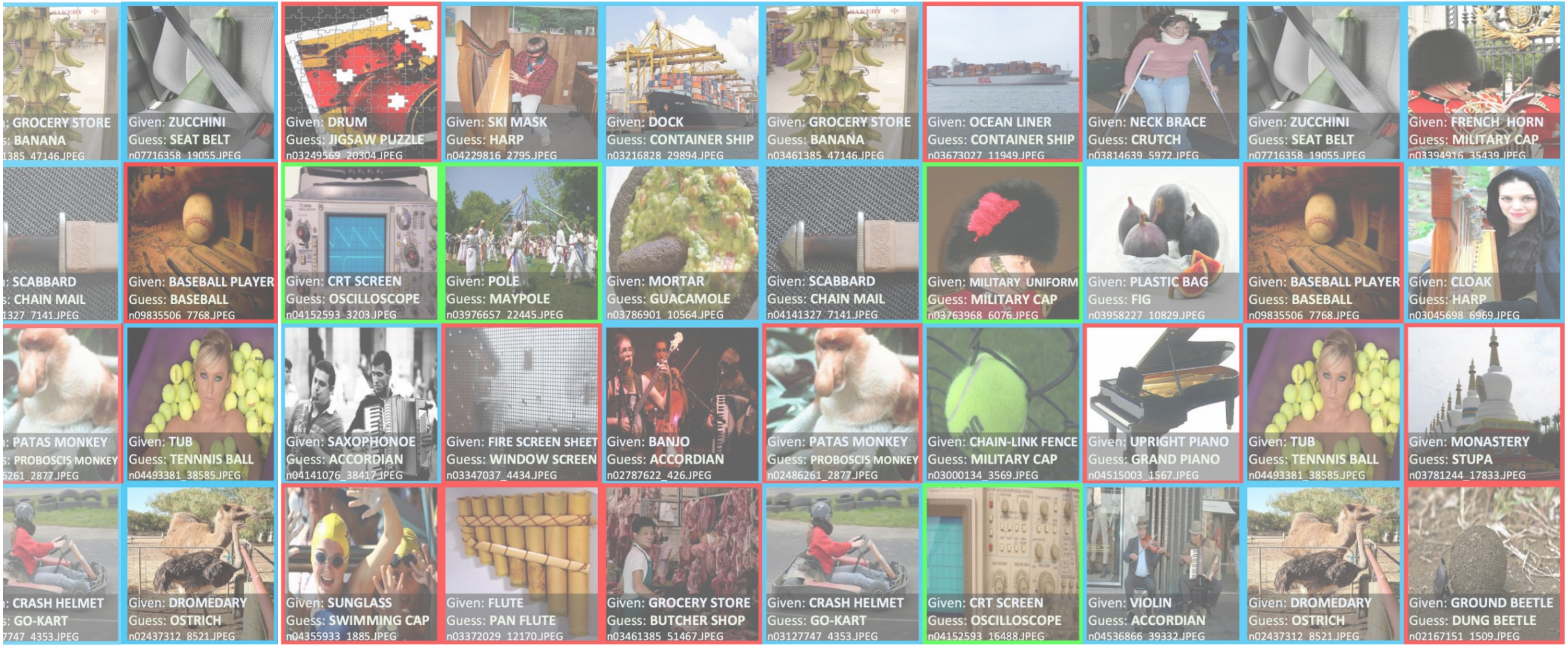


Confident Learning: Estimating Uncertainty in Dataset Labels

Esmaeil Shakeri

ENSF619.2, November 2021

University of Calgary

Outline

- Motivation and Introduction
- Methodology
- Experimental Evaluation
- Conclusion and Future Work

Motivation and Introduction

- Yet, large datasets with noisy labels have become increasingly common.
- Existing learning models mainly focus on predictions, instead of label quality.
- Prior works learn with noisy labels by modifying the model or training loss function, restricting the class of models.
- Confident learning (CL) is an alternative approach which focuses on label quality by characterizing and identifying label errors in datasets.

