

# Image Classification With Semi- Supervised Learning

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Stat 453 | SP21

**INTRODUCTION 01**

**MOTIVATION 02**

**RELATED WORK 03**

# **TABLE OF CONTENTS**

**04 DATASET**

**05 MODELS &  
METHODS**

**06 RESULTS &  
CONCLUSION**

# 01

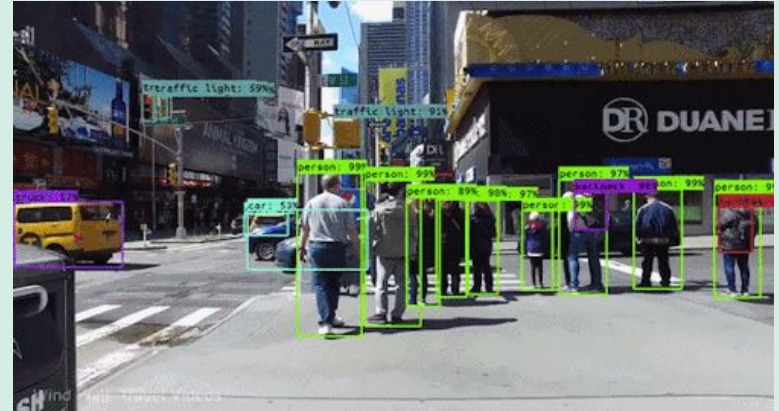
## INTRODUCTION

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# INTRODUCTION

## What is an Image Classification?

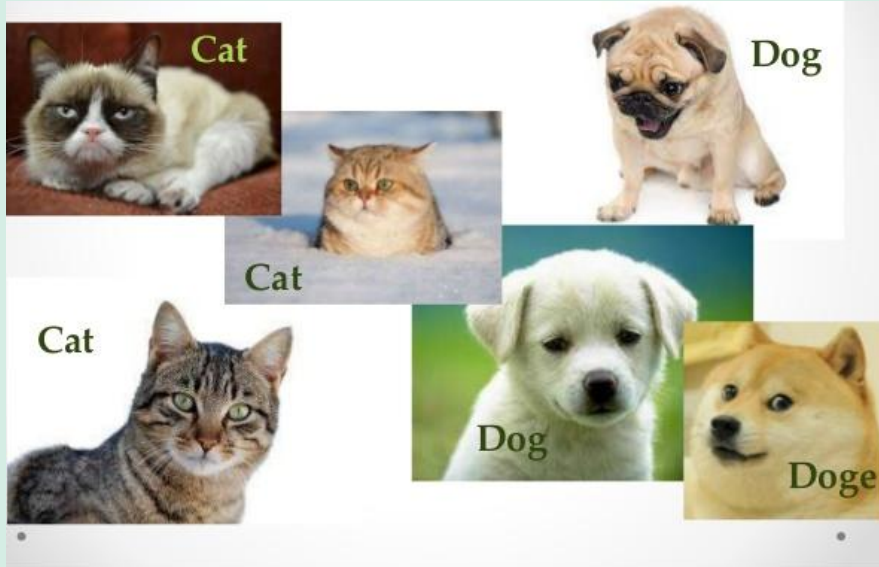
- Defining set of target classes and train a model to recognize them using labels



