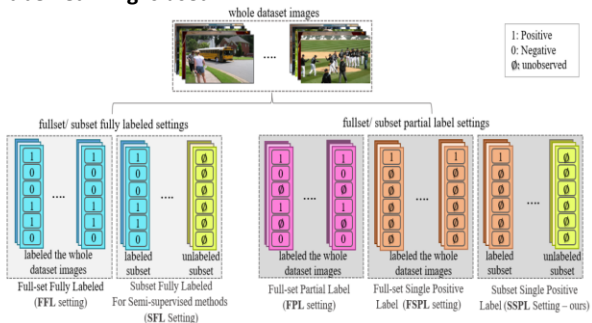
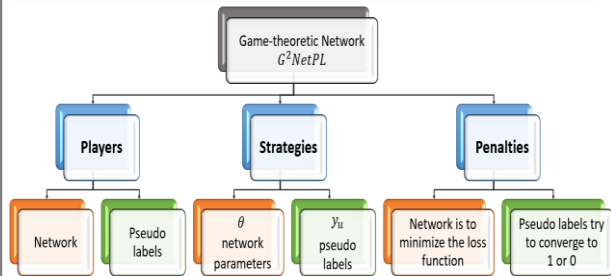


## Motivation

- Multi-label image classification aims to predict all possible labels in an image which it is **expensive** to annotate all the labels.
- To relieve the annotation burden of full labeling, **partial-label learning** is used.

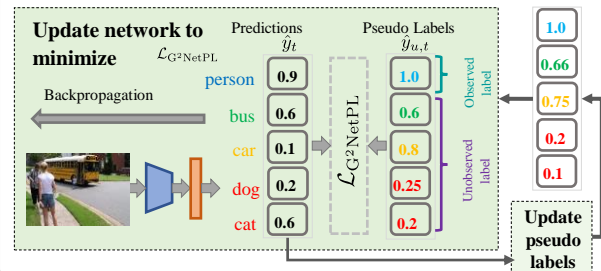


## Basic elements of Game



## Overview of $G^2NetPL$

In  $G^2NetPL$ , each unobserved label is associated with a soft pseudo label, which, together with the network, formulates a two-player non-zero-sum non-cooperative game.

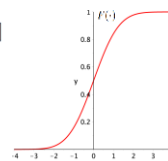


## Loss Functions

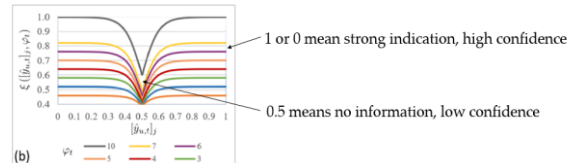
$$\mathcal{L}_{ACE}(\hat{y}_t, y_{u,t}) = \sum_{j=1}^J [\mathcal{L}(\hat{y}_{t,j}; F(y_{u,t,j})) + \lambda_j F(y_{u,t,j})(1 - F(y_{u,t,j}))]$$

$$\mathcal{L}_{G^2NetPL} = \mathcal{L}_{obs} + \mathcal{L}_{unobs}$$

$$\mathcal{L}_{unobs} = \sum_{i \in \mathcal{I}} \sum_{j \in \mathcal{U}_i} \xi(\hat{y}_{u,t,j}, \phi) \mathcal{L}(\hat{y}_{t,j}, \hat{y}_{u,t,j})$$



The pseudo labels will gradually build up their confidence during iterations.

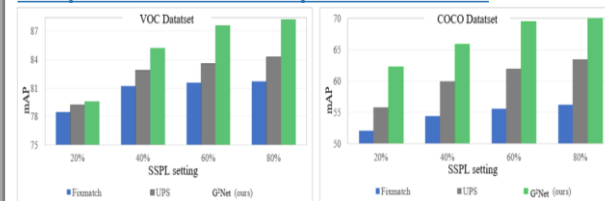


## Experiments

Table 1: Quantitative results (mAP) of multi-label image classification on four different datasets. Bold represents the highest mAP and underline represents the second-best among FSPL setting (Single positive and No negative).

Losses	Observed		End-to-End Setting		
	Positive	Negative	VOC	COCO	NUS
$\mathcal{L}_{BCE}$ [25]	All	All	89.1	75.5	52.6
$\mathcal{L}_{BCE-LS}$	All	All	90.0	76.8	53.5
$\mathcal{L}_{AN}$ [18]	Single	No	85.1	64.1	42.0
$\mathcal{L}_{AN-LS}$ [7]	Single	No	86.7	<u>66.9</u>	44.9
$\mathcal{L}_{WAN}$ [22]	Single	No	86.5	64.8	<u>46.3</u>
$\mathcal{L}_{EPR}$ [7]	Single	No	85.5	63.3	46.0
$\mathcal{L}_{ROLE}$ [7]	Single	No	<u>87.9</u>	66.3	43.1
$\mathcal{L}_{G^2Net}$ (ours)	Single	No	<b>88.8</b>	<b>72.4</b>	<b>49.7</b>

## Comparison with Semi-supervised models:



## Convergence of pseudo labels during the epochs:

