Building Face Dataset

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Building Face Dataset

- Ramanan et al, ICCV 2007, Leveraging Archival Video for Building Face Datasets
  - Motivation to collect faces from Video
    - Get large, labeled datasets of faces. 611,770 faces
    - Get continuous changes of footage

Leveraging Archival Video for Building Face Datasets

- Introduction to the dataset
  - – Dataset based on 10 years TV show *Friends*
  - – Used a semi-supervised method
  - – Work done by human very limited (<30min)

Leveraging Archival Video for Building Face Datasets

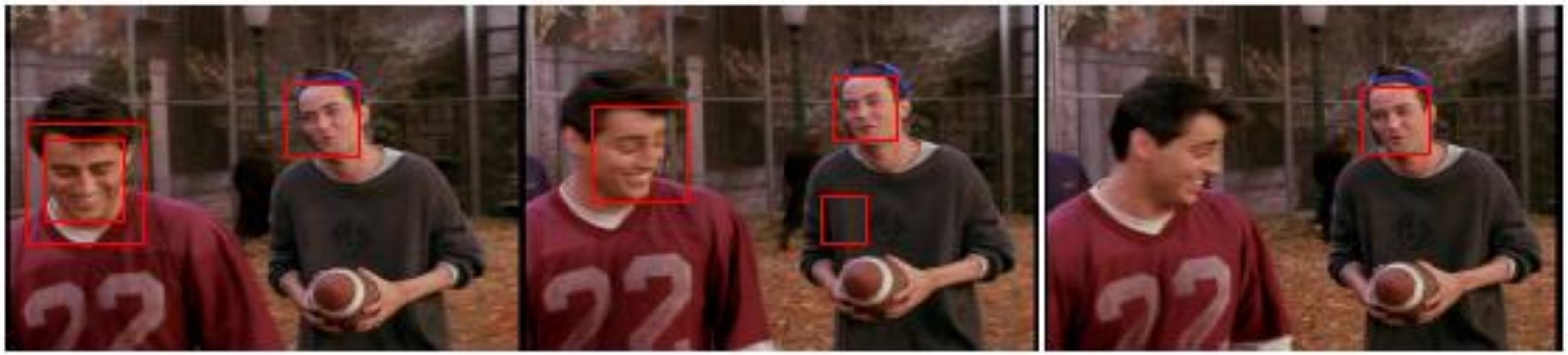
- Introduction to the dataset (contd)
  - Large quantity of faces: 611,770 faces, claimed to be largest face dataset
  - Contain changes of pose changes, age, weight gain, hairstyles, etc.

Leveraging Archival Video for Building Face Datasets

- Introduction to the dataset (contd)
  - Group similar faces of one person
    - *A hierarchical procedure of multiple time scales*
    - Group frontal faces to tracks in a scene (faces, hair, clothing)
    - Add non-frontal faces to track (faces, hair, clothing)
    - Cluster tracks within a episode
    - Label tracks in a reference episode manually
    - Cluster and label tracks between episodes

Leveraging Archival Video for Building Face Datasets

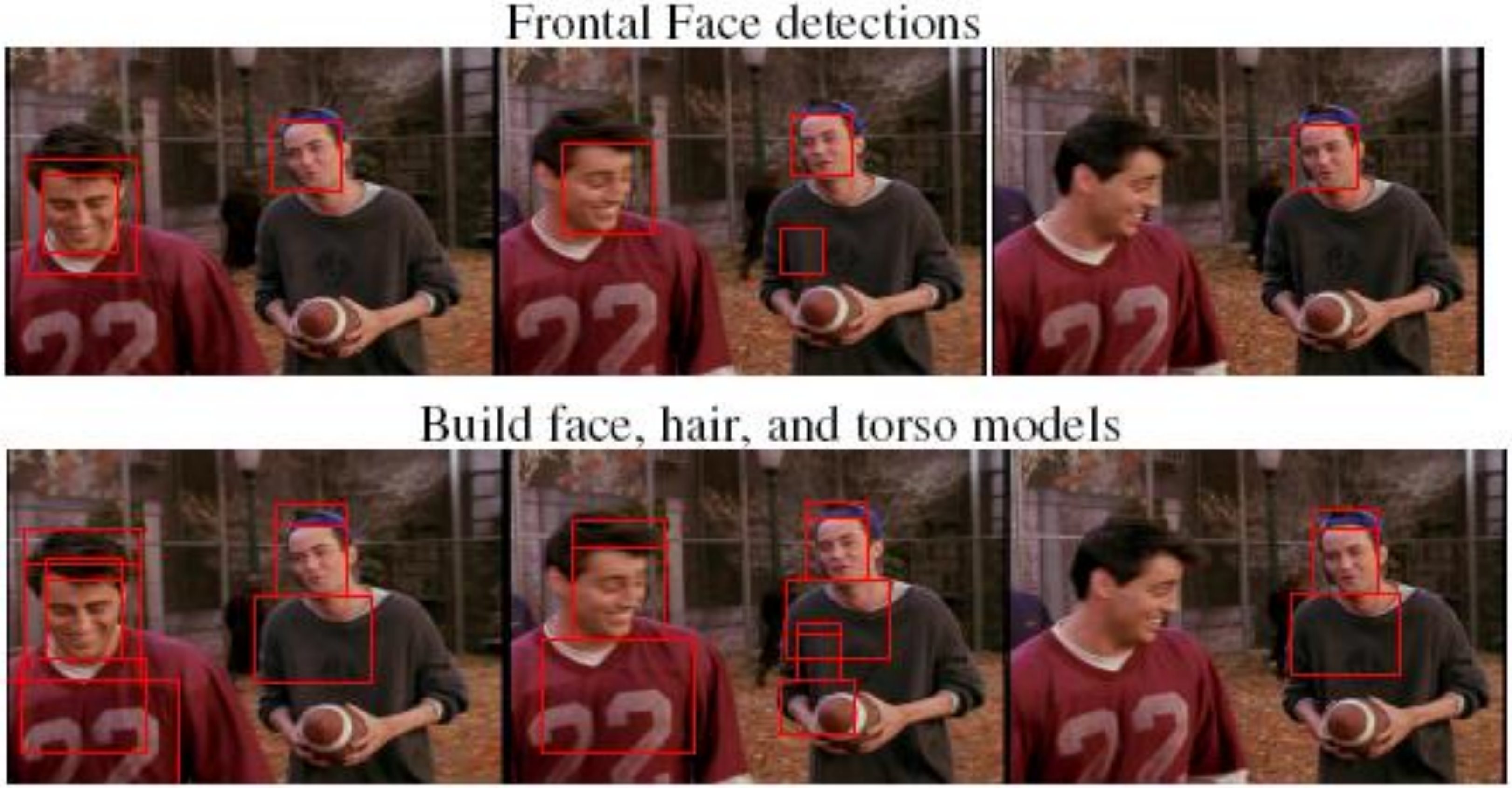
- Detect similar faces in one shot
  - Detect faces with a frontal face detector to find out potential faces



