# L1 Graph Based Sparse Model for Label De-noising

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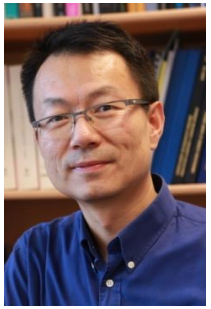


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Centre for Intelligent Sensing
Queen Mary University of London

# Motivation

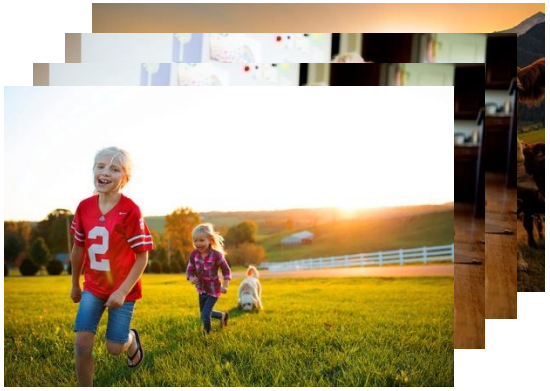
- Vision research recently focuses on large scale problems
- Large amount of labelled images from large number of categories are required

| | #Samples | #Categories |
|---|---|---|
| ImageNet | 1.2 million | 1000 |
| MS COCO | 328 K | 91 |
| NUS-WIDE | 270 K | 81 |

# Motivation

Manual Annotated Dataset

Visual Resource:



Visual Data
From Web

Manual Annotation

Labels:
Person
Dog
Grass
Sky
Sun
…

Associated User Provided Tags:
Sunshine, Run, Girls, Dog, …

Social Media Dataset

CIS centre for intelligent sensing

*Image samples from Flickr.com

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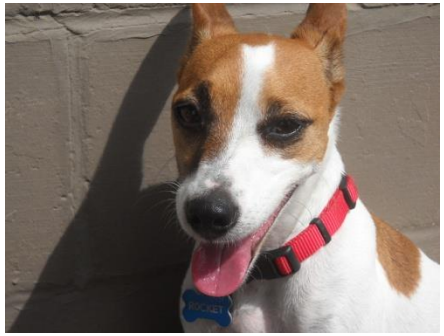
# Comparisons on Labels/Tags

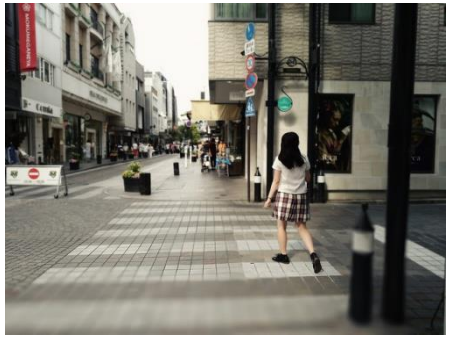
| | Pros | Cons |
|---|---|---|
| Manual Annotated Datasets | Accuracy | Expensive |
| Social Media Datasets | Accessibility | Noisy labels/tags |

# Noisy Tags (Labels)



User-Provided Tags:
Rocket
Animal
Dog

De-noised Tags:
Animal
Dog



User-Provided Tags:
Street
Japan

De-noised Tags:
Street
Japan
Person

BLUE: Correct Tag
RED: Wrong Tag
GREEN: Missing Tag

} Noisy Tags (Labels)

# Solutions

In order to exploit the Social Media Dataset with Noisy Labels, two common paradigms:

Our Approach

- Label De-noising: Preprocessing to improve labels' quality before use by downstream tasks.

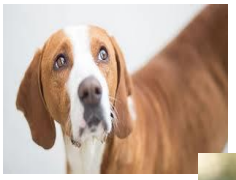
- Noise Robust Method: The object recognition algorithm is robust to Noisy Tags/Labels.

# Cues For Label De-noising

- **Visual Appearance Smoothness**

- Label Noise Pattern Modelling

# Visual Appearance Smoothness


dog


dog


Dog


dog


dog


person
dog


dog

person
dog


person


person

Visual Appearance Smoothness: Labels should vary smoothly with visual appearance.