Motivation and Introduction

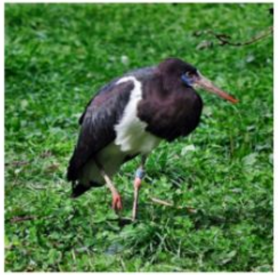
- CL estimates the joint distribution between noisy labels (given) & uncorrupted labels (unknown) to find the exact label errors.
- CL is not coupled to specific data modality or model.
- Utilizing CL on ImageNet to quantify ontological class overlap & increase model accuracy by cleaning data prior to training.

given: 5
corrected: 3

given: cat
corrected: frog

given: lobster
corrected: crab

given: ewer
corrected: teapot



given: white stork
corrected: black stork

given: tiger
corrected: eye

Confidence Learning

- CL defines the data that is mislabeled
- Detects the presence of noisy labels by addressing two main questions:

    1. How can we identify examples with label errors ?
    2. how can we learn well despite noisy labels, irrespective of the data modality or model employed?

Confidence Learning

Confidence learning works with this assumption that label noise is class-conditional, depending only on the latent true class, not the data.

Leopard

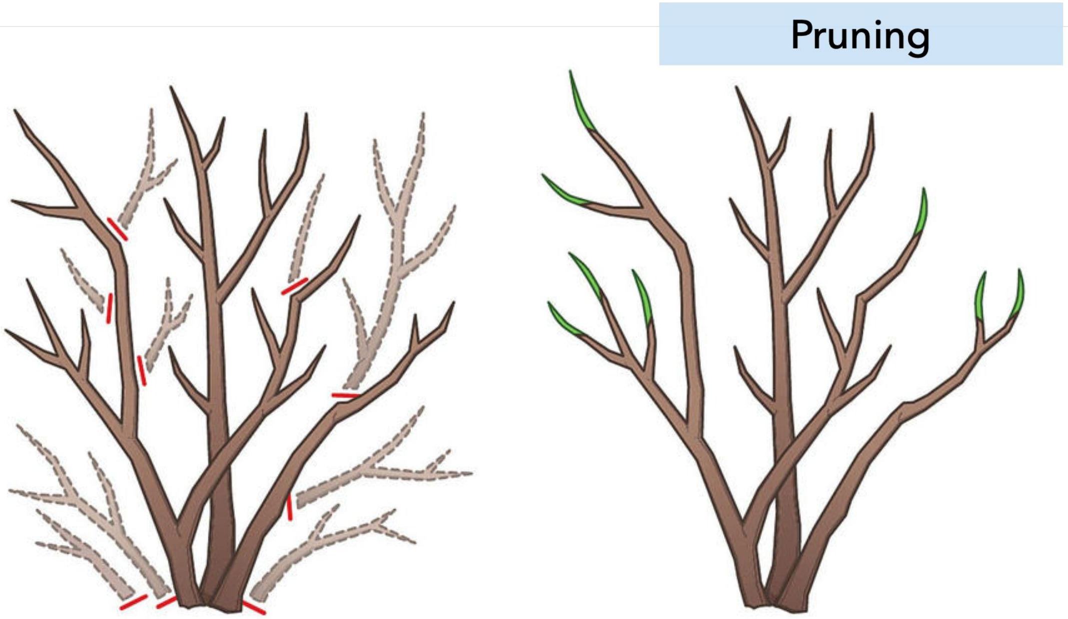
Jaguar

Bathtub

Methodology

CL estimates the joint distribution between noisy (given) & true (unknown) labels based on three principal approaches

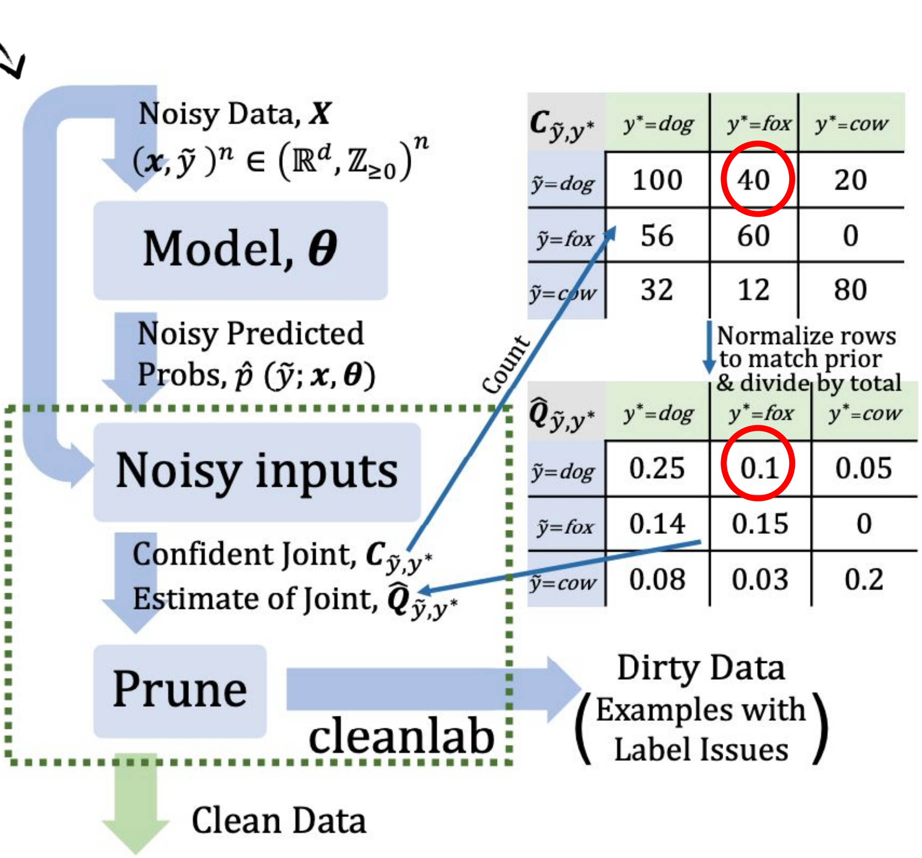
1. Prune
2. Count
3. Rank



Methodology

- Counts is a statistical data structure in CL to directly find label errors.
- Any rank & prune approach can be used to clean the data.
- This modularity property allows CL to find label errors using interpretable and explainable ranking methods.
- Prior works typically couple estimation of the noise transition matrix with training loss.

Example

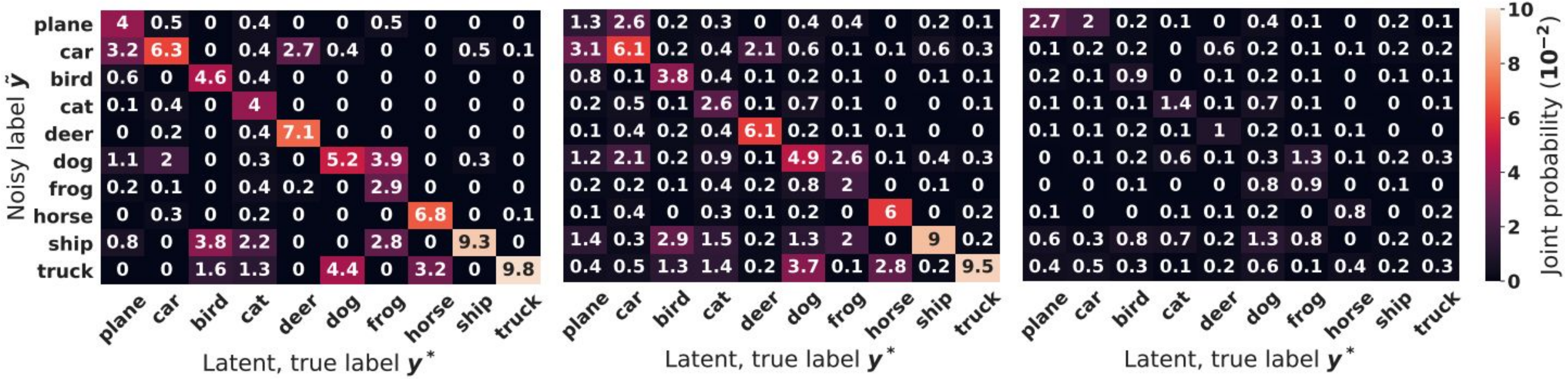


$\boldsymbol{C}_{\tilde{y},y^*}$	y^*=dog	y^*=fox	y^*=cow
$\tilde{y}$=dog	100	40	20
$\tilde{y}$=fox	56	60	0
$\tilde{y}$=cow	32	12	80