Frontal Face detections

Leveraging Archival Video for Building Face Datasets

– Build a histogram of hair, face and torso for each potential face detected



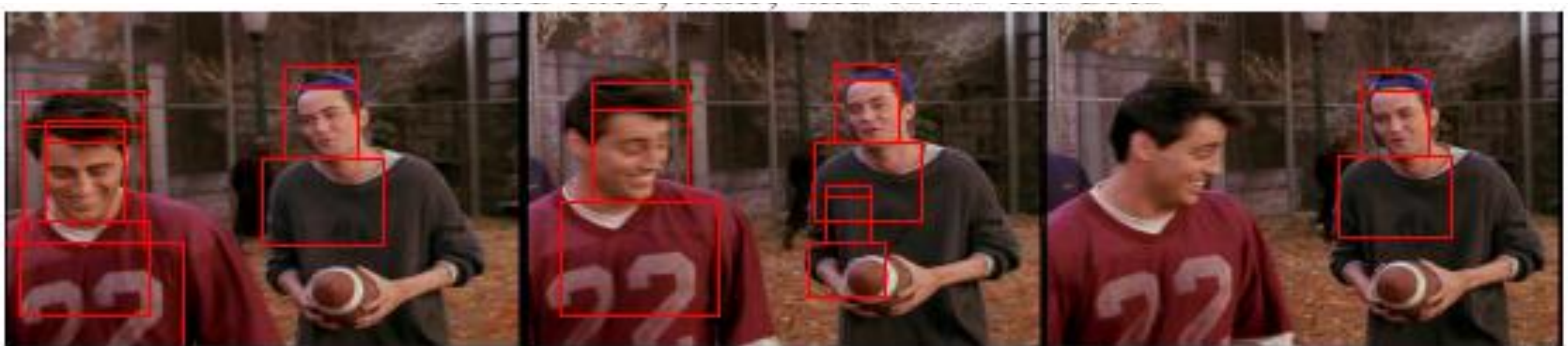
Frontal Face detections

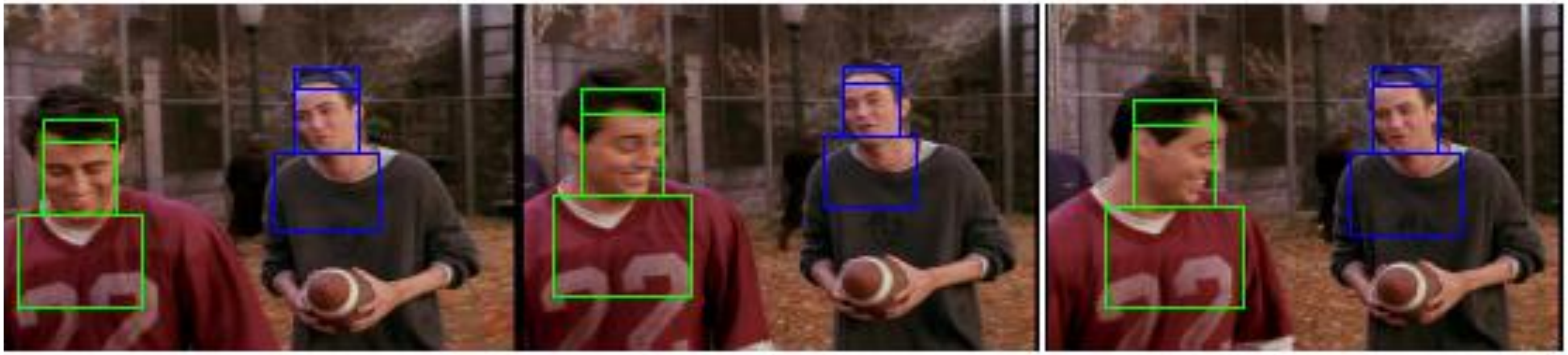
Build face, hair, and torso models

Leveraging Archival Video for Building Face Datasets

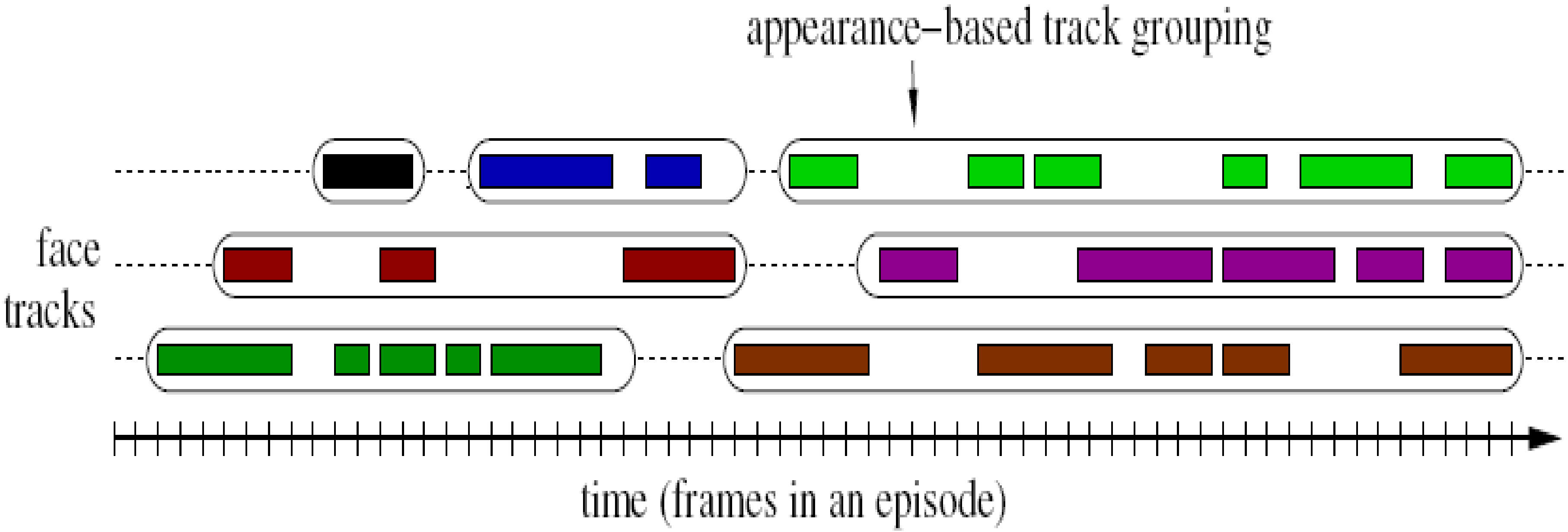
– Build track of histogram from neighbor fames

– Remove tracks with fewer than 20 faces (non-face histogram)





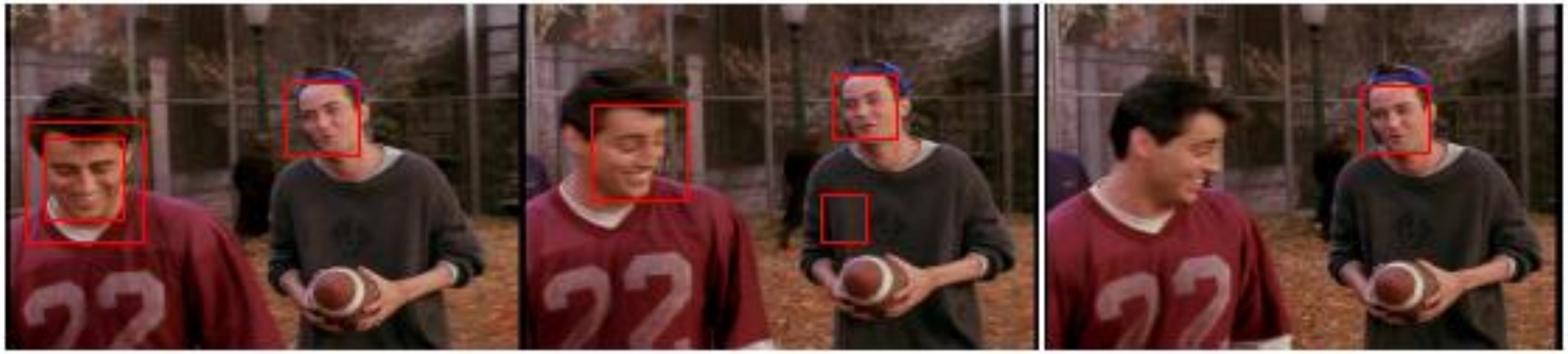
Leveraging Archival Video for Building Face Datasets



Leveraging Archival Video for Building Face Datasets

- Add non-frontal faces to tracks
  - Difficult to tell only based on similarity of faces
  - How about match similar histogram (similar hair and body)?

