#### **Collaborative Learning of Semi-Supervised** Clustering and Classification for Labeling **Uncurated Data**

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#### Large image collections are common

- Applications, e.g.,
  - Autonomous driving
  - Healthcare
  - Finance and banking
- Benchmarking datasets
  - ImageNet, COCO, Open Images, CIFAR, ...



### **Specialized domains**

- E.g., forensics, material science, biology, medical, ...
  - No pre-existing labels
  - Limited transferability of labeling efforts from other datasets
- Present potential value in various areas of science and business
- Require curation to answer research questions and search within the data
  - Expensive
  - Time consuming



#### **Curation challenges**

- Many datasets are too large for completely manual curation
- Privacy/proprietary/expertise concerns may preclude crowd-sourcing curation Sensitive data (medical, personal, financial, ...)
- - Requires domain expertise
- Conclusion: Efficient image labeling is an essential task needed to unlock valuable information in such image collections

### **Unsupervised and Supervised methods**

- Unsupervised methods do not depend on labeled data
  - Cluster image data using their feature representations
  - Good representations are hard to be obtained for domain specific data
  - Evaluation requires manual intervention
    - Time consuming
    - Expensive (requires domain expertise)
- Supervised methods depend on labeled data
  - Labeled data is not readily available for all domains

#### Plud: a Platform for Labeling Uncurated Data

- Human-machine collaboration (semi-supervised) for labeling data
  - Accelerates the labeling process to handle large amounts of uncurated data
  - Minimizes the labeling effort by experts to utilize the limited availability of experts
- A workflow consisting of unsupervised and supervised components

#### Human decomposition dataset

- Daily photos of ~500 subjects in an 8-year period
- Multiple images from various body part per subject (Arm, Hand, Foot, Legs, Full body, Head, Backside, Torso, Stake, Plastic)
- Various decomposition stages due to:
  - Weather changes
  - Time of death
  - Prior conditions of subjects





Decay/time

- Iterates over
  - Clustering
  - Human supervision
  - Classification
- Objective: accelerate and simplify manual labeling



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#### **Cluster evaluation interface**

- Provides an overview of clusters
- Experts can remove mis-clustered images
- Experts label an entire cluster of images
- Labeling time and effort is reduced

	150 images	300 images		
Labeling	13m.22s	43m.52s		
Labeling via Plud	4m.41s	11m.34s		

# **Overview of clusters Cluster view (hand)**

CONTRACTOR AND INVESTIGATION



#### **Plud - F-Score**

- 5500 manually labeled test images
- Inception outperformed RestNet50 and VGG16



Number of images for val + train for each model



#### **Plud - Precision and recall**

- Inception based classifier
- Tested on 5500 images of human decomposition

Model		Precision of Classes								AP		
		Arm	Hand	Foot	Legs	Full Body	Head	Backside	Torso	Stake	Plastic	AI
Inception	Top 1	45.73	85.60	93.72	60.52	92.69	94.33	68.25	87.22	96.30	73.61	79.80
	Top 3	80.23	96.86	97.75	86.96	97.53	98.29	89.57	97.20	98.87	88.88	93.21
Model		Recall of Classes							AR			
		Arm	Hand	Foot	Legs	Full Body	Head	Backside	Torso	Stake	Plastic	
Inception	Top 1	53.88	67.36	62.34	97.60	77.21	94.91	55.84	91.97	98.86	1	80.00
	Top 3	92.69	87.63	90.66	99.57	96.34	99.75	81.81	96.27	1.	1.	94.47

#### Conclusion

- Speeds up the labeling and curation process in large image collections when
  - No prior labeled data exists
  - Classes are vastly different from common datasets
  - Human supervision and expertise is required
- Enables fringe domains put their image data to use

#### Future work

- Provide label suggestions for the expert to validate
- Removing the human from iterations by developing an end-to-end method based on only a limited amount of domain expert input
- Expanding the image level labeling to image segmentation

## Thank you!

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