$\hat{\boldsymbol{Q}}_{\tilde{y},y^*}$	y^*=dog	y^*=fox	y^*=cow
$\tilde{y}$=dog	0.25	0.1	0.05
$\tilde{y}$=fox	0.14	0.15	0
$\tilde{y}$=cow	0.08	0.03	0.2

Experimentation

- Joint estimation
- Accuracy of finding label errors
- Accuracy learning with noisy labels



(a) True $Q_{\tilde{y},y^*}$ (unknown to CL) (b) CL estimated $\hat{Q}_{\tilde{y},y^*}$ (c) Absolute diff. $|Q_{\tilde{y},y^*} - \hat{Q}_{\tilde{y},y^*}|$

Experimentation

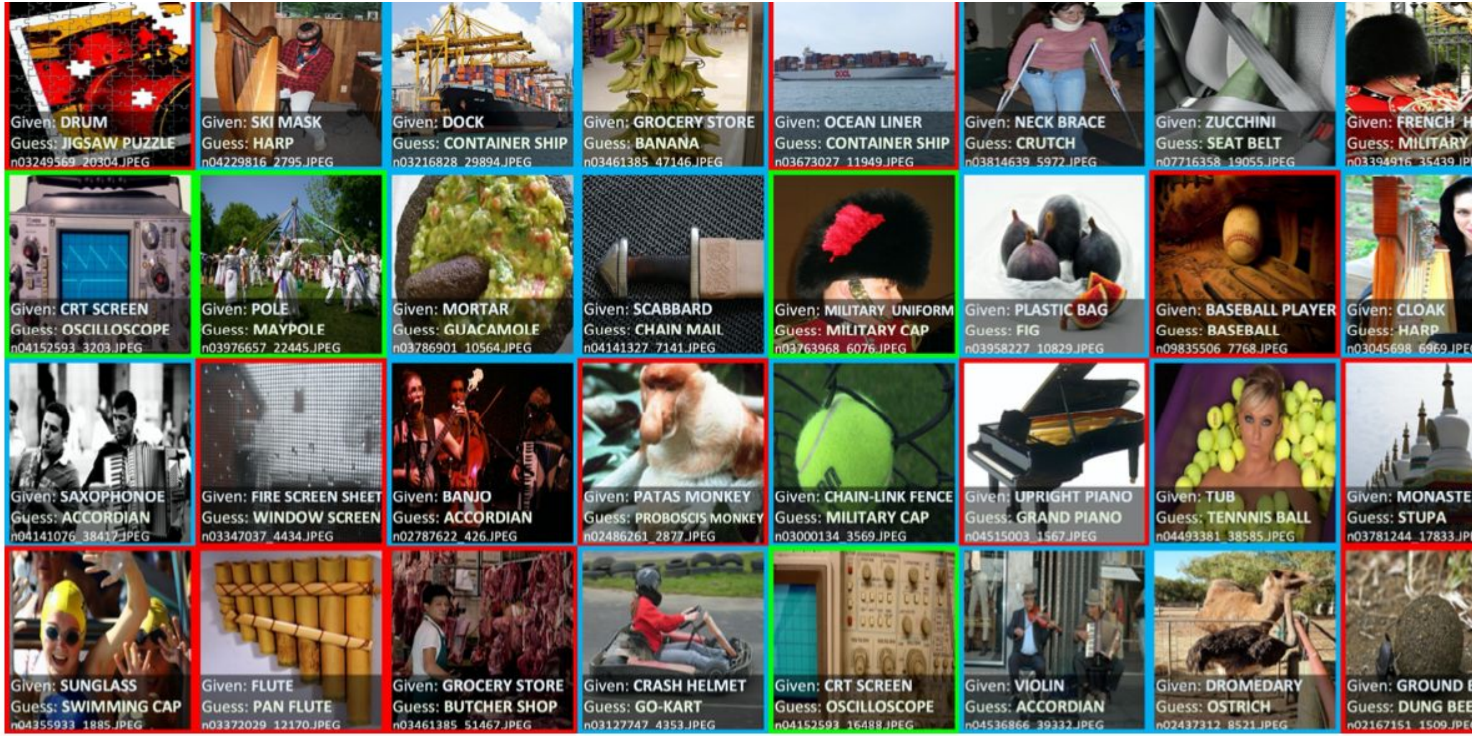
- Joint estimation
- Accuracy of finding label errors
- Accuracy learning with noisy labels