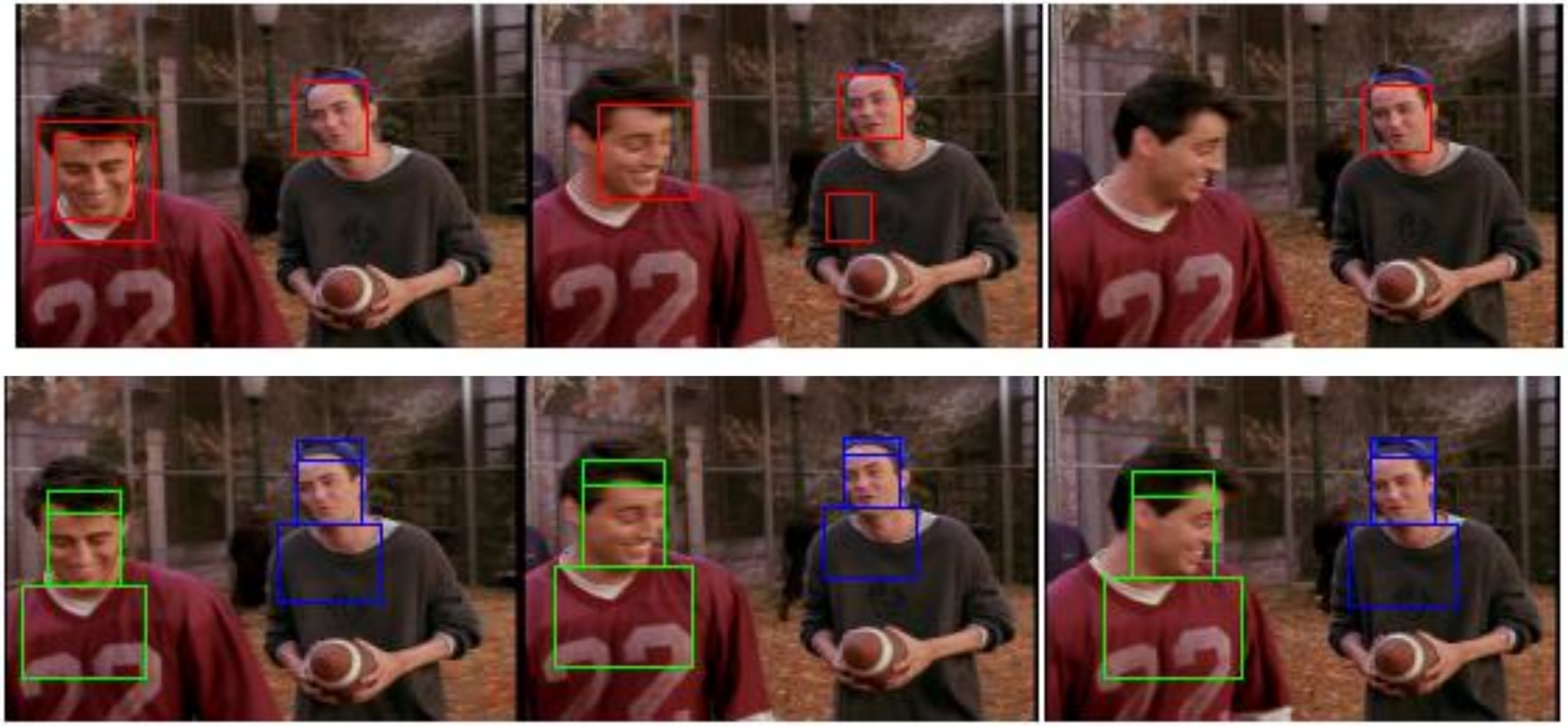
Frontal Face detections



Leveraging Archival Video for Building Face Datasets

- Add non-frontal faces to tracks

Frontal Face detections



Leveraging Archival Video for Building Face Datasets

- Group faces tracks in an episode
  - – Resize images of faces, bodies and hairs into 50x50 pixels
  - – Each face image is a vector with 2500 values
  - – Pick a reference episode and calculate 50 dimensional eigenspace by PCA
  - – Represent each face image in eigenspace

Leveraging Archival Video for Building Face Datasets

- Group faces tracks in an episode
  - Calculate distance between two groups:
    - Defined as smallest distance between any image pairs, one in each group
    - Histograms with same color clothing or hair don’t affect distance
    - Clothing or hair with different color adds to distance

Leveraging Archival Video for Building Face Datasets

- Group faces tracks in an episode
  - Cluster tracks
    - Group close tracks together
    - Use a conservative threshold to stop

Leveraging Archival Video for Building Face Datasets

Leveraging Archival Video for Building Face Datasets

- Label a reference episode
  - Take an episode “half-way” from 5th season
  - Label 80 clusters by hand
  - About 10-15 minutes
- Cluster between episodes

Leveraging Archival Video for Building Face Datasets

- Evaluation
  - 22 episodes from TV show Friends
  - 611,770 faces

Leveraging Archival Video for Building Face Datasets

- Evaluation
  - Precision: what fraction of the images labeled ‘Joey’ really are ‘Joey’
  - Recall: what fraction of all the Joey images in the video are in the dataset?

