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Active Learning Query Approach for Visual Tagging and Clustering

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ABSTRACT: In the world of big data, multimedia data from heterogeneous sources are growing at high rate. It is very difficult to process image data efficiently in terms of computational power and noisy data. Handling uncertain data is also a big challenge for us. Rather than asking a user to provide manual labels so as to minimize the uncertainty of labels across the entire data set, we ask the user to provide labels that minimize the uncertainty of his/her query result To overcome these problems we introduce active learning query driven approaches for face recognition .we use Gaussian process model to write probabilistic estimates into probabilistic database. Contextual constraints and attributes were used for cluster refinement and to get desired list of images in ranked order with minimum user participation.

KEYWORDS: Face tagging, query-driven active learning, contextual constraints.

I. INTRODUCTION

In the "Big data" world we see many challenges for visual processing like variability, velocity and volume Consider a user is wishing to analyze large data set from internet through face clustering and tagging by using semi automated techniques. Later interactive method with Active Learning framework is used but it has a drawback -it assumes that all tags and all data is accessible by everyone and need to process each image with all possible tags hence it is not tenable to use "offline setting".

In this paper, we used "query-driven" approach with respect to interactive face tagging/clustering. To implement this strategy, we introduce a notion of query-driven active learning. So, Instead of providing a label that minimizes label uncertainty over all the data set, our system asks for a label that reduces the uncertainty in answers for particular query.

II. RELATED WORK

Face tagging and clustering techniques have been extensively explored in the prior literature. The primary goal is to guide users to tag faces as quickly and accurately .An active learning framework has been widely utilized to design the sample selection criteria and Gaussian process based active learning paradigm which incorporates constraints as a prior to guide users to tag the faces with maximum expected in formativeness. These techniques,though interactive, are still applied in an "offline" setting and is simply not tenable.

Immense computational power and human resources needed to handle uncertain data. While the query-driven approachis attractive, it opens a whole set of new challenges, such as query processing on uncertain data, and "query-driven" active learning framework. The database community has widely explored the probabilistic query processing problem, and developed many advanced techniques one of the successful approaches describe a relational database encoding of factor graphs that can leverage probability inference techniques to compute query results. Therefore, to

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process probabilistic queries, we will handle this problem from a database perspective. And then we propose a novel "query-driven" active learning strategy to select questions that can Reduce uncertainties in answers

III. SCHEMA DEFINITION

We begin by describing our database schema. Suppose that we are given a human-centered photo album that contains M images I = {I1, I2, . . . , IM}, see Figure 2. Assume that n faces are detected, F = {f1, f2, . . . ,fn }, with each face denoted as fi or f Iki (that is, fi is extracted from image Ik). Suppose that middle-level semantic concepts can be extracted from images and faces leveraging the pre-trained classifiers or provided by users, such as image captured time denoted as Ik.time, Geo-location Ik .loc, and images tags Ik .tag. Besides, face attributes can be extracted from each face intrinsic attributes like "gender", "age", "ethnicity", and describable attributes "black hair", "big nose", etc., denoted as fi .attr. Each face is associated with an identity attribute fi .t. importantly, the domain of fi .t is unknown.

Notation	Meaning
$\mathcal{I}$	the set of images $\mathcal{I} = \{I_1, I_2, \ldots, I_M\}$
$\mathcal{F}$	the set of detected faces $\mathcal{F} = \{f_1, f_2, \ldots, f_n\}$
$\mathcal{C}$	the set of initial face clusters $\mathcal{C} = \{C_1, C_2, \ldots, C_N\}$
F_L	the set of labeled faces $F_L = \{f_1, f_2, \ldots f_L\}$
T_L	the set of provided face tags $T_L = \{t_1, t_2, \ldots t_L\}$
$\mathcal{R}$	given a query, the set of result nodes $\mathcal{R} = \{r_1, r_2, \ldots r_m\}$
$H(f_i)$	the entropy of face f_i
$I(f_i)$	the information gain of face f_i
$H^q(f_i)$	the query-driven entropy of face f_i
$\widetilde{H^q}(f_i)$	the query-driven entropy with constraints for face f_i

Table 1 : Summary of Notations Used

Database Constraints:Contextual constraints gives clues about the face identities. co-occurring faces in one image usually refer to different people. Such a relationship can be defined as a "diff" constraint ε− in our schema. Faces from the same face track in a video should refer to the same person, denoted as "identical" (or "same") constraint ε+.

Weak Supervision: We construct a probabilistic database using the entity-relationship diagram in Figure 2. On top of this probabilistic database, users can present a query to extract the interested knowledge. To indicate the target people in the query, users can specify several face samples of this target person. Therefore, the whole face dataset F will be partitioned into labeled face set FL = {f1, f2, . . .fL }, with tags TL ={t1, t2, . . . tL }, and unlabeled face set FU . Our goal is to choose which faces to tag (or questions to ask users) in order to achieve the accurate query answers as soon as possible

IV. QUERY DRIVEN APPROACH

A query language allows us to focus user effort on labelling data. SQL allows to algebraically compose fairly complex queries by composing the basic operators such as selections, aggregations and joins. Figure 2 illustrates the designed interface for an example complex selection query. Query answers are displayed to users as a ranking list based on the relevance to queries .if user is not satisfied again iterations will be continued until the user gets desired result.

