

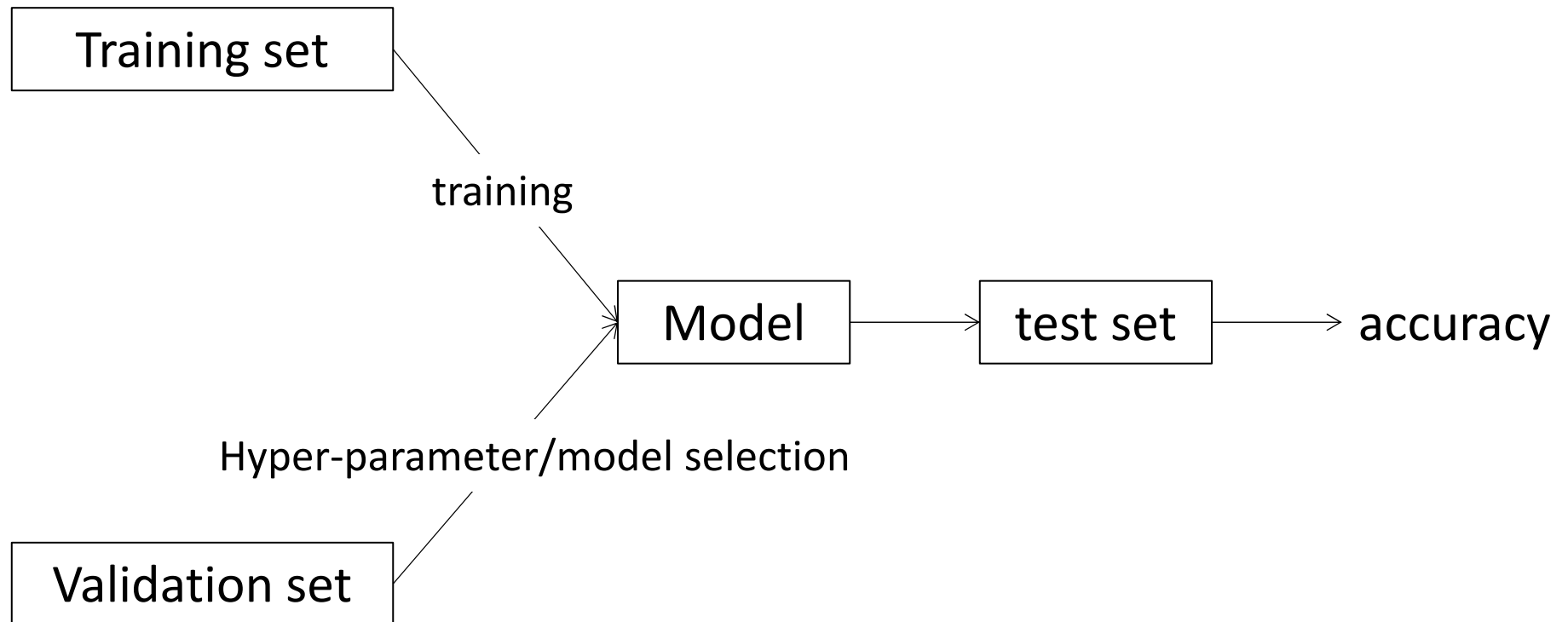
# Data-centric Computer Vision

Liang Zheng

Australian National University

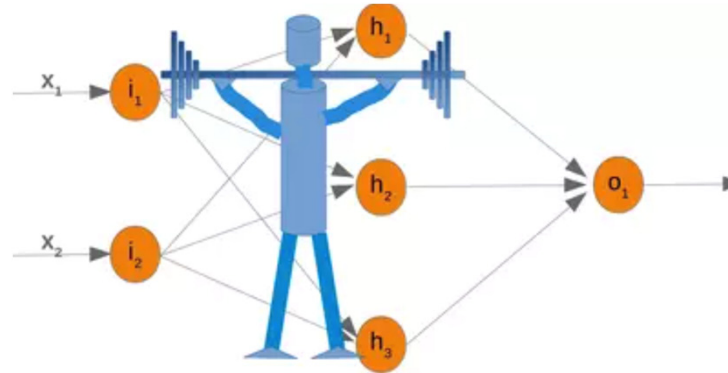
20 February 2023

# Pillars in machine learning

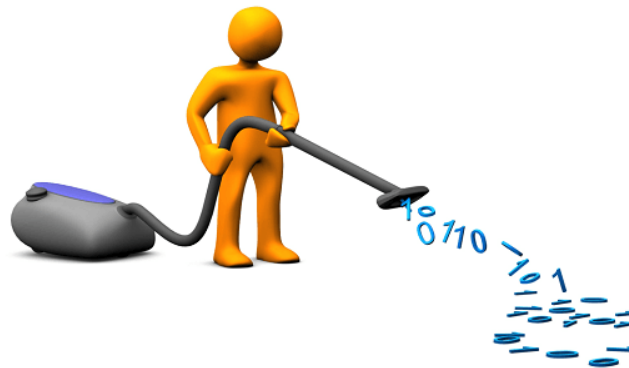


Now suppose you are a researcher working at Google. You probably spend

- half your time configuring your network

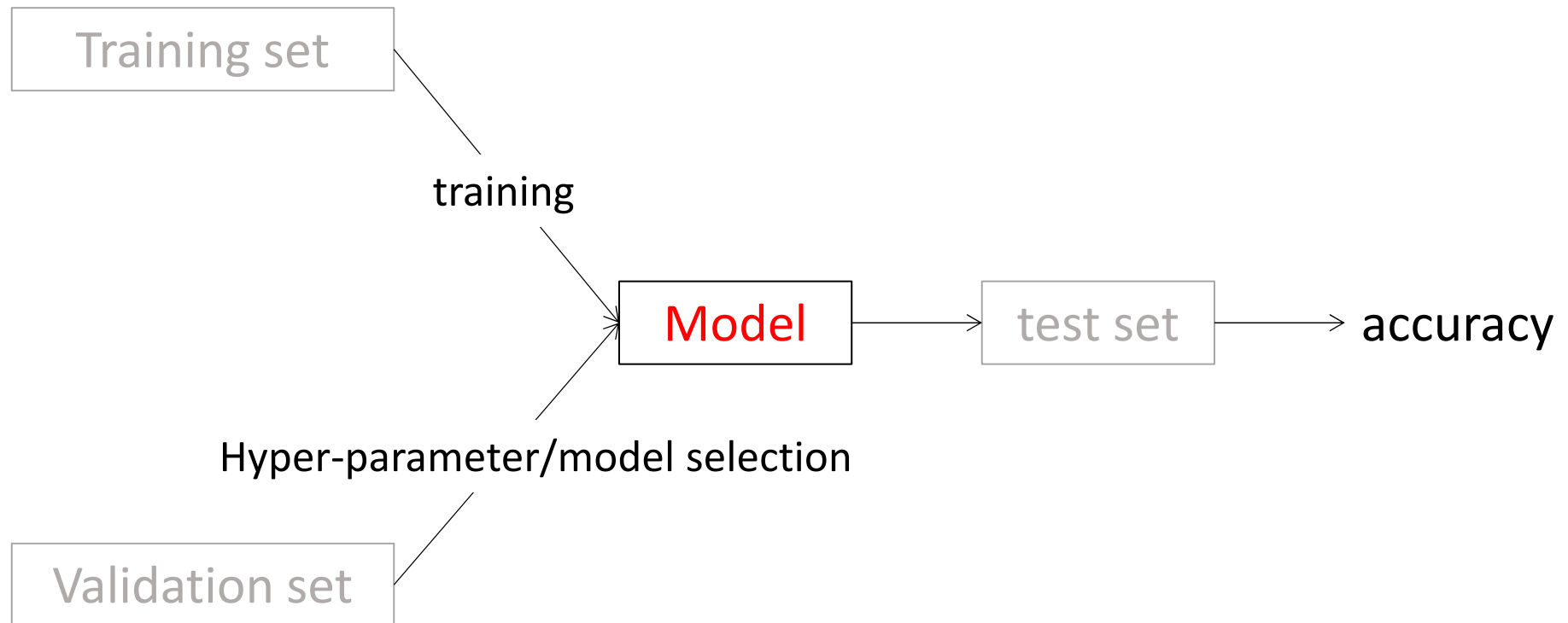


- the other half of your time collecting/cleaning data



# What most works are studying

*algorithm-centric research*



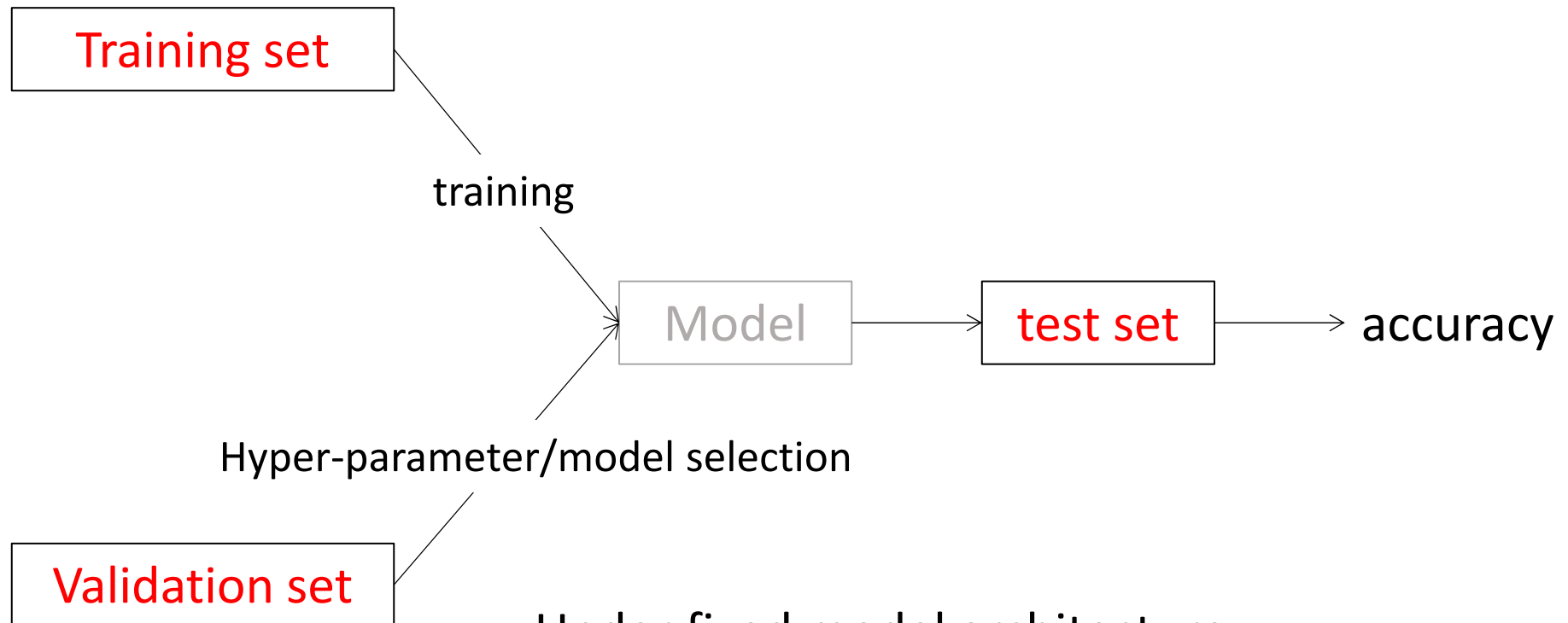
**Features:** SIFT, GIST, color histogram, etc

**Hand-crafted models:** SVM, boosting, sparse coding etc

**Deep models:** ResNet, DenseNet, Transformers...

# What I'm going to talk about

## *data-centric research*



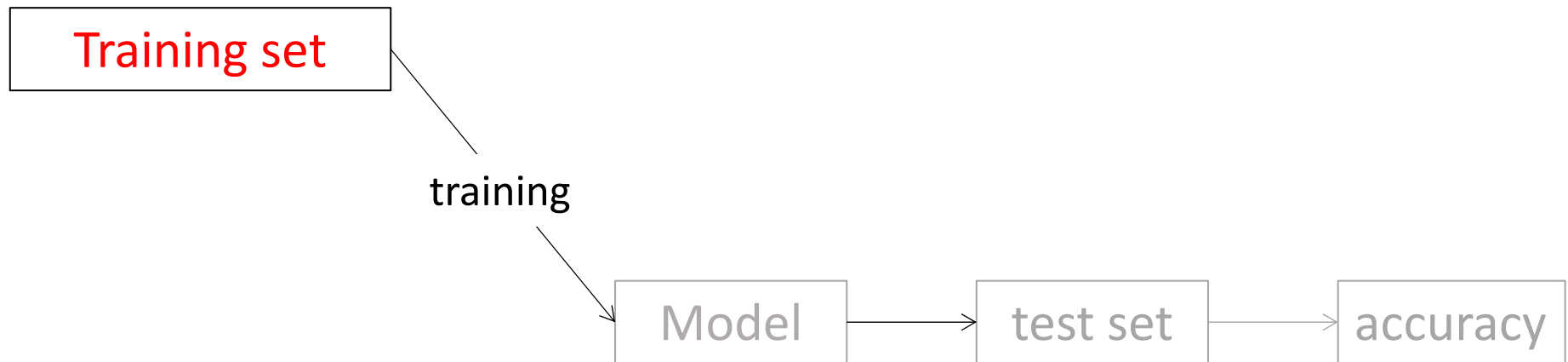
Under fixed model architecture,

- Can we improve the training data?
- Can we find good validation data?
- Can we estimate test set difficulty?

# Outline

- Training data optimization
- Validation data search
- Label-free model evaluation (estimate test set difficulty)

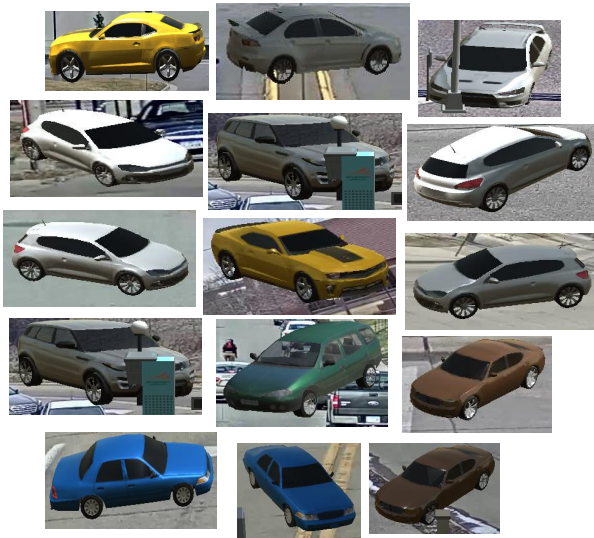
# Training data optimization



Objective: Given a model and a test set, we want to create a training set that gives us possibly high accuracy.

# Training (source) data optimization

source



target



domain gap?