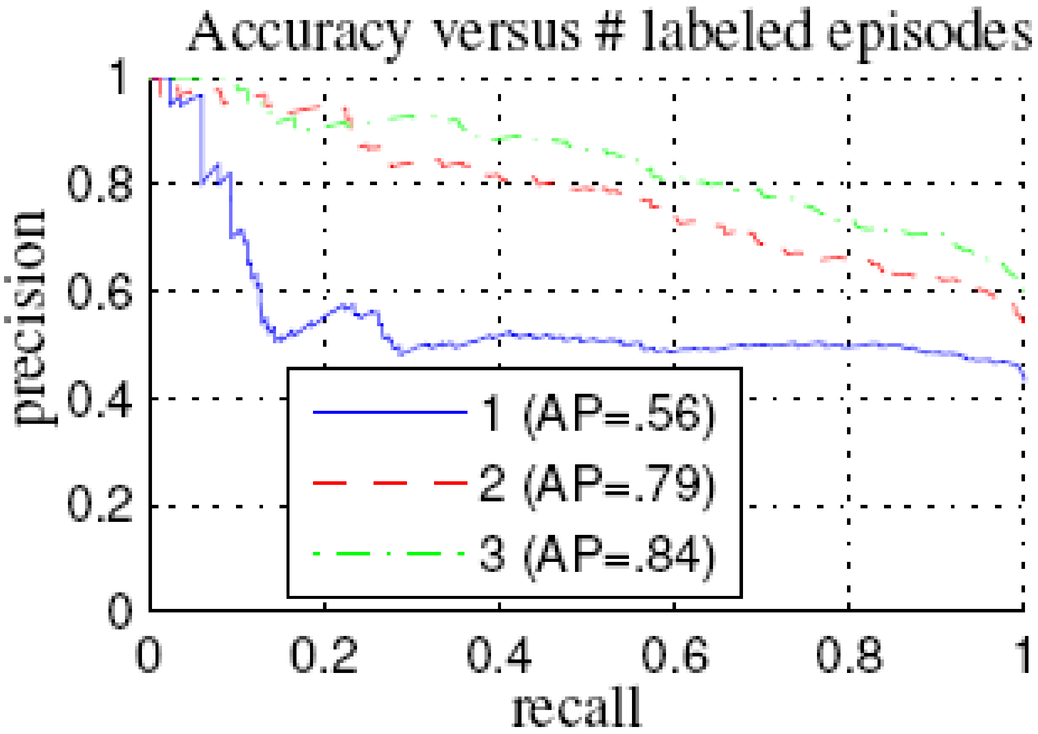
Leveraging Archival Video for Building Face Datasets

- Evaluation
  - Precision:
    - Randomly select 50 tracks
    - 92% find correct person
  - Recall:
    - Select 300 frames over all 22 episodes
    - 50% of them are tracked (impressive given the unconstrained nature of the people)

Leveraging Archival Video for Building Face Datasets

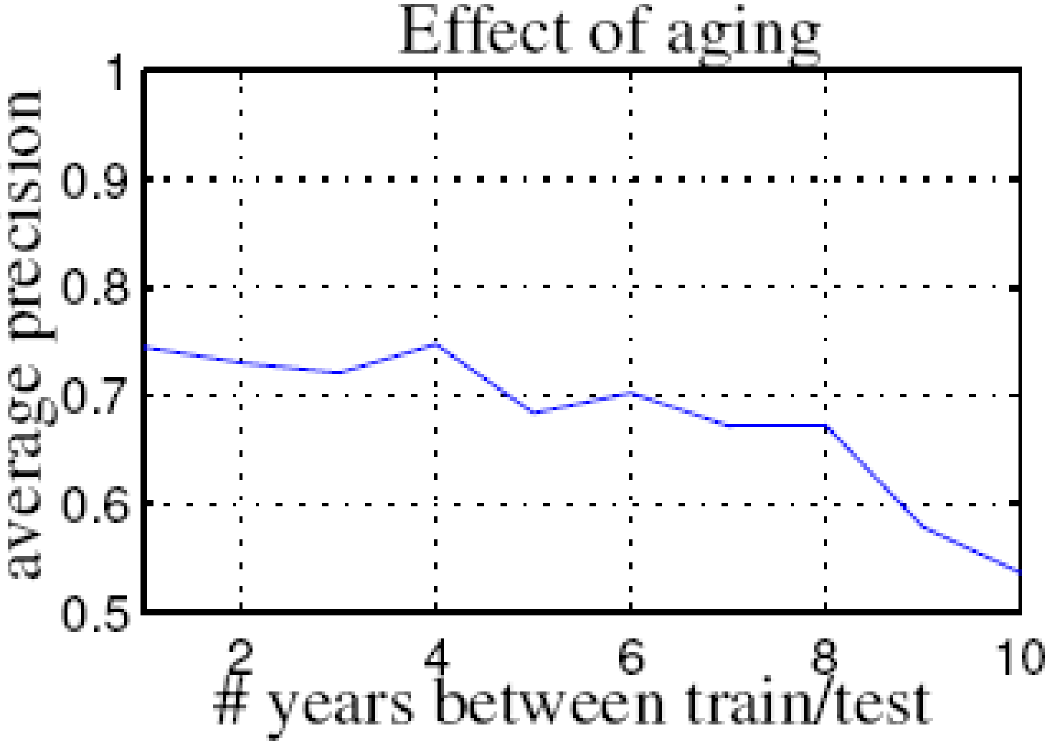
- Accuracy vs. Supervision (# of manual tracking episodes)

AP = average precision



Leveraging Archival Video for Building Face Datasets

- Aging (# of manual tracking episodes)
  - – Most dataset rely on few tens of images
  - – Our dataset rely on thousands images every age



People-LDA using Face Recognition

Lijie Heng

12/11/2007

Outline

- Background
- Latent Dirichlet allocation
- People-LDA
- Experiments
- Conclusion

Background

- Modeling text corpora –Latent Dirichlet allocation (LDA)
- Newspaper articles (including captions + images)

  captions->LDA->topic

  images->face recognition->people
- Could we built a joint model on both image and text information?

Latent Dirichlet allocation

- In the text corpora, assume

  a word <- vocabulary{1,2,…V}

  a documents <- N words

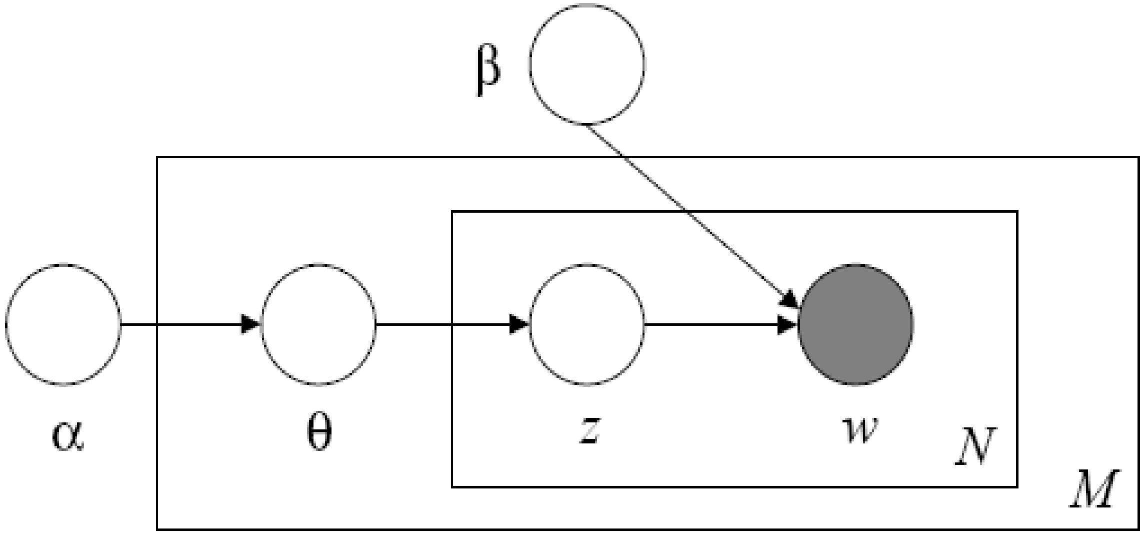
  a corpus <- M documents

Latent Dirichlet allocation-cont.