Measure	Accuracy (%) ± Std. Dev. (%)				F1 (%)				Precision (%)				Recall (%)			
Noise	20%		40%		20%		40%		20%		40%		20%		40%	
Sparsity	0.0	0.6	0.0	0.6	0.0	0.6	0.0	0.6	0.0	0.6	0.0	0.6	0.0	0.6	0.0	0.6
CL: $\boldsymbol{C}_{\text{confusion}}$	84±0.07	85±0.09	85±0.24	81±0.21	71	72	84	79	56	58	74	70	**98**	**97**	**97**	**90**
CL: $\boldsymbol{C}_{\tilde{y},y^*}$	89±0.15	**90**±0.10	86±0.15	**84**±0.12	75	78	84	**80**	**67**	**70**	78	77	86	88	91	84
CL: PBC	88±0.22	88±0.11	86±0.17	82±0.13	76	76	84	79	64	65	76	74	96	93	94	85
CL: PBNR	89±0.11	**90**±0.08	**88**±0.12	**84**±0.11	77	**79**	**85**	**80**	65	68	**82**	**79**	93	94	88	82
CL: C+NR	**90**±0.21	**90**±0.10	87±0.23	83±0.14	**78**	78	84	78	**67**	69	**82**	**79**	93	90	87	78

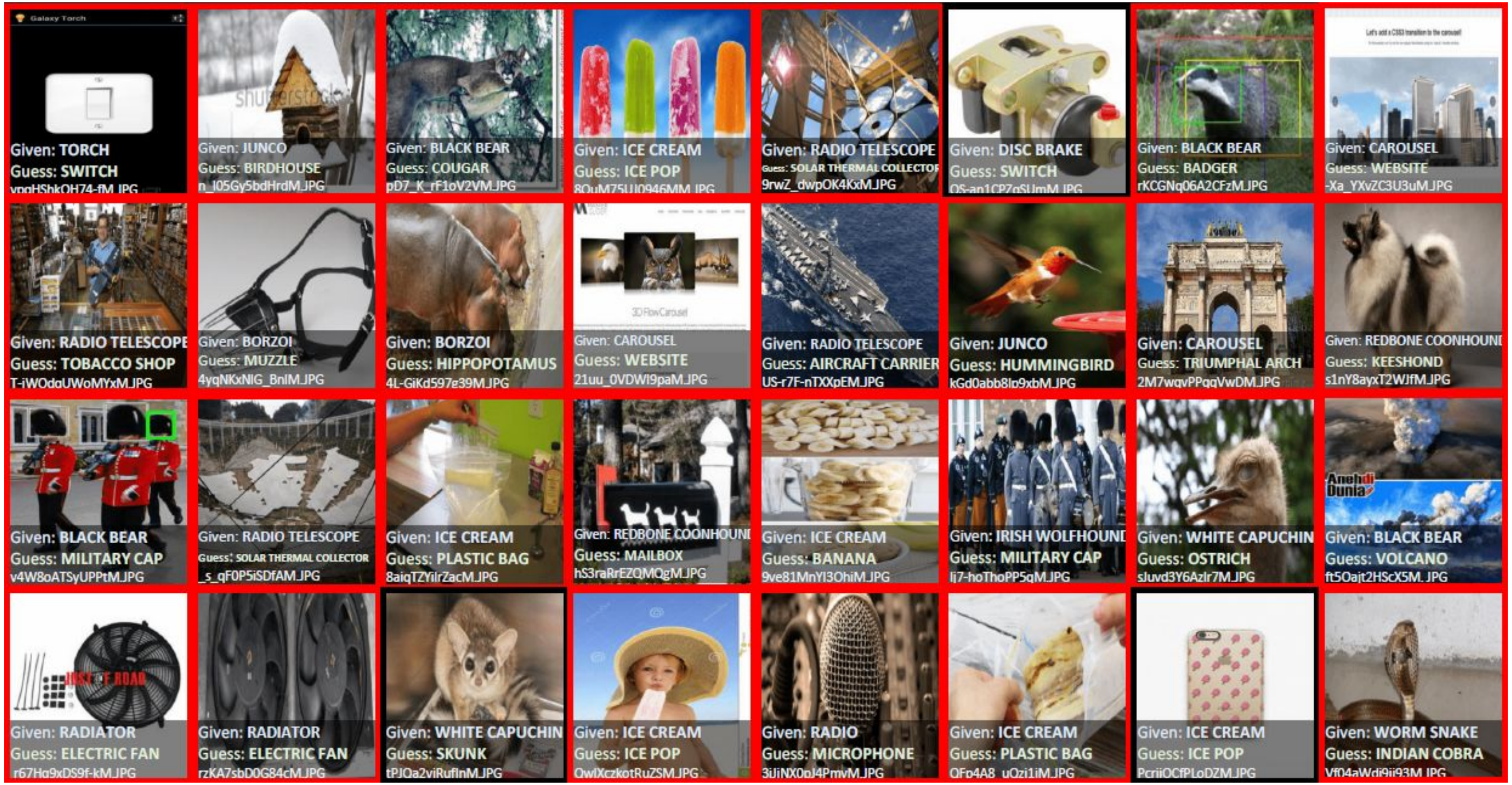
Experimentation

- Joint estimation
- Accuracy of finding label errors
- Accuracy learning with noisy labels

Noise	20%				40%				70%			
Sparsity	0	0.2	0.4	0.6	0	0.2	0.4	0.6	0	0.2	0.4	0.6
CL: $\boldsymbol{C}_{\text{confusion}}$	89.6	89.4	90.2	89.9	83.9	83.9	83.2	84.2	31.5	39.3	33.7	30.6