Style/feature alignment

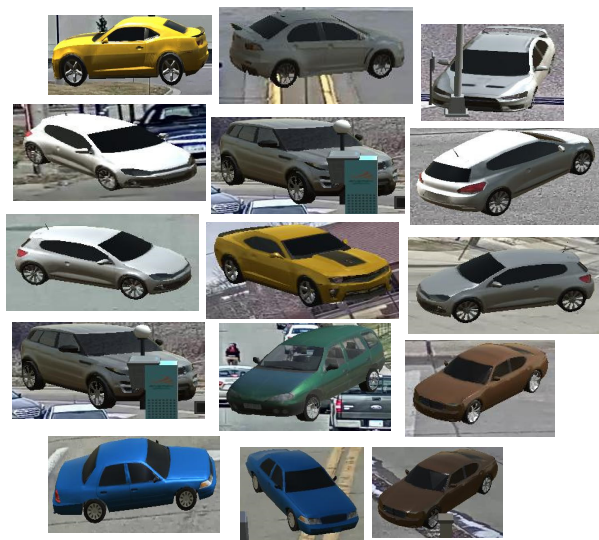
Content alignment



# Training (source) data optimization

idea

source



target



Objective: create a training set that has similar content with target data

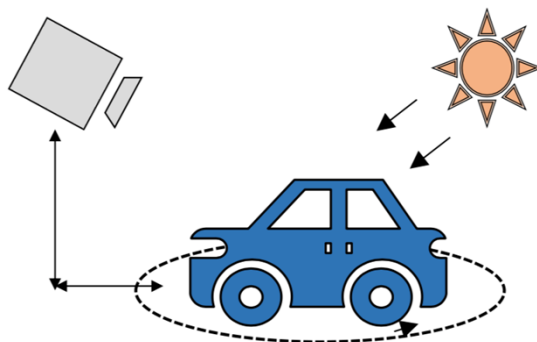
# We propose to use synthetic data



- + large-scale, quickly, accurately, cheaply Sun and Zheng, CVPR 2019
- + **controllability and editability**
- + challenging situation (danger forecast)
- + security and privacy issues
- + corner cases (heavy occlusion)
- different data distribution

# We collected the VehicleX Dataset

- 1,209 vehicles
- ~350 types of vehicles
- Platform: Unity
- Editable attributes: lighting direction, lighting intensity, vehicle orientation, camera height, camera distance



A Platform



B Vehicle identities

# Editable Attributes

vehicle orientation: 0° —————> 359°



light direction: East (0) —————> West (100)



light intensity: dark (0) —————> bright (100)



camera height: low (0) —————> high (100)

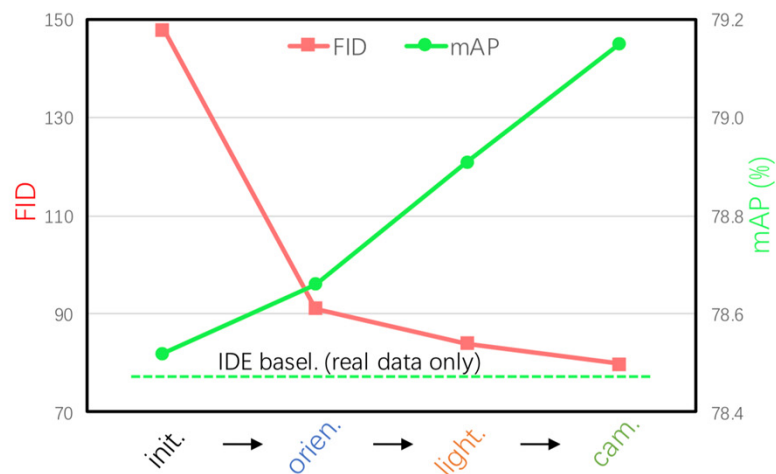


camera distance: near (0) —————> far (100)





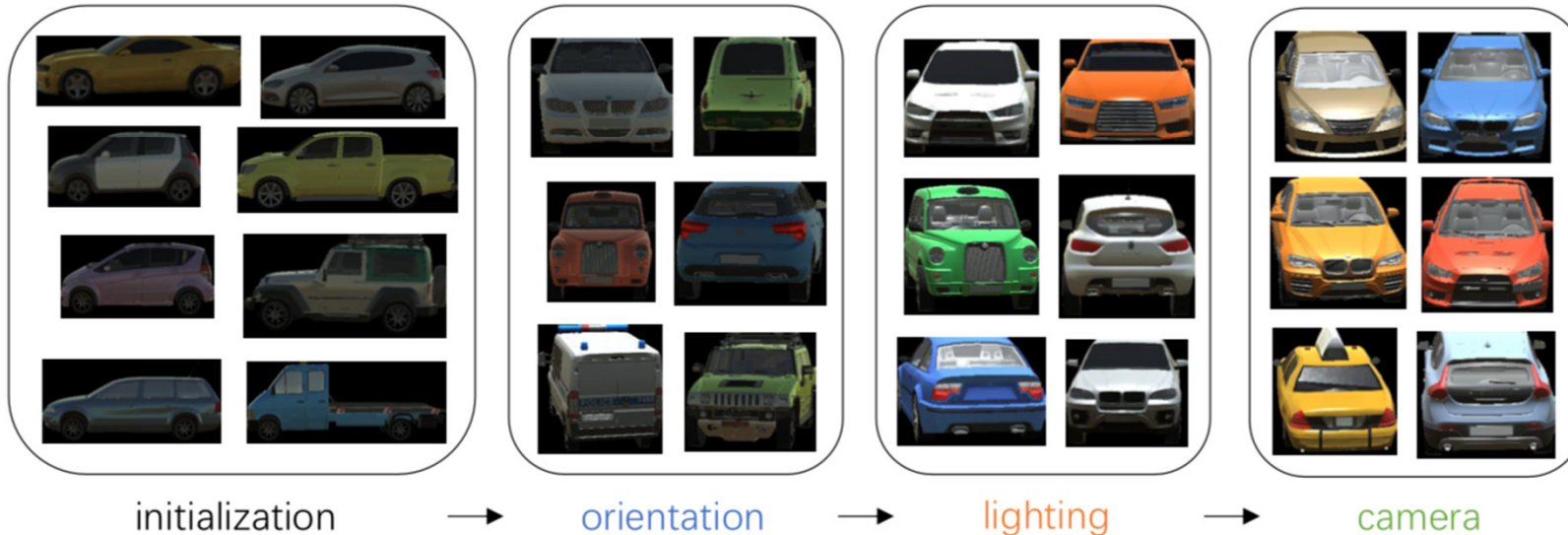
# Attribute descent



C real images



B vehicles simulated after different iterations



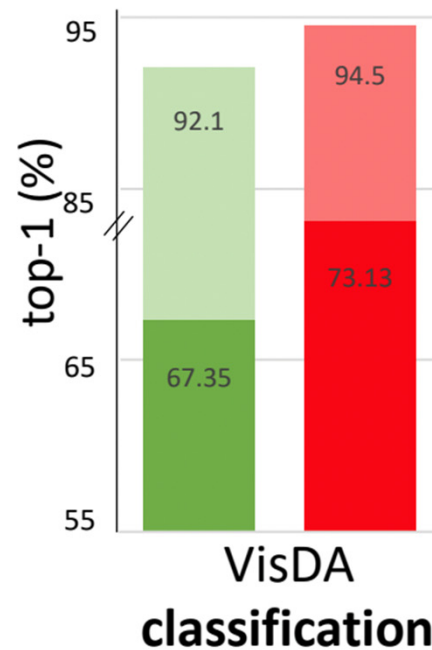
We optimize the value of each attributes successively

For a given attribute, we search (brute-force) for its optimum value such that FID is minimized