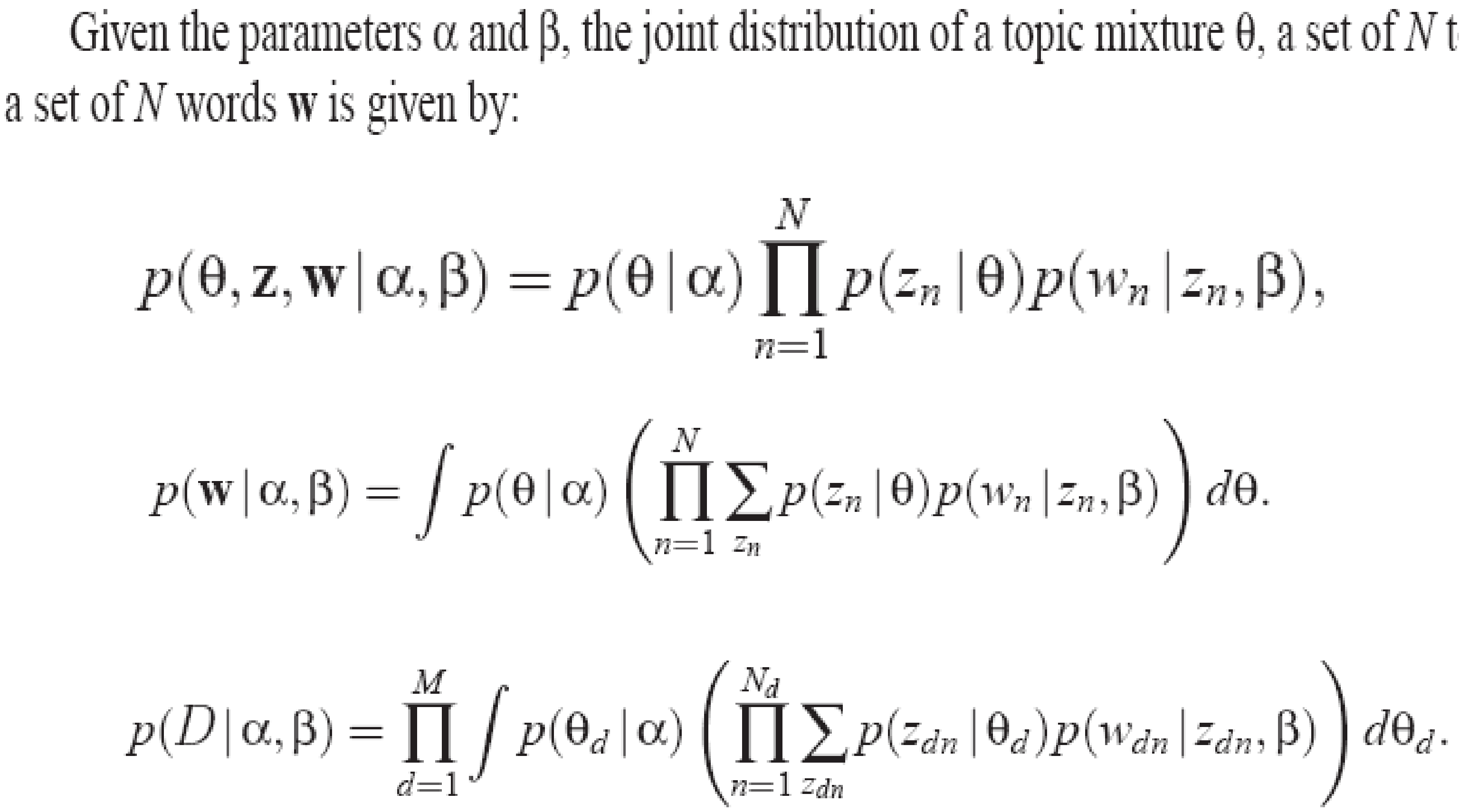
- To generate a document, we assume each document is generated from *K* topics and each topic is from *N* words from the vocabulary

1. Choose *N* ~ Poisson(x).
2. Choose θ ~ Dir(a).
3. For each of the *N* words *w_n*:
   (a) Choose a topic *z_n* ~ Multinomial(θ).
   (b) Choose a word *w_n* from *p*(*w_n* | *z_n; β*), a multinomial probability conditioned on the topic *z_n*.

Latent Dirichlet allocation-cont.



Latent Dirichlet allocation-cont.



Given the parameters α and β, the joint distribution of a topic mixture θ, a set of N topics **z**, and a set of N words **w** is given by:

$$p(\theta, \mathbf{z}, \mathbf{w} \mid \alpha, \beta) = p(\theta \mid \alpha) \prod_{n=1}^{N} p(z_n \mid \theta) p(w_n \mid z_n, \beta),$$

$$p(\mathbf{w} \mid \alpha, \beta) = \int p(\theta \mid \alpha) \left(\prod_{n=1}^{N} \sum_{z_n} p(z_n \mid \theta) p(w_n \mid z_n, \beta) \right) d\theta.$$

$$p(D \mid \alpha, \beta) = \prod_{d=1}^{M} \int p(\theta_d \mid \alpha) \left(\prod_{n=1}^{N_d} \sum_{z_{dn}} p(z_{dn} \mid \theta_d) p(w_{dn} \mid z_{dn}, \beta) \right) d\theta_d.$$

People-LDA

- Take into account of image information in the documents
- Anchor each topic to a single person

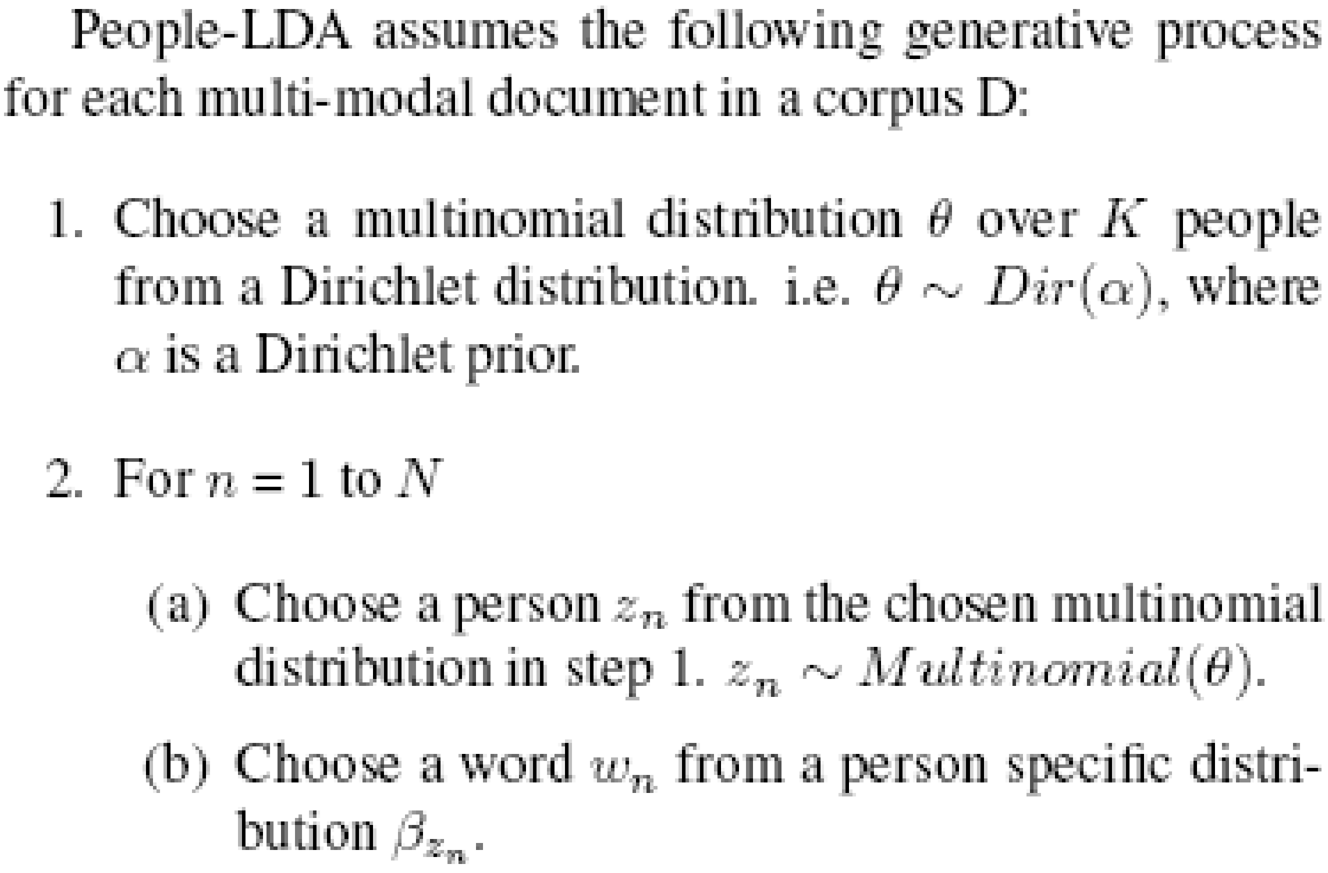
  politics->George Bush, sports->Yao Ming

