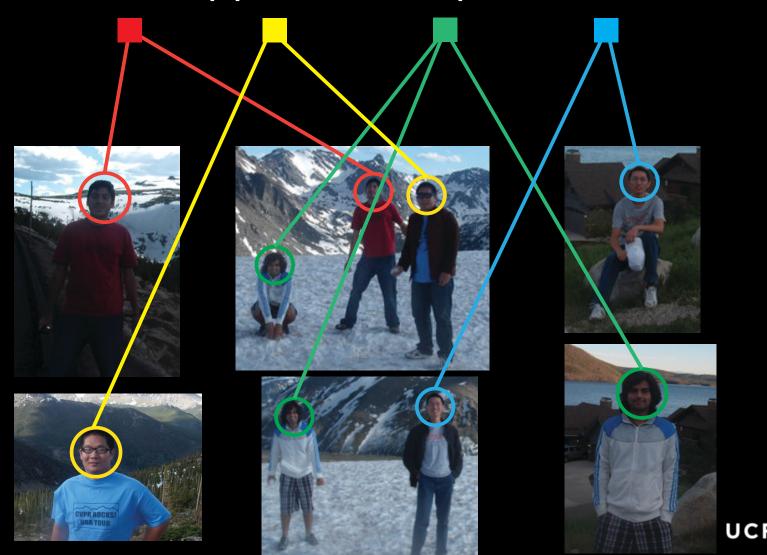




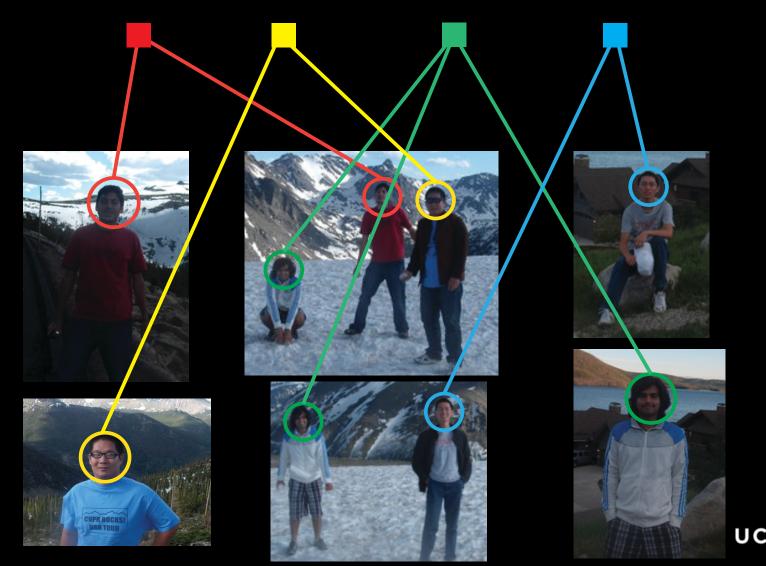




Notice: The same small set of people appear in the photos



How can we use the *structural* information of the albums to improve recognition?





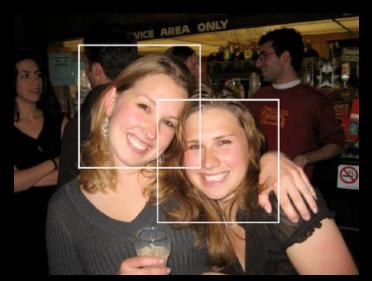
Idea of Our Paper

- Basic assumption: albums tend to contain multiple photos of a small number of people
- We propose a mathematical model that combines album information and image features to significantly improve recognition
- Extend with other social features based on facebook meta data



Previous Work on Co-occurrence

- Stone et al. proposed an imagelevel co-occurrence model
 - Consider the frequency of people appear together in single photos



- Requirement: Only considered photos with *exactly* two faces.
- Is this requirement too strict to apply to realistic facebook images?



Quantitative Study

- Use Facebook API to download all pictures visible to a single user's account
- Total: 8078 pictures of 2849 people
 - Considered only tagged faces
 - Validated with OpenCV face detector



Model Applicability

- 71% photographs(5735/8078) contained only one tagged face
- Image-level co-occurrence only helps when there are two or more people in the photograph
- A model based on image-level co-occurrence is only useful for 29% of photos

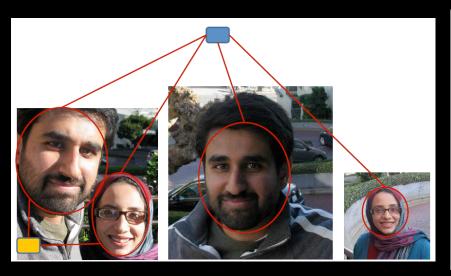


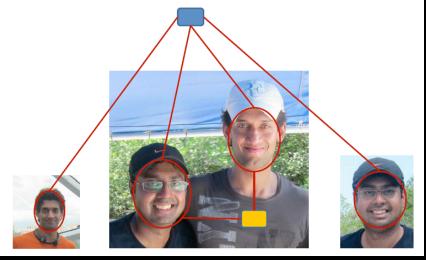
We treat Co-occurrence differently

- We consider co-occurrence at the album level
 - Need not be restricted by number of people appearing in each photograph
 - Albums provide additional social information that can benefit recognition



An Example





- For these two albums, an image-level co-occurrence model (yellow) can help with only 1 of the 3 photos
- A model based on album co-occurrence (blue) can help recognize faces in all photos



Can Album Level Co-Occurrence Help?