# Experiment – statistical significance

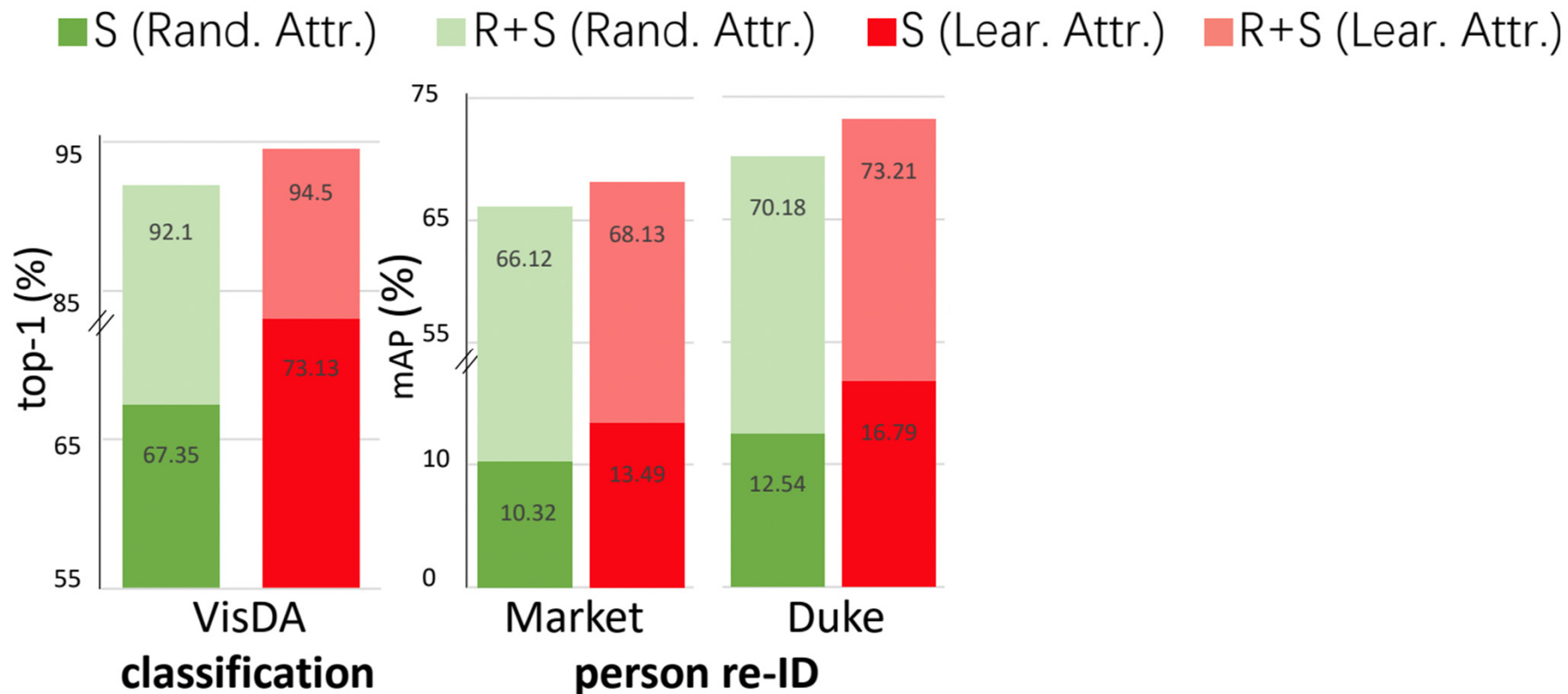
- Learned attribute vs. random attribute

■ S (Rand. Attr.)   ■ R+S (Rand. Attr.)   ■ S (Lear. Attr.)   ■ R+S (Lear. Attr.)



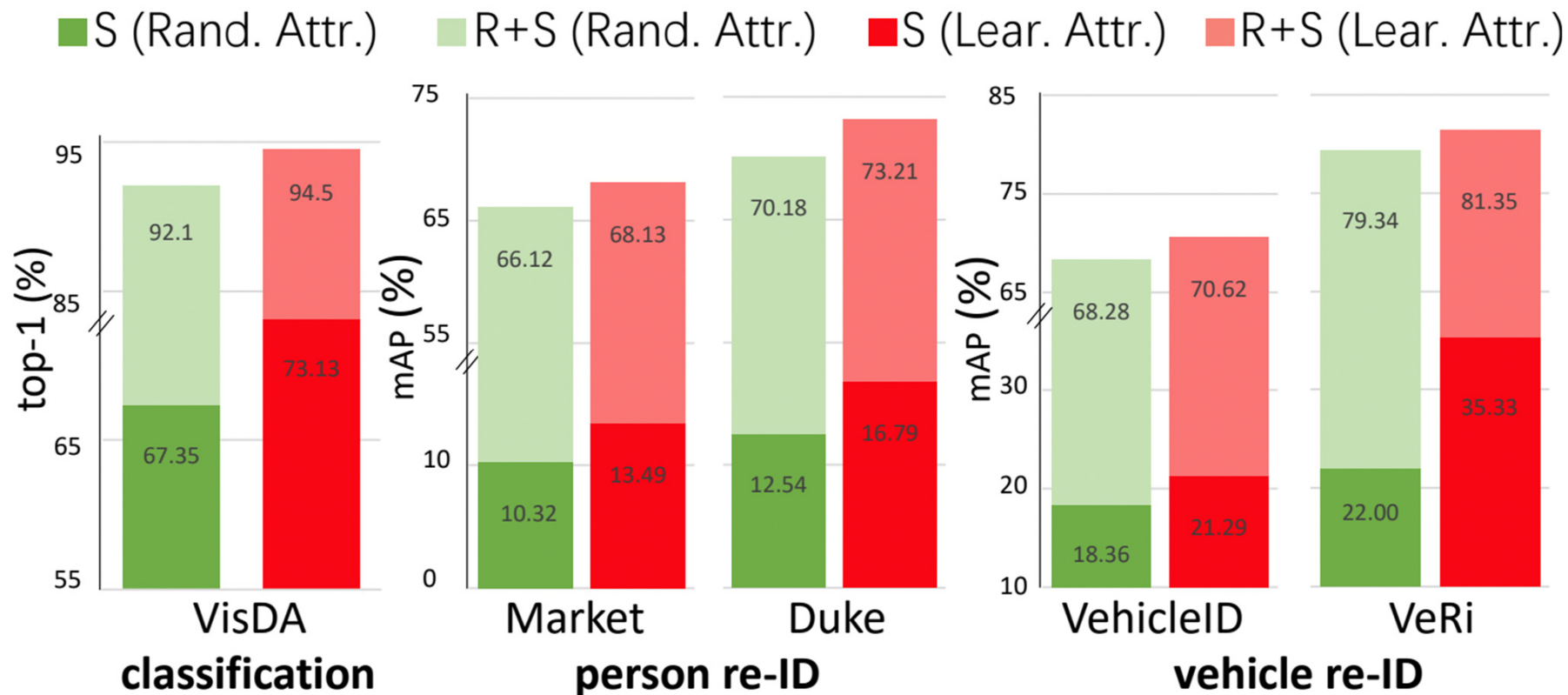
# Experiment – statistical significance

- Learned attribute vs. random attribute



# Experiment – statistical significance

- Learned attribute vs. random attribute

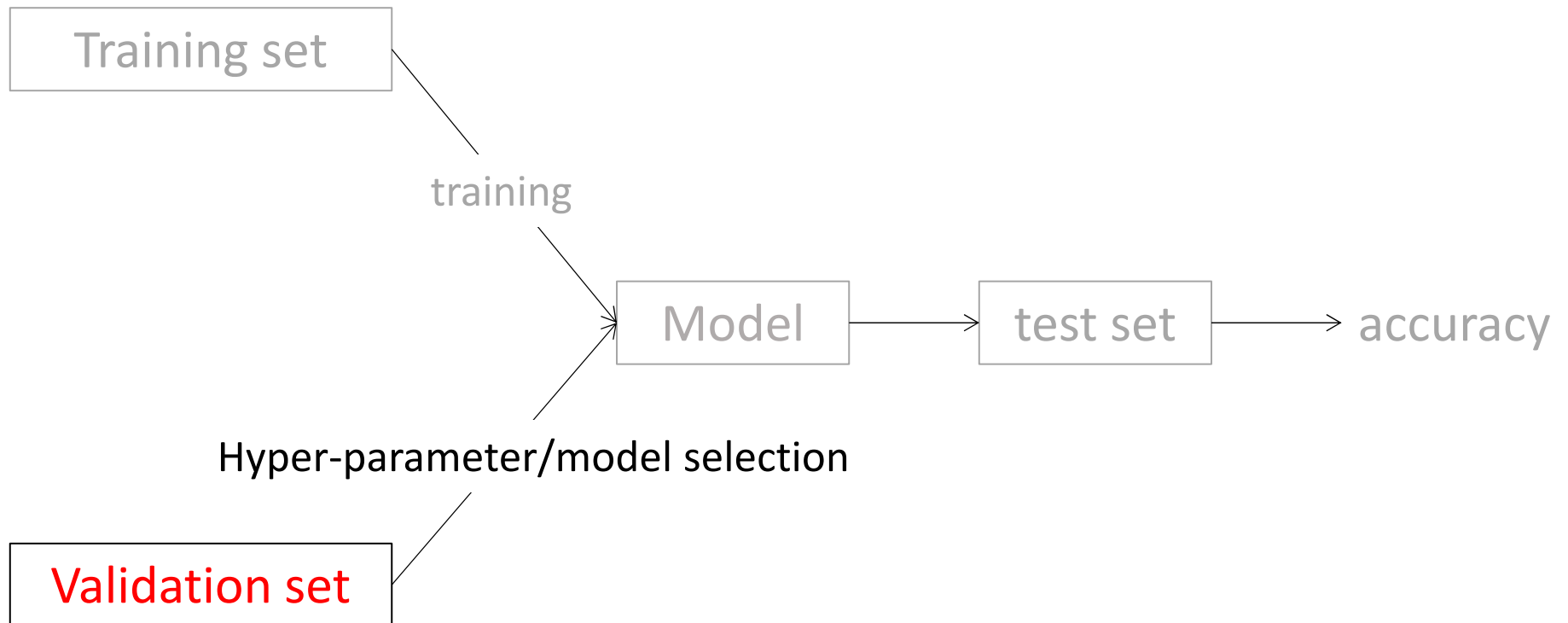




# Outline

- Training data optimization
- Validation data search
- Label-free model evaluation (estimate test set difficulty)

# Validation data search



# We usually select models using a validation set



Training set



Models A, B, C, D, E



Model comparison

**B** > **D** > **C** > **A** > **E**



validation set

We will deploy **B** in testing

However, if we deploy the models to another domain...