A. *Framework of query-driven face tagging:*

Given a media dataset, we first built a probabilistic database by extracting semantic attributes using visual concept detectors When users present a high-level semantic query (translated to SQL query algebra),the database manager will process thequery and return an answer to the query. If users are not satisfied with the answer, the human-in-the-loop component will be activated. It will automatically generate questions to ask users for feedback, based on which the final query answer will be updated until users are satisfied. Queries are processed on aprobabilistic database to generate

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the tentative answers. And then the query-driven active learning strategy will select questions to return to users for feedback, which will be leveraged to update the query answers

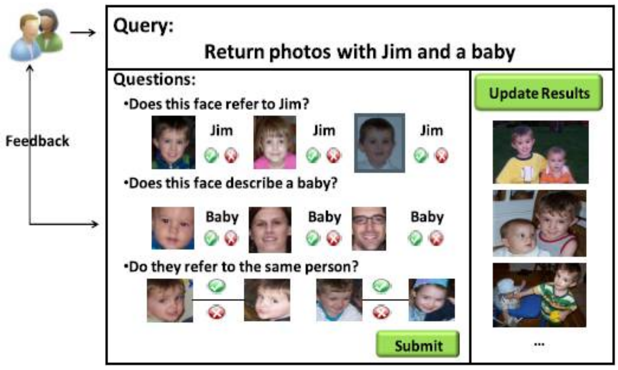

Figure 2: User Interface of query driven approach

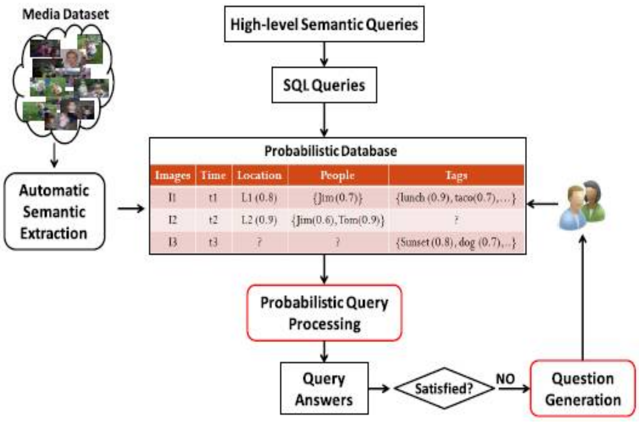

Figure 3: Framework of query-driven face tagging

B. *Choosing Questions for feedback*

Algorithm 1 Greedy Algorithm for K Questions

input : Unlabeled set $\mathbb{S}$; Parameter K
output: Selected set Ω, where $|\Omega| = K$

```
Ω ← ∅
Q ← ∅
foreach node C_i ∈ S do
    Compute H̃^q(C_i)
    Q.insert(C_i, H̃^q(C_i))
while |Ω| < K and |Q| > 0 do
    C_top ← Q.pop()
    C_Ω ← {C_j : C_j ∈ Ω ∧ (C_top, C_j) ∈ ε⁻}
    if C_Ω = ∅ then
        Ω ← Ω ∪ {C_top}
        S_cand ← S_cand \ {C_top}
    else
        Update H̃^q(C_top)
        Q.insert(C_top, H̃^q(C_top))
return Ω
```

Figure4:Algorithm flow for K Questions

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Select K Questions in a Batch: So far, we have discussed the criteria to choose samples for feedbacks. However, in the real applications, it is inefficient to return only 1 question tousers in each iteration. Therefore, next we will explore the strategy to choose K questions in each iteration, described in Algorithm 1. At the first thought, the samples ranked in the top K list can be returned to users. However, with further consideration, we discover that constraints make this problem a little more complex. For instance, as illustrated in Figure 7,suppose that we set K = 2, and C2 and C3 rank in the top 2list, it is not wise to return them together, since the resolve ofC2 might lead to the resolve of C3. Therefore, once we chooseC2, the impact of C3 should be updated.

C. *Cluster Refinement based on Contextual Constraint*

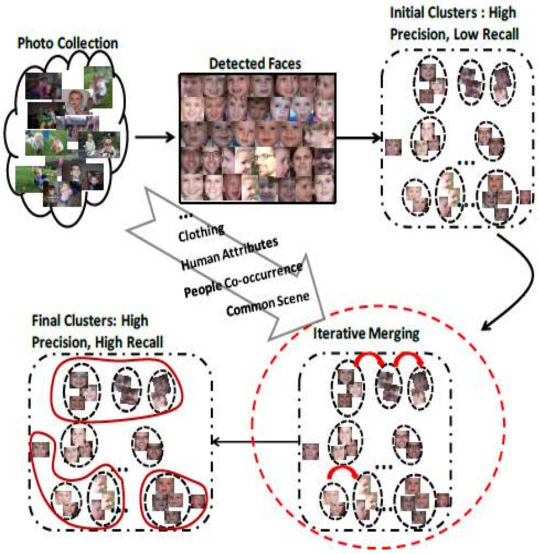

Figure 5: Clustering with Contextual Constraints

Here initial set of clusters generated by the standard approach for the given photo collection. The initial clusters have high precision but low recall. We iteratively merge the clusters that are likely torefer to the same entities to gethigher recall. We use contextual and facial features in two regards: for computing similarities and for defining constraints. Gaussian Process (GP) prior with contextual constraints to predict posterior distribution of tag labels over a set of unlabeled faces. We use a simplified form of their model, using the GP to only produce "local" predicts of face identity. We make use of the probabilistic database manager to enforce contextual constraints

V. CONCLUSION

We have introduced a query-drive paradigm for face clustering/tagging which can be seamlessly integrated into image analysis/retrieval process, to address the challenges of big data like velocity, speed and speed. Our proposed query-driven active learning strategy provides accurate query answers with minimum user participation and also prevents unnecessary vision processing by reducing uncertain data processing

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