People-LDA cont.

- Assumptions

1. D documents in the corpus
2. K topics/people inside the corpus
3. Each document includes an image I and a caption W
4. Image I includes M faces, each faces contains H patches

People-LDA cont.



People-LDA assumes the following generative process for each multi-modal document in a corpus D:

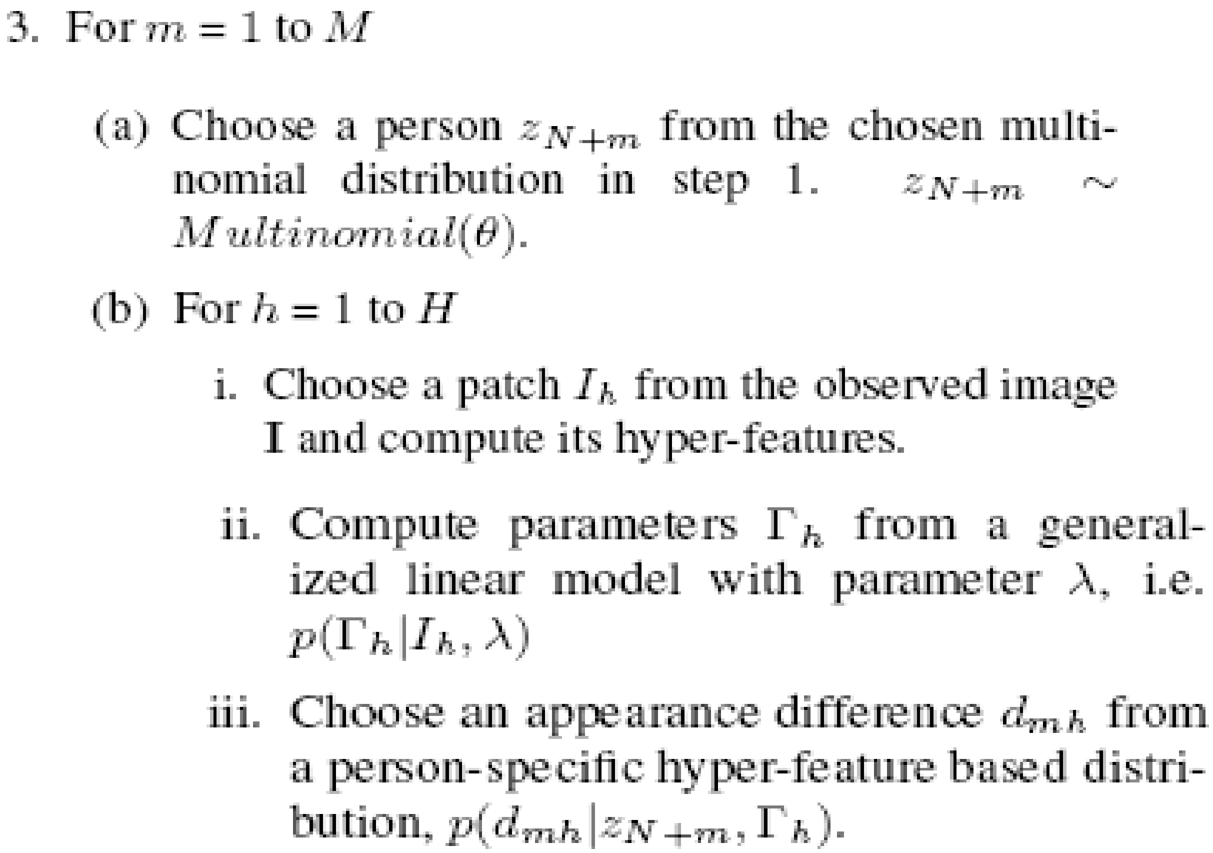
1. Choose a multinomial distribution θ over K people from a Dirichlet distribution. i.e. $\theta \sim Dir(\alpha)$, where α is a Dirichlet prior.

2. For n = 1 to N

   (a) Choose a person z_n from the chosen multinomial distribution in step 1. $z_n \sim Multinomial(\theta)$.

   (b) Choose a word w_n from a person specific distribution β_{z_n}.

People-LDA cont.



3. For $m = 1$ to M

   (a) Choose a person z_{N+m} from the chosen multinomial distribution in step 1. $z_{N+m} \sim Multinomial(\theta)$.

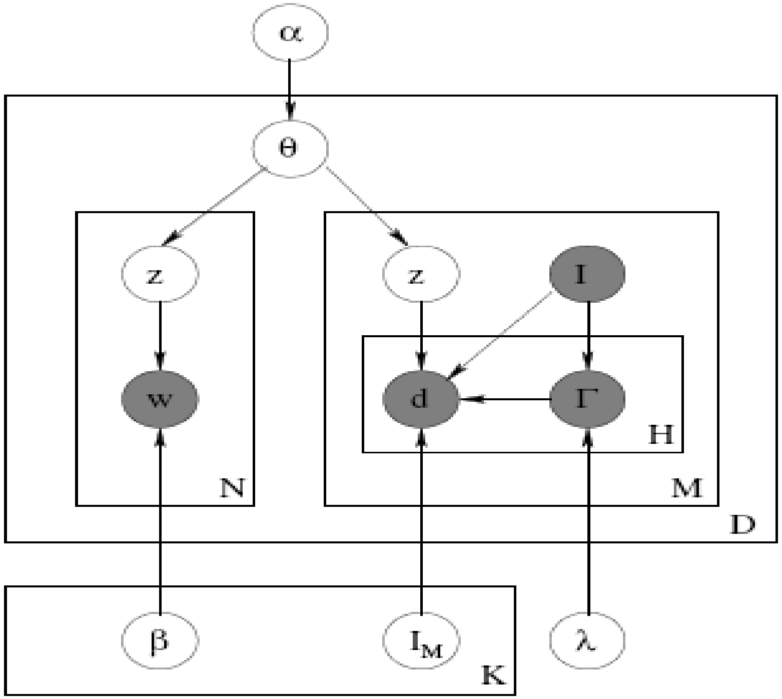
   (b) For $h = 1$ to H

      i. Choose a patch I_h from the observed image **I** and compute its hyper-features.

      ii. Compute parameters Γ_h from a generalized linear model with parameter λ, i.e. $p(\Gamma_h | I_h, \lambda)$

      iii. Choose an appearance difference d_{mh} from a person-specific hyper-feature based distribution, $p(d_{mh} | z_{N+m}, \Gamma_h)$.