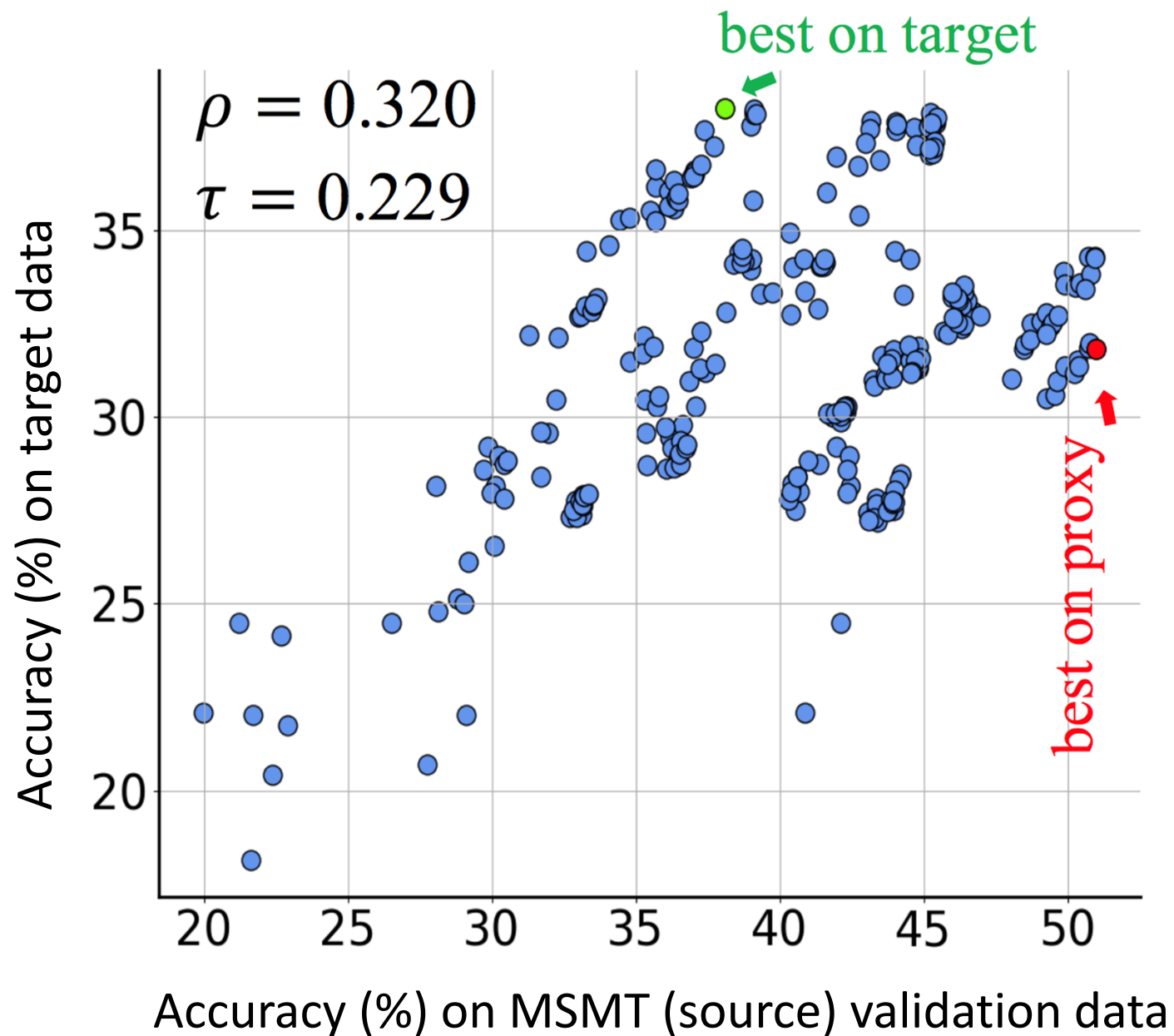
Training (source) data



Target data

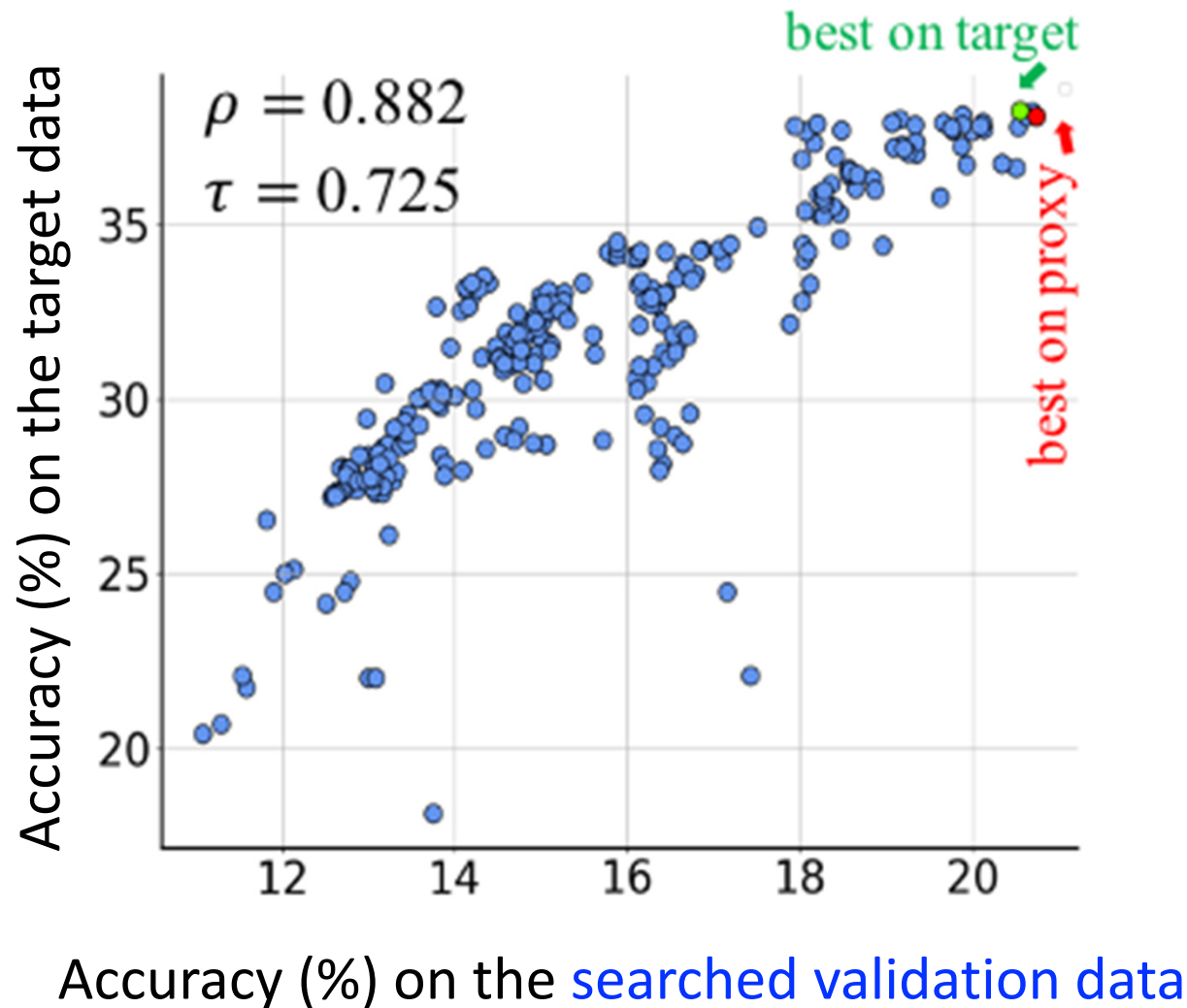
Will we still have  $B \succ D \succ C \succ A \succ E$  on this target domain?