CL: PBC	90.5	90.1	90.6	90.7	84.8	85.5	85.3	86.2	33.7	40.7	35.1	31.4
CL: $\boldsymbol{C}_{\tilde{y},y^*}$	**91.1**	**90.9**	**91.1**	**91.3**	86.7	86.7	86.6	86.9	32.4	**41.8**	34.4	34.5
CL: C+NR	90.8	90.7	91.0	91.1	**87.1**	**86.9**	**86.7**	**87.2**	**41.1**	41.7	39.0	32.9
CL: PBNR	90.7	90.5	90.9	90.9	**87.1**	86.8	86.6	**87.2**	41.0	**41.8**	**39.1**	**36.4**
INCV (Chen et al., 2019)	87.8	88.6	89.6	89.2	84.4	76.6	85.4	73.6	28.3	25.3	34.8	29.7
Mixup (Zhang et al., 2018)	85.6	86.8	87.0	84.3	76.1	75.4	68.6	59.8	32.2	31.3	32.3	26.9
SCE-loss (Wang et al., 2019)	87.2	87.5	88.8	84.4	76.3	74.1	64.9	58.3	33.0	28.7	30.9	24.0
MentorNet (Jiang et al., 2018)	84.9	85.1	83.2	83.4	64.4	64.2	62.4	61.5	30.0	31.6	29.3	27.9
Co-Teaching (Han et al., 2018)	81.2	81.3	81.4	80.6	62.9	61.6	60.9	58.1	30.5	30.2	27.7	26.0
S-Model (Goldberger et al., 2017)	80.0	80.0	79.7	79.1	58.6	61.2	59.1	57.5	28.4	28.5	27.9	27.3
Reed (Reed et al., 2015)	78.1	78.9	80.8	79.3	60.5	60.4	61.2	58.6	29.0	29.4	29.1	26.8
Baseline	78.4	79.2	79.0	78.2	60.2	60.8	59.6	57.3	27.0	29.7	28.2	26.8