# Visual Appearance Smoothness

- Challenge: Visual Outliers


Wedding Wedding

Visual Different, Label Similar


Cat Tiger

Visual Similar, Label Different

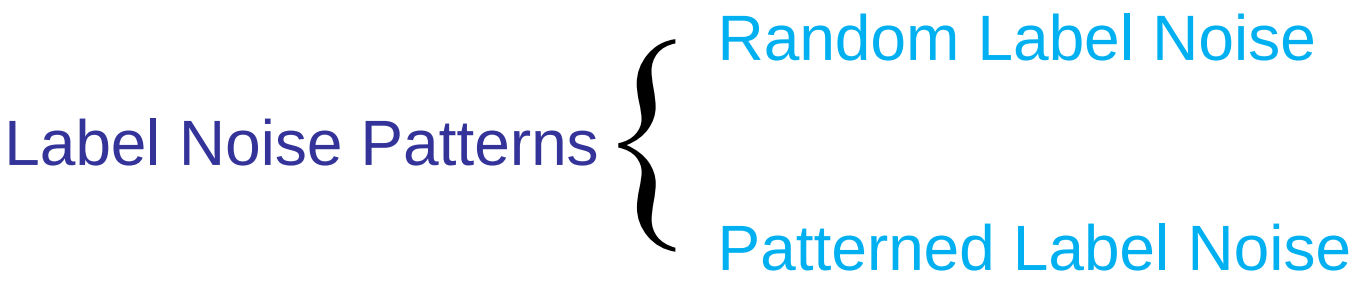
Conventional models are sensitive to visual outliers.

# Cues For Label De-noising

- Visual Appearance Smoothness

- **Label Noise Pattern Modelling**

# Label Noise Patterns Modelling



# Label Noise Patterns Modelling

## Random Label Noise

ocean / sunset / person / wedding

rainbow / animal / bird

birds / lake / moon / sky

BLUE: Correct Label
RED: Wrong Label
GREEN: Missing Label

- User-Specific Tagging Habits
- Random Labelling Mistakes

# Label Noise Patterns Modelling

Patterned Label Noise widely exists in User Provided Noisy Tags.

garden / flowers

garden / flowers

Highly Correlated

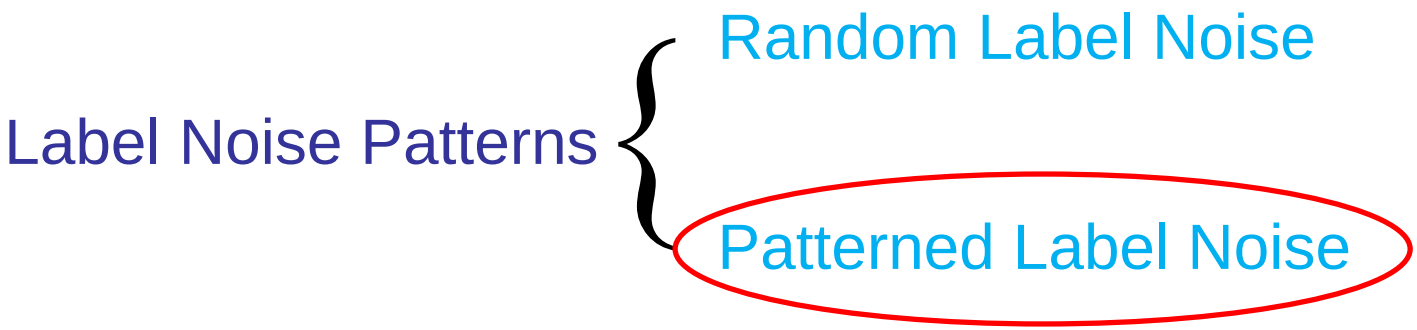
person / flowers / grass

ocean / sunset / person / wedding

General User Tagging Bias

BLUE: Correct Label
RED: Wrong Label
GREEN: Missing Label

# Label Noise Patterns Modelling




Limitations of existing approaches:

1. Requiring a subset of clean labels, which may not exists;

2. Not combining with other cues (e.g. visual appearance smoothness).

# Our Approach

| Limitations of existing models | Our Approach |
|---|---|
| Sensitive to Visual Outliers | 1.More robust ($L_1$ Graph); |
| Clean labels are required | 2. No need clean labels;<br>3. Explicit noise pattern modelling; |
| | 4.Combining the two cues |

**$L_1$ G**raph based **S**parse model with explicit noise **P**attern modelling ($L_1$GSP)

# Objective

$$\min_{\hat{Y},Q} \left\| S\hat{Y} \right\|_1 + \gamma \left\| \hat{Y} - YQ \right\|_1 + \frac{\beta}{2} \left\| Q \right\|_F^2$$

Notations:

$\hat{Y}$ : De-noised Labels

$Q$ : Transition Matrix

$Y$ : Noisy Labels

$L$ : Image Laplacian Graph

$L = S^T S$

Combining Visual Similarity Cue with Label Noise Pattern Cue

# Results on PascalVOC2007

mean Average Precision (mAP)

| | GT | NL | $L_2$VG [ICML'04] | $L_2$VGLG [ICPR'14] | RPCA [ICM'10] | $L_1$GSP |
|---|---|---|---|---|---|---|
| De-noising | - | - | 52.21 | 55.01 | 56.39 | **60.09** |
| Testing | 71.98 | 42.34 | 40.33 | 42.10 | 53.54 | **58.66** |

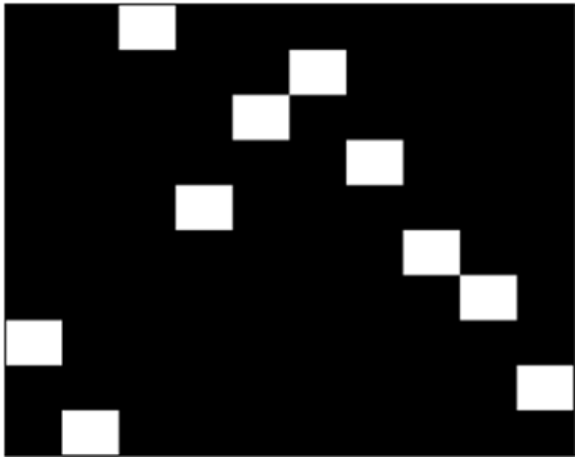
The De-noising performance of $L_1$GSP is 3.70 higher than the best competitor's result;
Consequently, $L_1$GSP achieves 5.12 higher Testing performance than RPCA.

# Label Noise Patterns

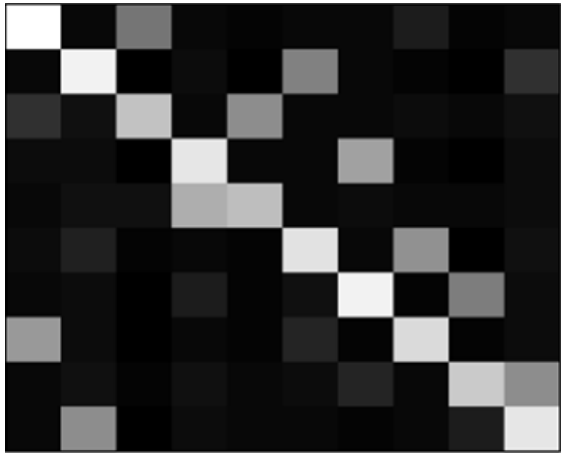
GT Patterns

Learned Patterns

MNIST

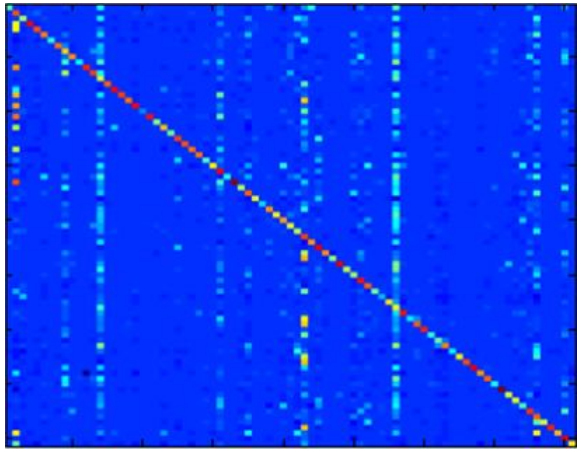


(a)

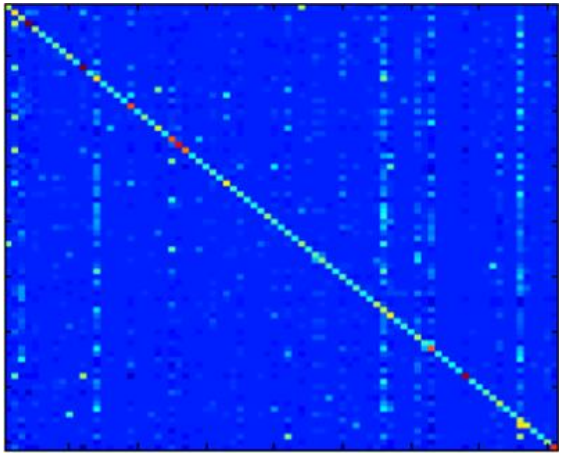


(b)

NUS-WIDE



(c)



(d)

# Q & A

Thanks For Your Attention