280 models  
trained on the  
source



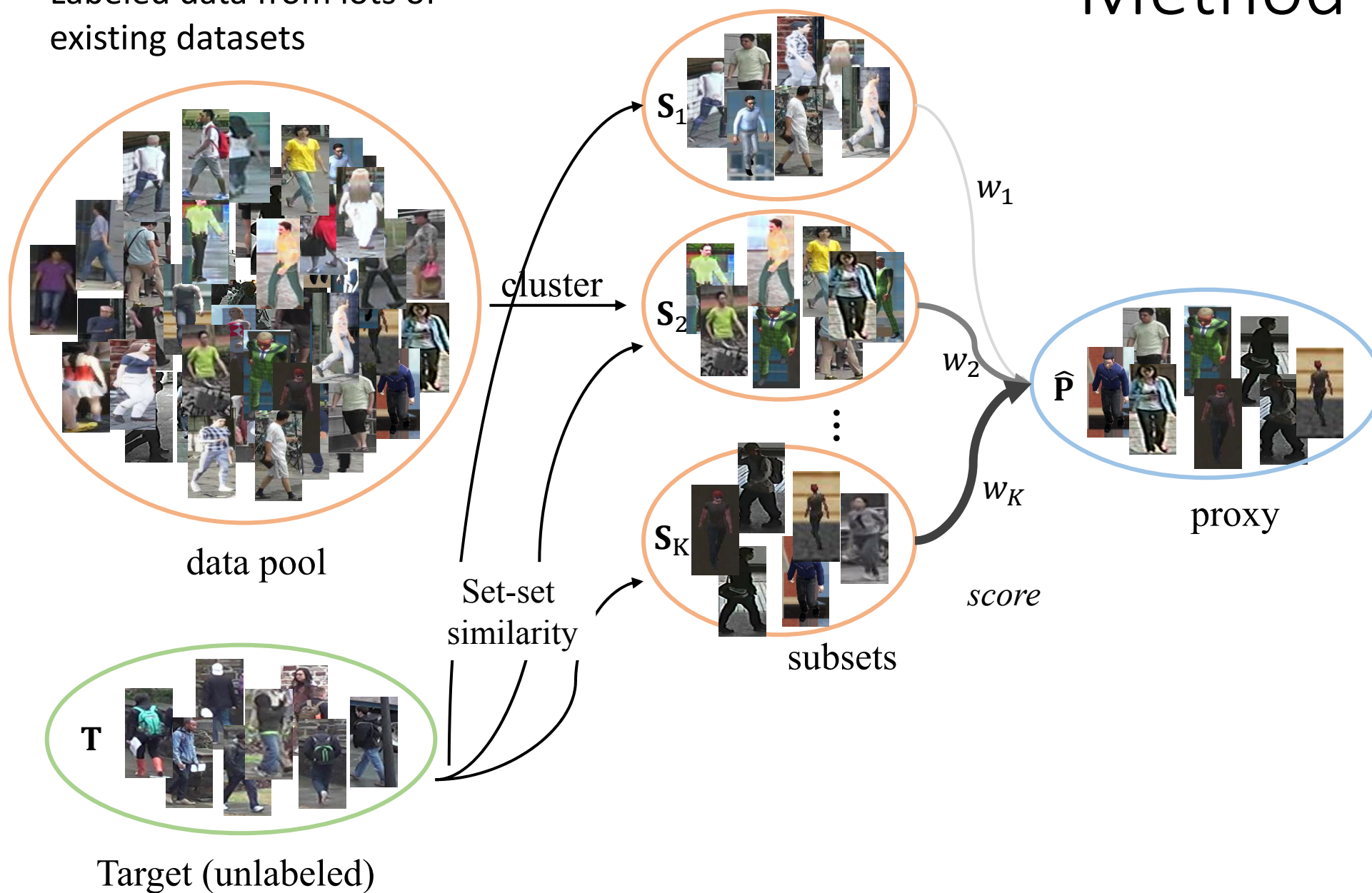
# We want to search a validation set that

- is fully labeled
- has similar distributions with the target data

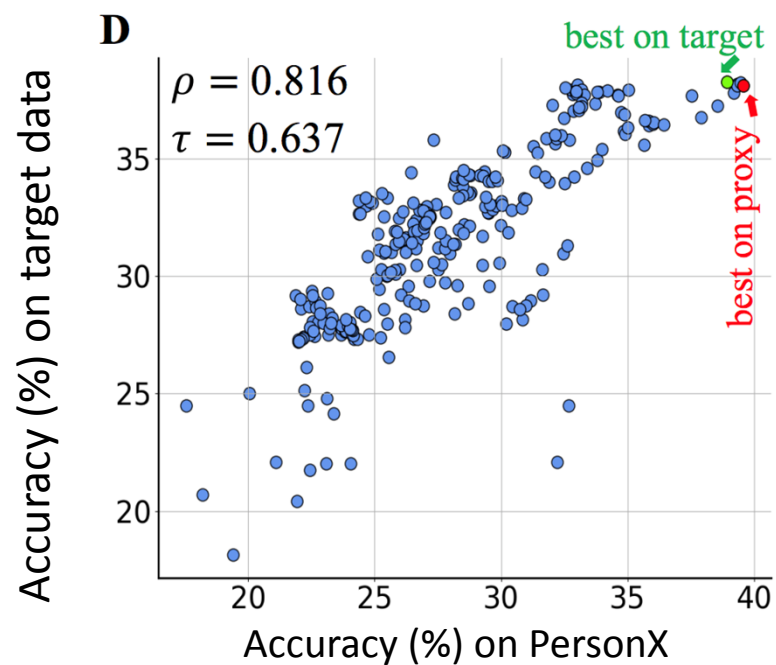
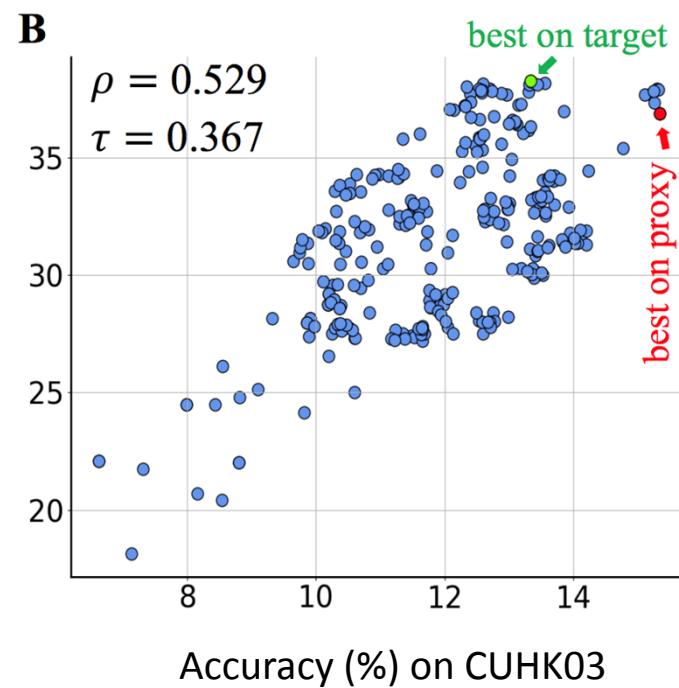
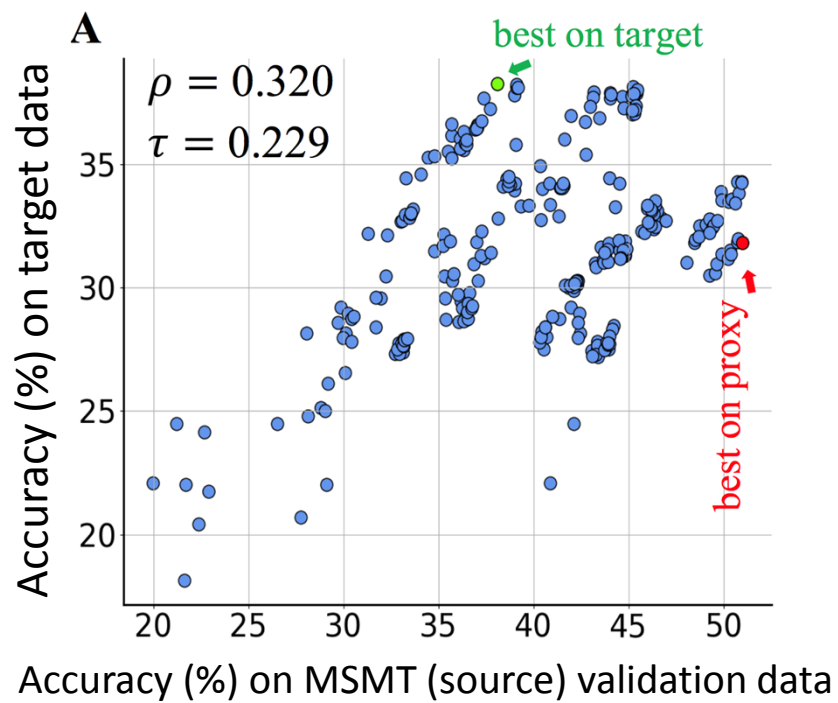