## Most popular learning methods for Image Classification?

- CNN

# INTRODUCTION

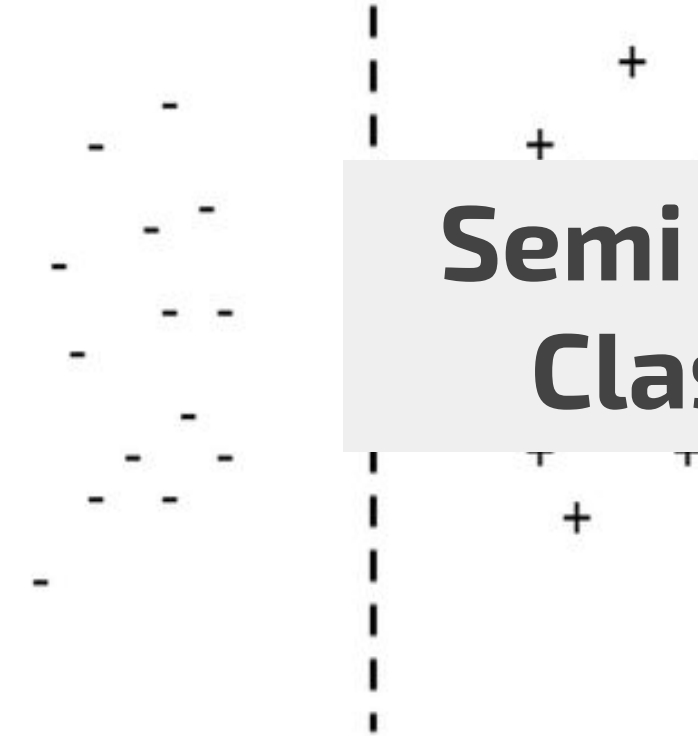


## Types of Image Classification

- Supervised Classification
- Unsupervised Classification
- Object-based Image Analysis

+ and - are labeled points  
● are unlabeled points

# Semi - Supervised Classification!



(a)



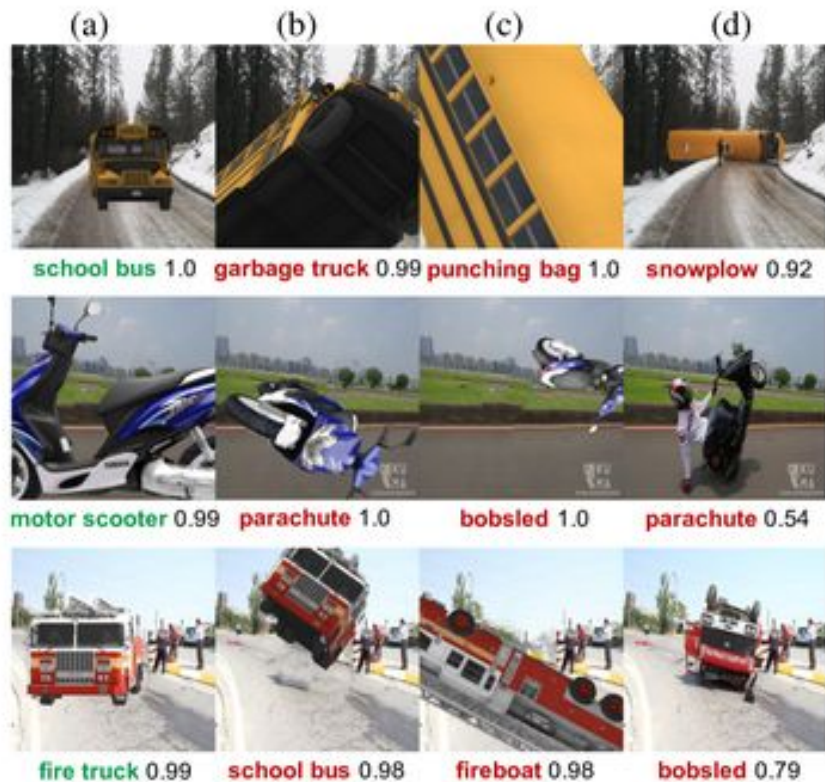
(b)

**02**

**MOTIVATION**

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# MOTIVATION





# MOTIVATION

**“Minimizing combined  
loss function of  
autoencoder and  
classifier”**



**“Modeling joint  
distribution of an input  
vector and target  
class”**

# MOTIVATION

**Less Accurate  
Complicated  
Slow**

“Minimizing combined  
loss function of  
autoencoder and  
classifier”

“Modeling joint  
distribution of an input  
vector and target  
class”

# Motivation

How to create **simple** yet **accurate**  
image classification method?

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# 03

## RELATED-WORK

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## Related Work: Summary

“For **Unlabeled data (Pseudo Labels)**,  
Choose the class with maximum predicted  
probability just like the **true labels**”



Dong-Hyun Lee, 2013

In another word,  
We provide **artificial** label to the unlabeled data by  
choosing the most likely predicted label

## Related Work: Why We Chose This Article - 1)

Classification Error on MNIST Test Set

METHOD	100	600	1000	3000
NN	25.81	11.44	10.7	6.04
SVM	23.44	8.85	7.77	4.21
CNN	22.98	7.68	6.45	3.35
TSVM	16.81	6.16	5.38	3.45
DBN-rNCA	-	8.7	-	3.3
EMBEDNN	16.86	5.97	5.73	3.59
CAE	13.47	6.3	4.77	3.22
MTC	12.03	5.13	3.64	2.57
DROPNN	21.89	8.57	6.59	3.72
+PL	16.15	5.03	4.30	2.80

+PL = Pseudo - Label section

- **Highly accurate among small sets of data**

(Smallest Error in each 100, 600, 1000, 3000 labeled data is highlighted in blue)

## Related Work: Why We Chose This Article - 2)



ple method that gives good but not optimal results. David Thaler and Lukasz Romaszko both observed that learning the sparse filtering features on the combination of the labeled and unlabeled data worked *worse* than learning the features on just the labeled data. This may be because the labeled data was drawn from the more difficult portion of the SVHN dataset. Dong-Hyun Lee [8] finished second in the contest, having independently rediscovered entropy regularization [9]. This very simple means of semi-supervised learning proved surprisingly effective and merits more attention. In third place, Dimitris Athanasakis and John Shawe-

# 04

## DATASETS

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# Datasets

## Labeled training set

→ 200 labels



### Class labels

n02124075

n04067472

n04540053

n04099969

n07749582

## Unlabeled training set

→ 90000(450\*200) images

## Validation set

→ 10000 images

Name	Label				
val0.JPEG	n03444034	0	32	44	62
val1.JPEG	n04067472	52	55	57	59
val2.JPEG	n04070727	4	0	60	55
val3.JPEG	n02808440	3	3	63	63
val4.JPEG	n02808440	9	27	63	48
val5.JPEG	n04399382	7	0	59	63