People-LDA cont.



$$p(\theta, \mathbf{z}, \mathbf{w}, \mathbf{d}|\alpha, \beta, \lambda, \mathbf{I}) = p(\theta|\alpha) \prod_{n=1}^{N} p(z_n|\theta)p(w_n|z_n, \beta)$$

$$\cdot \prod_{m=1}^{M} p(z_{N+m}|\theta) \prod_{h=1}^{H} p(d_{mh}|z_{N+m}, \Gamma_h)p(\Gamma_h|\mathbf{I}, \lambda). \quad (1)$$

Experiments

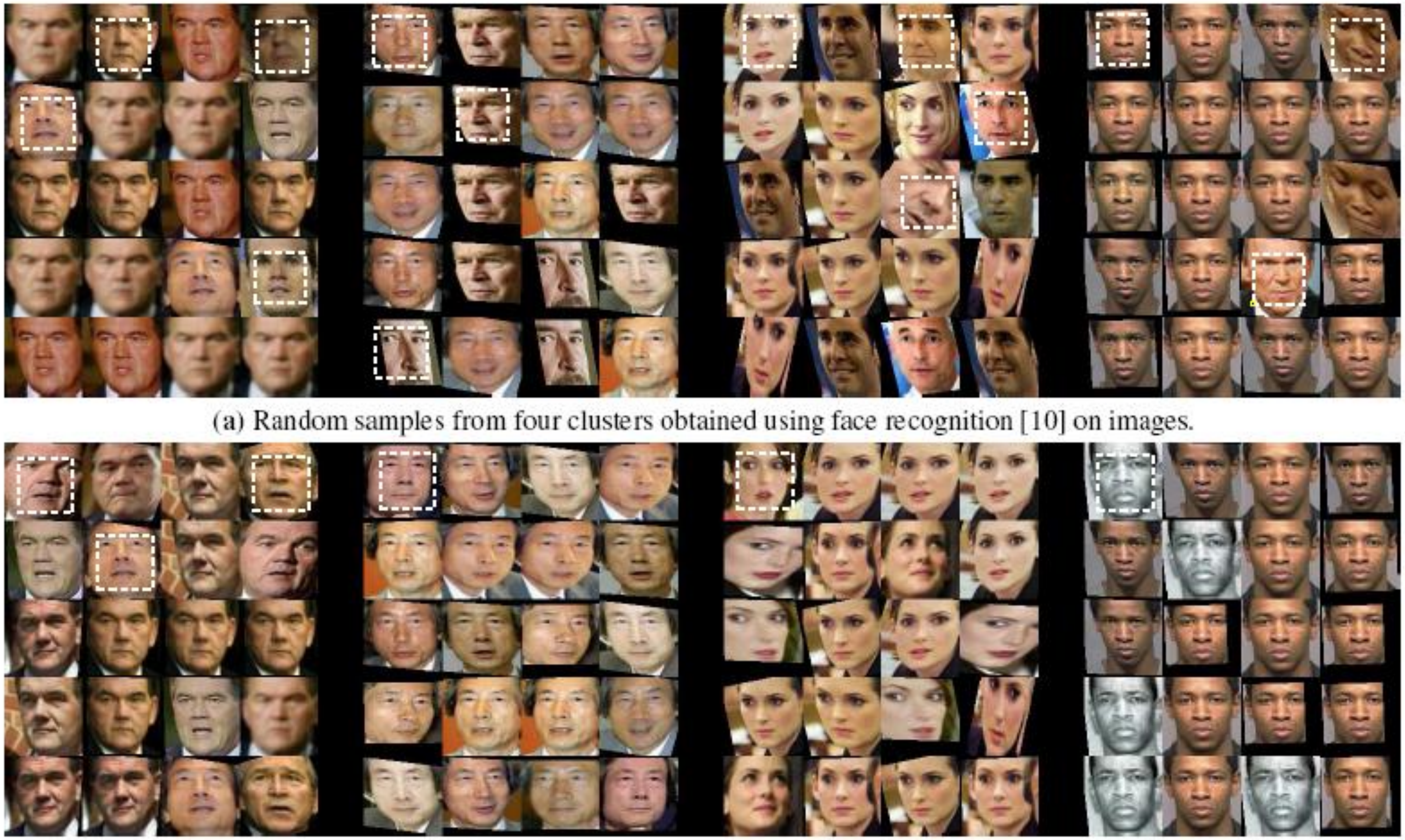
- Experiments:

1. 10000 documents from “Face in the wild”;
2. randomly select 25 names from 1077 distinct names showing in 10000 documents;
3. Obtain 25 reference faces(one image per person) as Reference Image
4. do image clustering

Experiments

- Image alone: using face identifier to clustering each image into one of the reference images
- Text alone: first cluster the caption text using LDA. then for each caption, assign the face images to their most likely names under the multinomial distribution of topics
- People-LDA