- Suppose an album prior is only useful if there are at least twice as many photos as people in an album
 - High standard intuitively, but valid for 57% of photos
 - When standard is not met, recognition degrades only 2%



Our method

- Our method introduce a label cost
- Assign a cost to each distinct label present in an album, regardless of the number of times it appears
- Effectively limits the number of people appearing in an album
- Matches our notion of a typical album



Formulation

 A traditional face recognition system can be described by the energy function

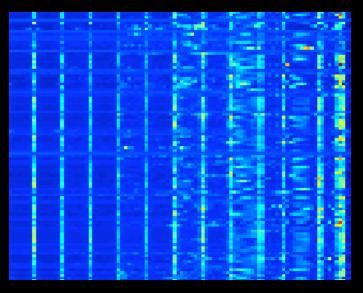
$$E(\vec{y}) = D(y; \vec{x}) = \sum_{f \in F} D_f(y_f; \vec{x}_f)$$
 All facial images in album F

where D_f is the data cost of assigning label y_f to face $f \in F$ and \vec{x}_f is the vector of features gathered from the image corresponding to the facial image f



Data cost

- The data cost term is essentially the result of a baseline, imageonly face recognition system
- We used high-dimensional V1like features
 - Shown to achieve excellent facerecognition results
- Each feature vector is large –
 86400 entries
 - Greedily selected 400 features



N. Pinto, J. DiCarlo, and D. Cox. How far can you get with a modern face recognition test set using only simple features? *Computer Vision and Pattern Recognition, IEEE Computer Society Conference on*, 0:2591-2598, 2009.



Label Cost

• Our model builds on this by adding a label cost $C(\vec{y})$ which is a function of label assignment \vec{y}

$$E(\vec{y}) = \sum_{f \in F} D_f(y_f; \vec{x}_f) + C(\vec{y})$$
 Album labeling

Overview of Label Cost

 Personal label cost: Every label should pay a cost to enter into the album. This cost restricts the number of individuals in an album

 The social label cost: Compatibility of different labels in the album based on facebook meta information



Personal Label Cost

- Expresses the idea that a limited number of people should appear in an album
 - Every label that enters the album must pay its cost

$$C_{personal}(\vec{y}) = \sum_{l \in \mathcal{L}} \lambda I(l, \vec{y})$$

All possible labels

$$I(l, \vec{y}) = \begin{cases} 1 & \text{if } l \in \vec{y} \\ 0 & \text{otherwise} \end{cases}$$



- The social label cost is constructed using various social metadata available via Facebook
 - Consider the interaction between a label and all other labels in the current album
 - Friendship Cost
 - Co-occurrence Cost
 - Uploader Cost

$$C_{social}(\vec{y}) = \sum_{l \in \mathcal{L}} S(l, \vec{y}) I(l, \vec{y})$$

$$S(l, \vec{y}) = \sum_{j \in \mathcal{L}} (\alpha_f C_f(l, j) + \alpha_c C_{co}(l, j)) I(l, \vec{y}) + \alpha_u C_u(l)$$

 Friendship cost – measures whether individuals co-occurring in the album are facebook friends

$$C_f(i,j) = \begin{cases} 0 & i \text{ and } j \text{ are friends} \\ 1 & \text{otherwise} \end{cases}$$



 Co-Occurrence cost – measures whether individuals in the album ever co-occurred in training albums

$$C_{co}(i,j) = \begin{cases} 0 & i \text{ and } j \text{ have co-occurred} \\ 1 & \text{otherwise} \end{cases}$$



 Uploader cost – indicates whether a user has previously appeared in photographs uploaded by a given uploader

$$C_u(i) = \begin{cases} 0 & \text{if } i \text{ has appeared in images} \\ & \text{uploaded by the owner of } F \\ 1 & \text{otherwise} \end{cases}$$



Inference

- Inference in the overall energy function is NPhard
 - Our model is similar to the uncapacitated facility location problem, which allows for a greedy approximation
 - Add one label to the album that maximizes the energy function at each iteration
 - Stop when adding new candidate labels does not result in further improvement



Learning

- We use the Structural SVM (SSVM) it can optimize parameter values even if inference can only return approximate solutions
- Need to learn weights for the personal label cost and the individual social costs

$$[\lambda, C_f, C_{co}, C_u]$$



Datasets

- Two datasets gathered from Facebook accounts of volunteers
 - First dataset: gathered from all albums visible to one user
 - Second dataset: gathered from a larger set of volunteers
- Accessed all photos in all albums available, and store relevant social network information