Labeled data from lots of existing datasets

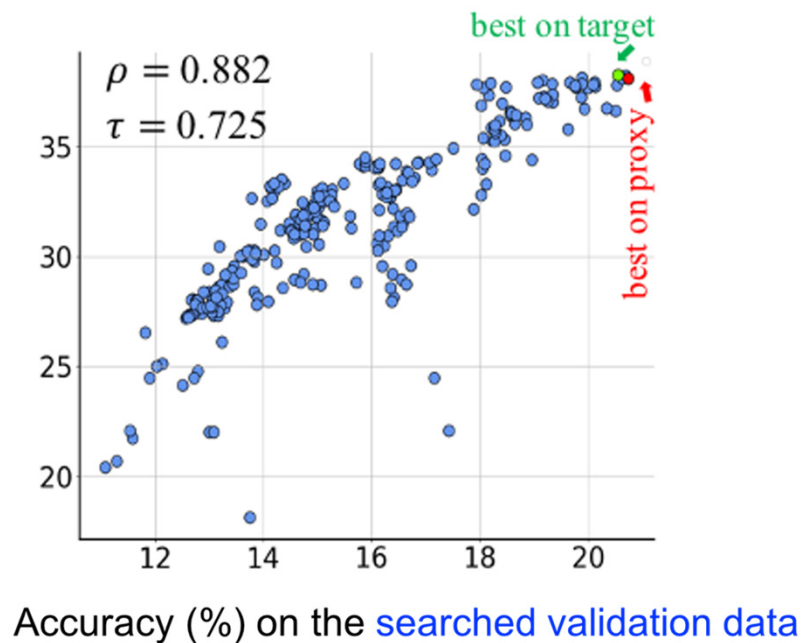
# Method







Accuracy (%) on target data

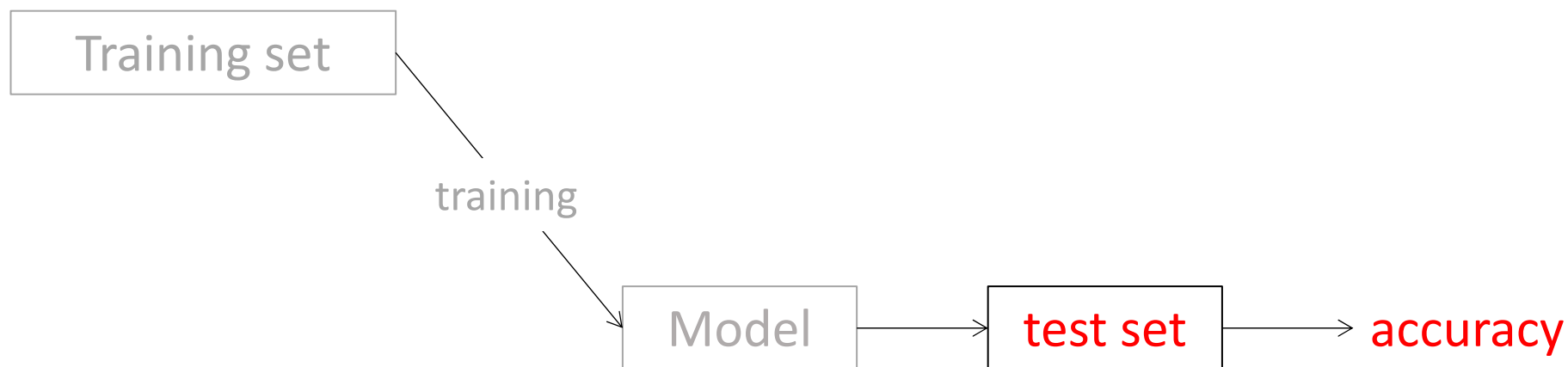




# Outline

- Training data optimization
- Validation data search
- Label-free model evaluation (estimate test set difficulty)

# Estimate test set difficulty (label-free model evaluation)



# Our usual way of evaluating models

- Yes



ImageNet



MSCOCO

Ground truths provided



LFW

However,...

We can't calculate a classifier accuracy!!

Suppose we deploy a cat-dog classifier to a swimming pool



Ground truths not provided

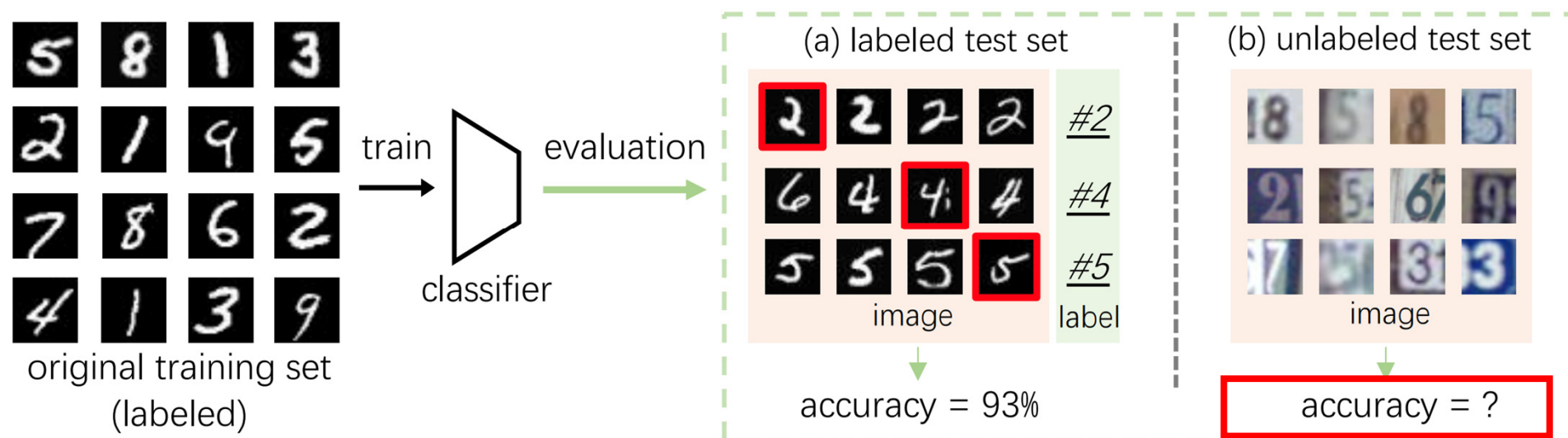
# We encounter this problem too many times in CV applications....