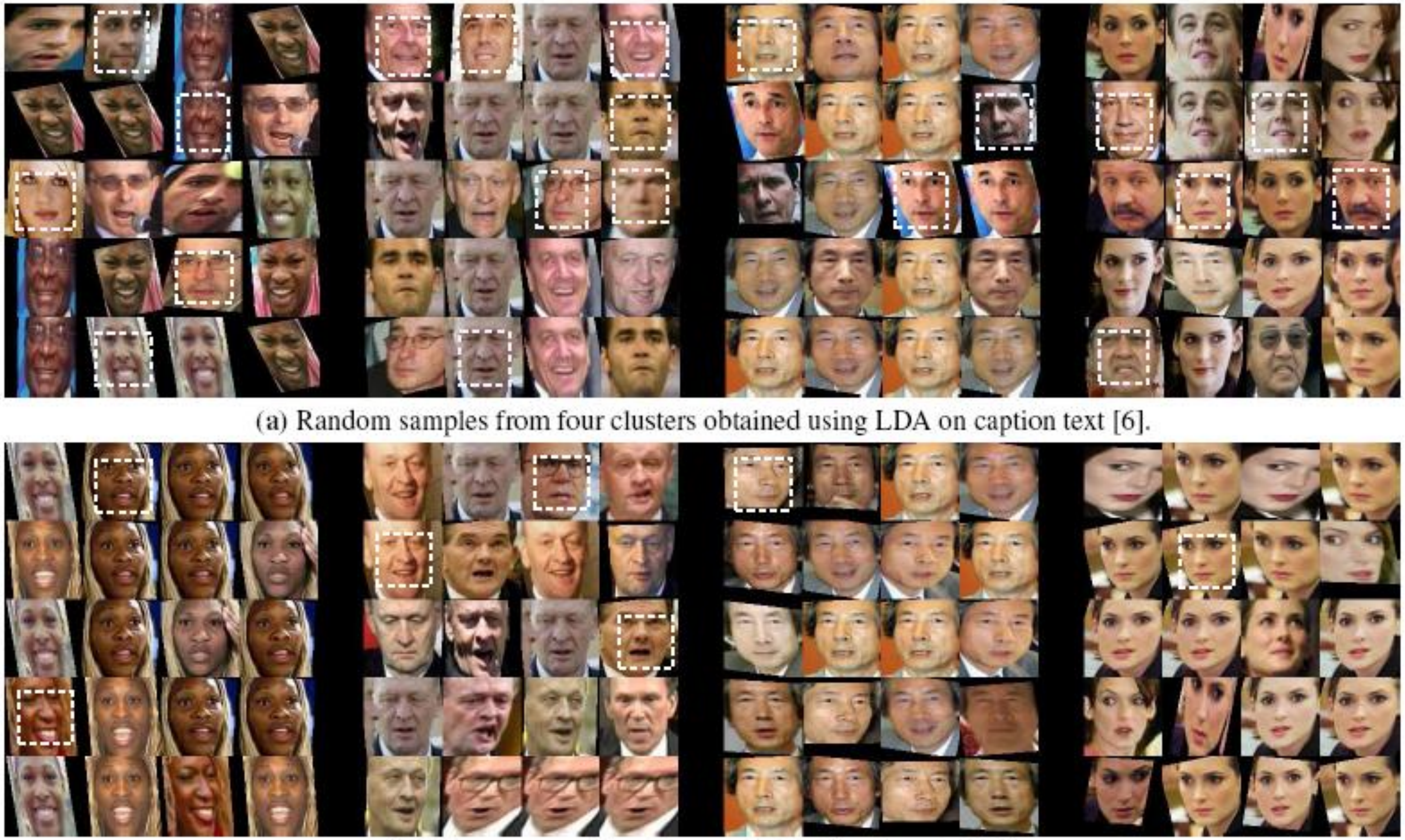
Experiments-*Clustering*



(a) Random samples from four clusters obtained using face recognition [10] on images.

(b) The corresponding clusters obtained by People-LDA.

Experiments-*Clustering*



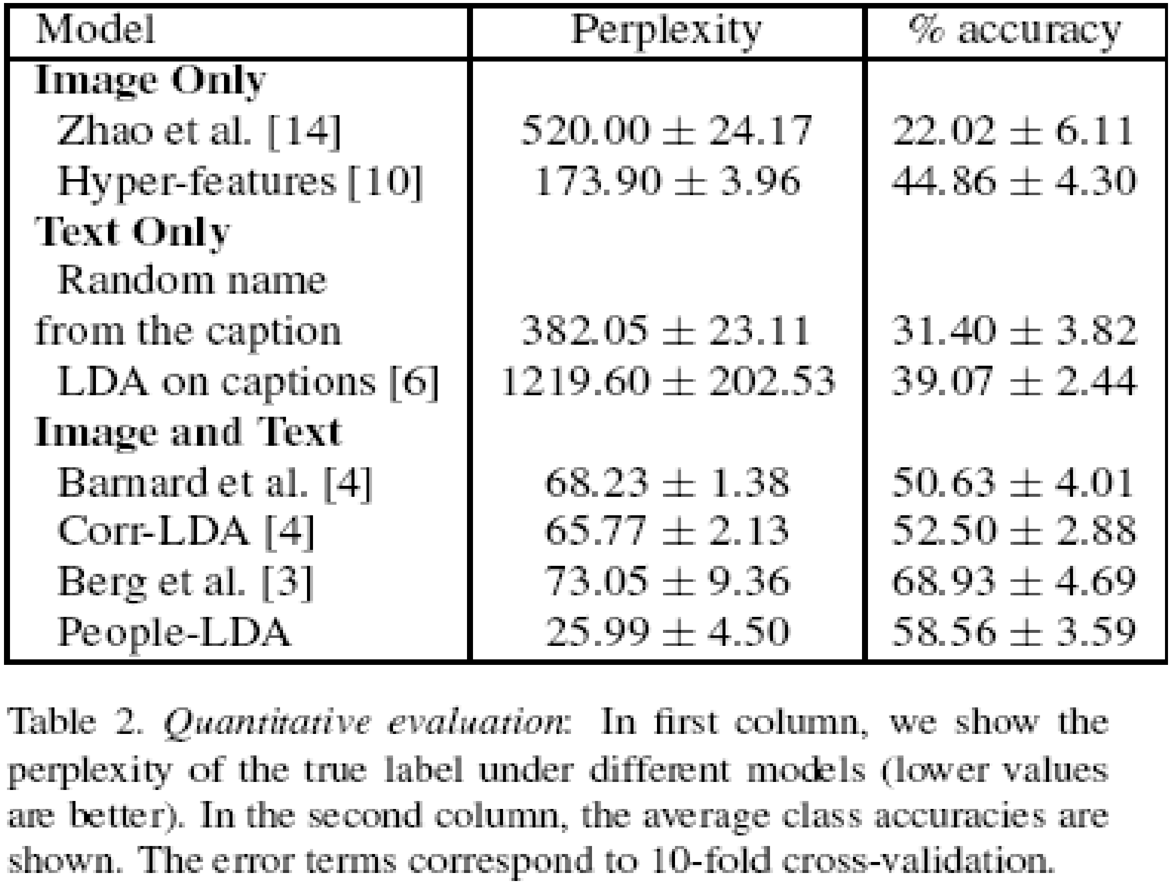
(a) Random samples from four clusters obtained using LDA on caption text [6].

(b) The corresponding clusters obtained by People-LDA.

Experiments- C*lassification*

- Manually label the test images
- Compare the result image with the true label
- Report accuracy and perplexity(lower perplexity assigns higher the probability to correct images)

Experiments- C*lassification*



Model	Perplexity	% accuracy
Image Only		
Zhao et al. [14]	520.00 ± 24.17	22.02 ± 6.11
Hyper-features [10]	173.90 ± 3.96	44.86 ± 4.30
Text Only		
Random name from the caption	382.05 ± 23.11	31.40 ± 3.82
LDA on captions [6]	1219.60 ± 202.53	39.07 ± 2.44
Image and Text		
Barnard et al. [4]	68.23 ± 1.38	50.63 ± 4.01
Corr-LDA [4]	65.77 ± 2.13	52.50 ± 2.88
Berg et al. [3]	73.05 ± 9.36	68.93 ± 4.69
People-LDA	25.99 ± 4.50	58.56 ± 3.59

Table 2. *Quantitative evaluation*: In first column, we show the perplexity of the true label under different models (lower values are better). In the second column, the average class accuracies are shown. The error terms correspond to 10-fold cross-validation.

Conclusion

- It’s a novel joint modeling of image and text.
- It has a better performance than other approaches.
- It can not associate names for people, whose reference images are not present.