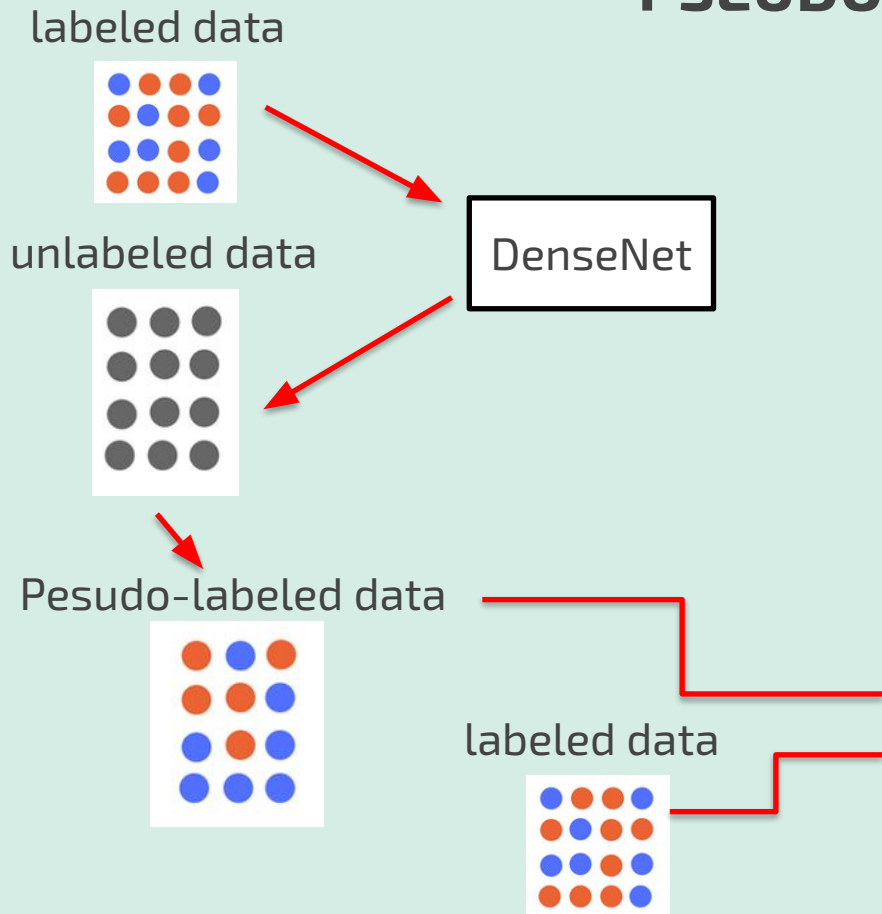
Table 2. Validation images and labels

## Test set

**05**

**MODELS & METHODS**

# PSEUDO - LABEL



1. Train the model with labeled data

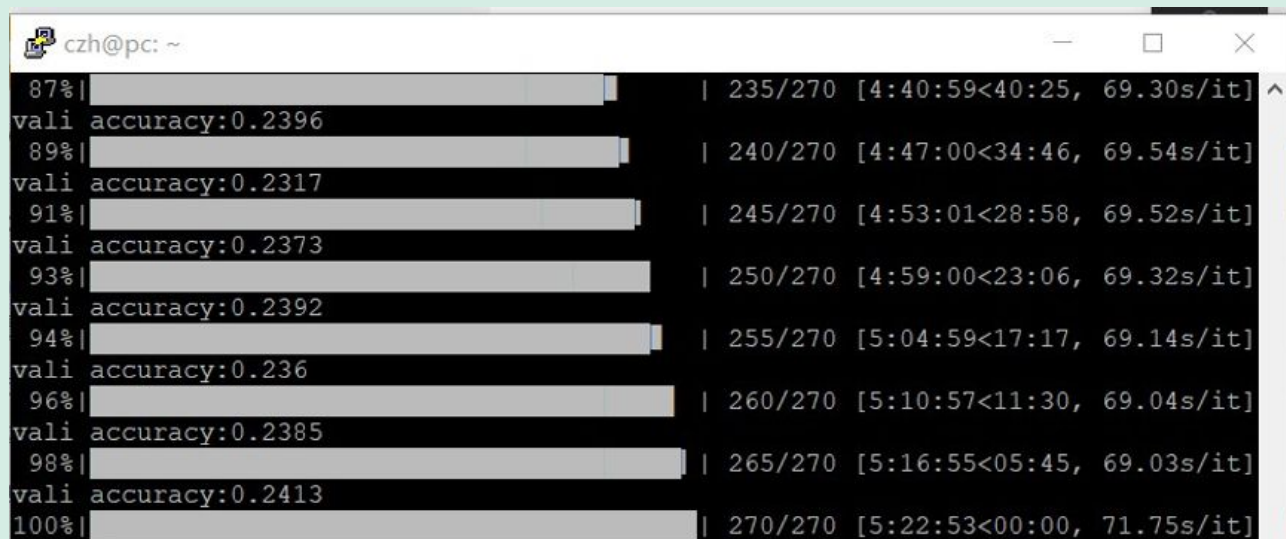
2. Use the trained DenseNet to predict labels for the unlabeled data

3. Retrained the DenseNet with the pseudo and labeled datasets together

**06**

**RESULTS &  
CONCLUSION**

# RESULTS



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# THANK YOU!

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