- Deploy a ReID model to a new community
- Deploy face recognition in an airport
- Deploy a 3D object detection system to a new city
- .....

We can't quantitatively measure the performance of our model like we usually do!!

Unless we annotate the test data..., but environment will change over time.... We need to annotate test data again

# Formally, we want to solve:



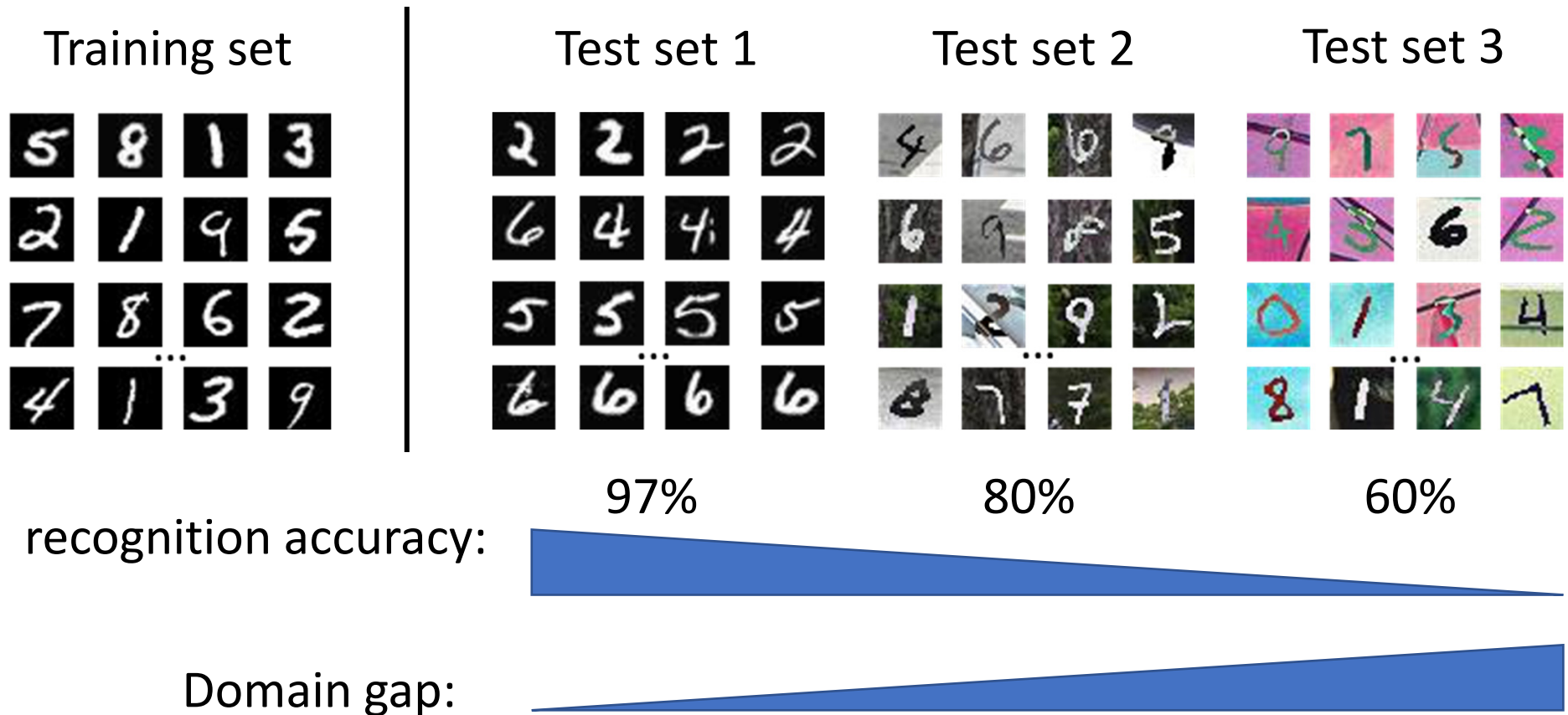
Given

- A training dataset
- A classifier trained on this dataset
- A test set **without labels**

We want to estimate:

**Classification accuracy on the test set**

# Our idea



Negative correlation between recognition accuracy and domain gap



# Our idea

Known (from existing literature)

Larger domain gap -> lower recognition accuracy

Unknown

Can we **quantify** this relationship?

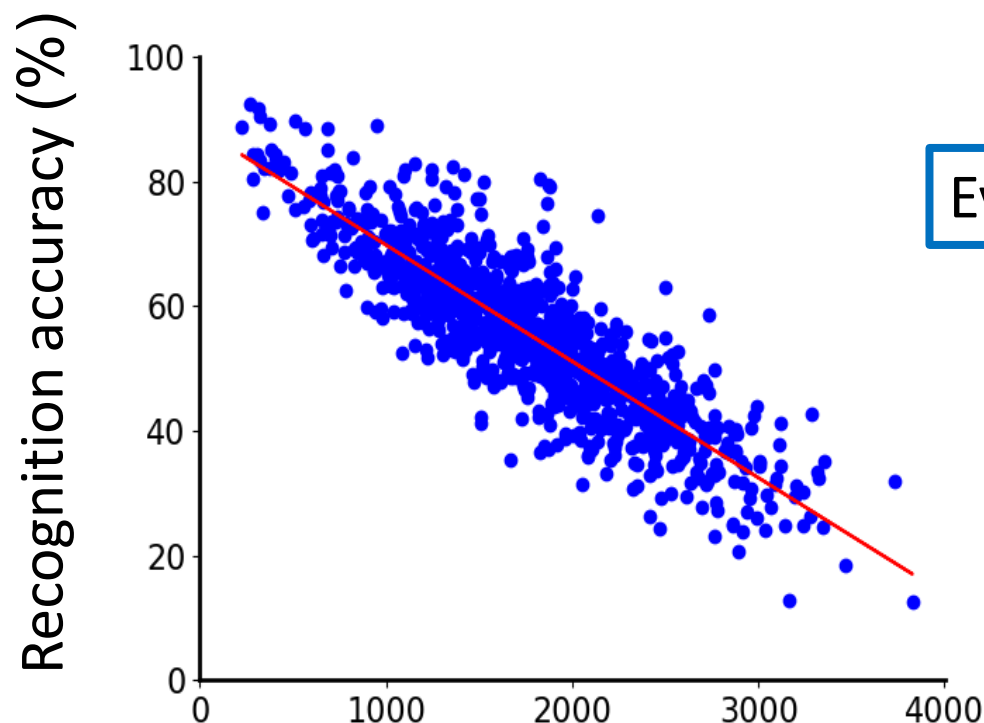
A regression problem!



# Some experiments



digit classification



Every point is a dataset

Fréchet distance

Domain gap between a training set and test sets

# Qualitative examples



Train

GT: 71.07%  
ours: 75.39%

GT: 40.19%  
ours: 38.43%

GT: 90.16%  
ours: 89.68%

We are organising the DataCV challenge @ CVPR 2023, on this label-free model evaluation problem.

<https://sites.google.com/view/vdu-cvpr23/competition>

# Conclusions and insights

- We study **data-centric** computer vision problems
- Optimize the training set
  - given the test set and model architect
- Search and compose a validation set
  - Given the training set, a test set and models
- Estimate test set difficulty
  - Given the training set, test set and model

# Conclusions and insights

- What else problems are data-centric?
  - Given a fine-tuning dataset, find a good pre-training dataset
  - Or the opposite
  - Estimate the noise level of a dataset
  - ....
- Key techniques
  - Dataset representation
    - attribute values, feature mean, covariance etc..
  - Dataset-dataset similarity estimation
    - Frechet distance etc.

# Thank you! Any question?

## Collaborators



Xiaoxiao Sun  
ANU



Yue Yao  
ANU



Yunzhong Hou  
ANU



Weijian Deng  
ANU



Stephen Gould  
ANU



Milind Naphade  
NVIDIA



Tom Gedeon  
ANU



Hongdong Li  
ANU



Xiaodong Yang  
NVIDIA