Datasets

- We collected photographs of hundreds of individuals, many of whom had very few photographs
- Pruned dataset to include only individuals with a large number of photos
 - First dataset: 1951 images of 25 people
 - Second dataset: 1994 images of 15 people



Datasets - Privacy

- This allows us to validate our model on realworld datasets
- Difficult to share data due to privacy concerns, potential for de-anonymization
- We will email the code if anyone asks



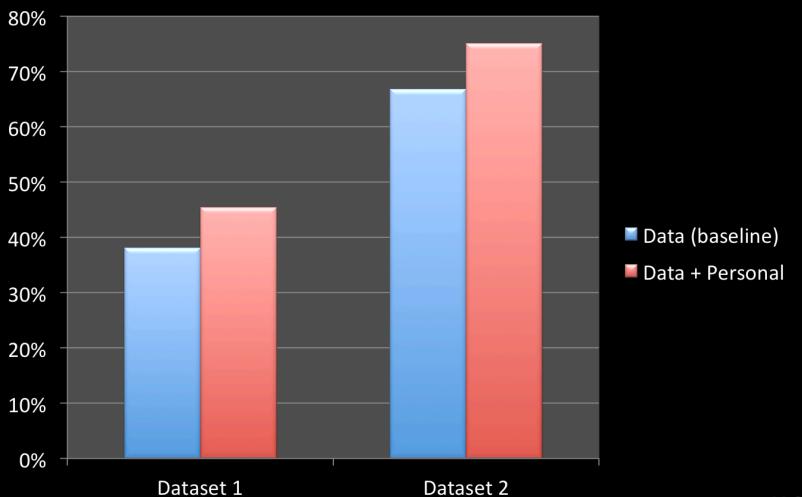
Partitioning

- Partitioned each dataset into three parts:
 - 1. A set used to train the weights for the data cost (image-only training)
 - 2. A set used to train the weights for the personal label and social costs
 - 3. A testing set (454 and 487 images for the two datasets)
- Albums were partitioned in the order of time



Experimental Results

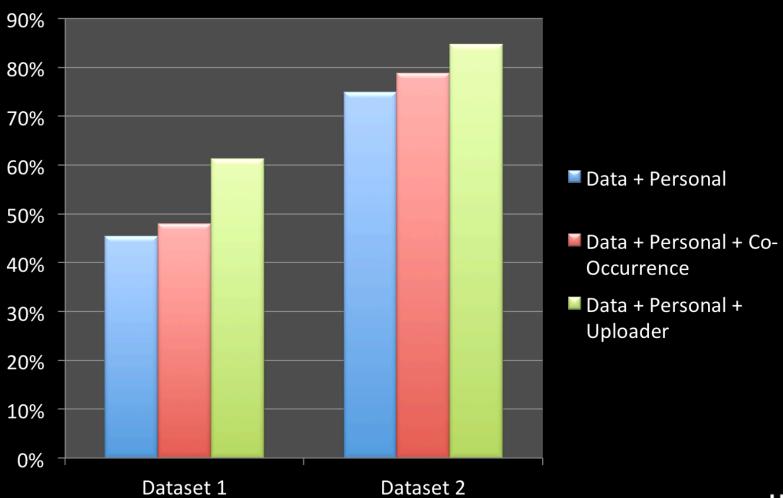
Baseline vs. Personal Label Cost





Experimental Results

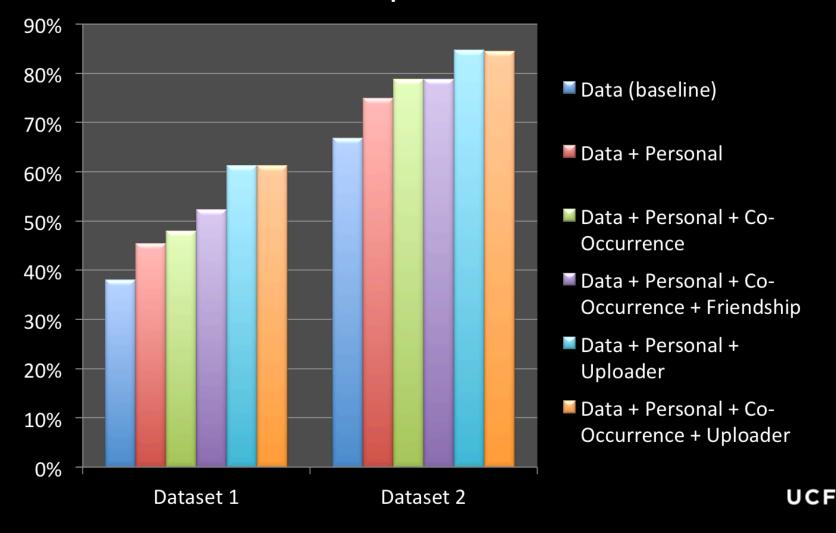
Further Social Costs





Experimental Results

All Experiments



Conclusion

- We propose using album-level co-occurrence information to improve face recognition
- We build a mathematical model that incorporates traditional image features and label information
- Our experiments show that our method significantly improves the face recognition performance



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Thank you