Label issues in the 2012 ILSVRC ImageNet train set using CL



Label issues in the WebVision train set using CL

Conclusion

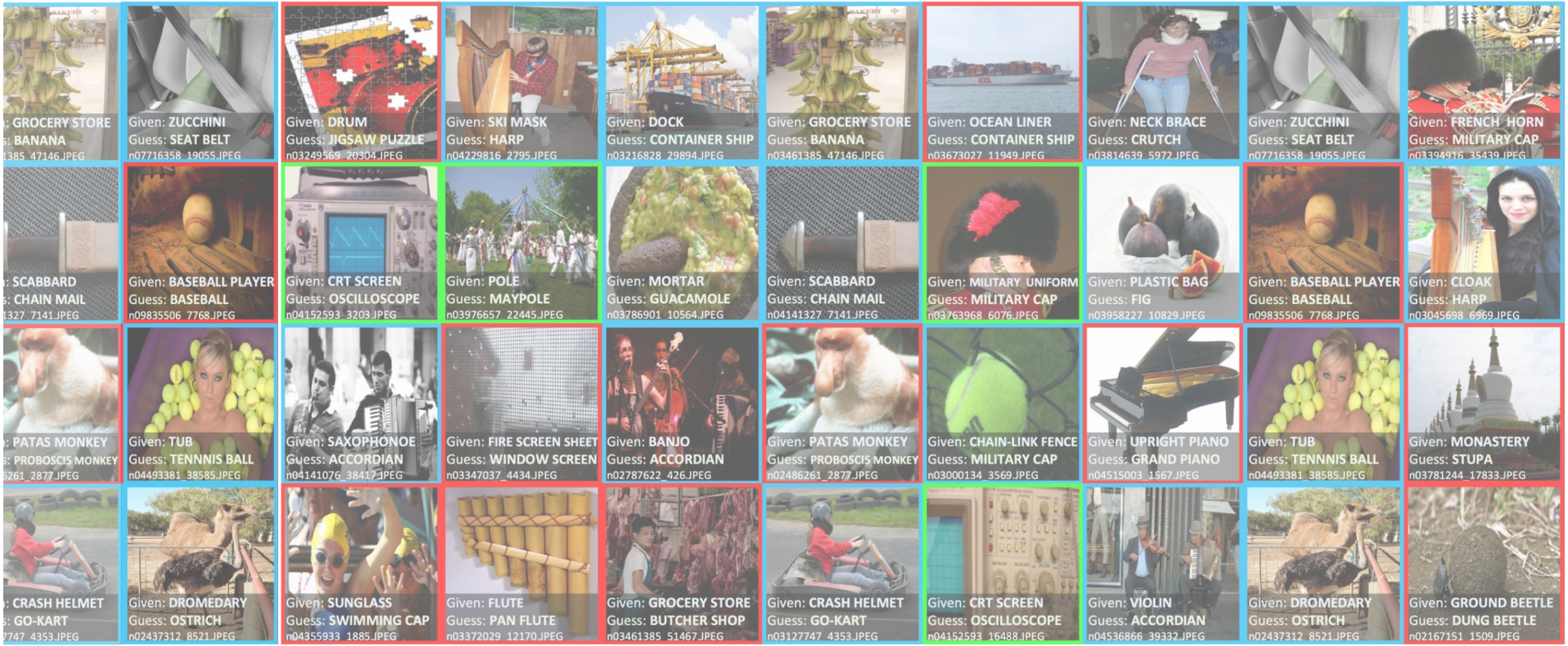
- The practical nature of confident learning by identifying numerous pre-existing label issues in ImageNet, Amazon Reviews, MNIST, and other datasets.
- CL can improve the performance of learning models like Deep Neural Networks by training on a cleaned dataset.
- CL motivates the need for further understanding of dataset uncertainty estimation, methods to clean training and test sets, and approaches to identify ontological and label issues for dataset curation.

Future work

- The validation of CL methods on more datasets
- Using other non-neural network models, su as random forests and XGBoost
- Examination of other threshold function formulations & examination of label errors i test sets and they affect machine learning benchmarks at scale

Reference

Paper Link: Confident Learning: Estimating Uncertainty in Dataset Labels



Confident Learning: Estimating Uncertainty in Dataset Labels

Esmaeil Shakeri

ENSF619.2, November 2021

UNIVERSITY OF CALGARY