Robust Nearest Neighbors for Source-Free Domain Adaptation under Class Distribution Shift

Antonio Tejero-de-Pablos

ECCV2024

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CyberAgent AI Lab

01

Our setting:
Source-free domain adaptation under class distribution shift

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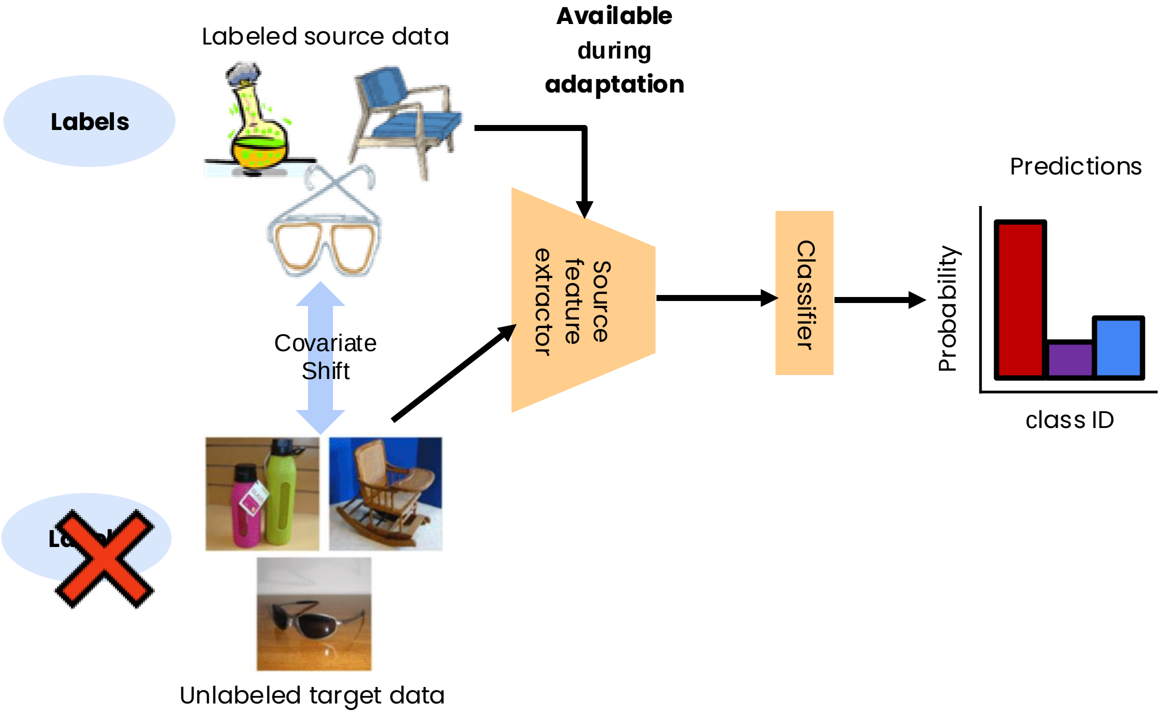
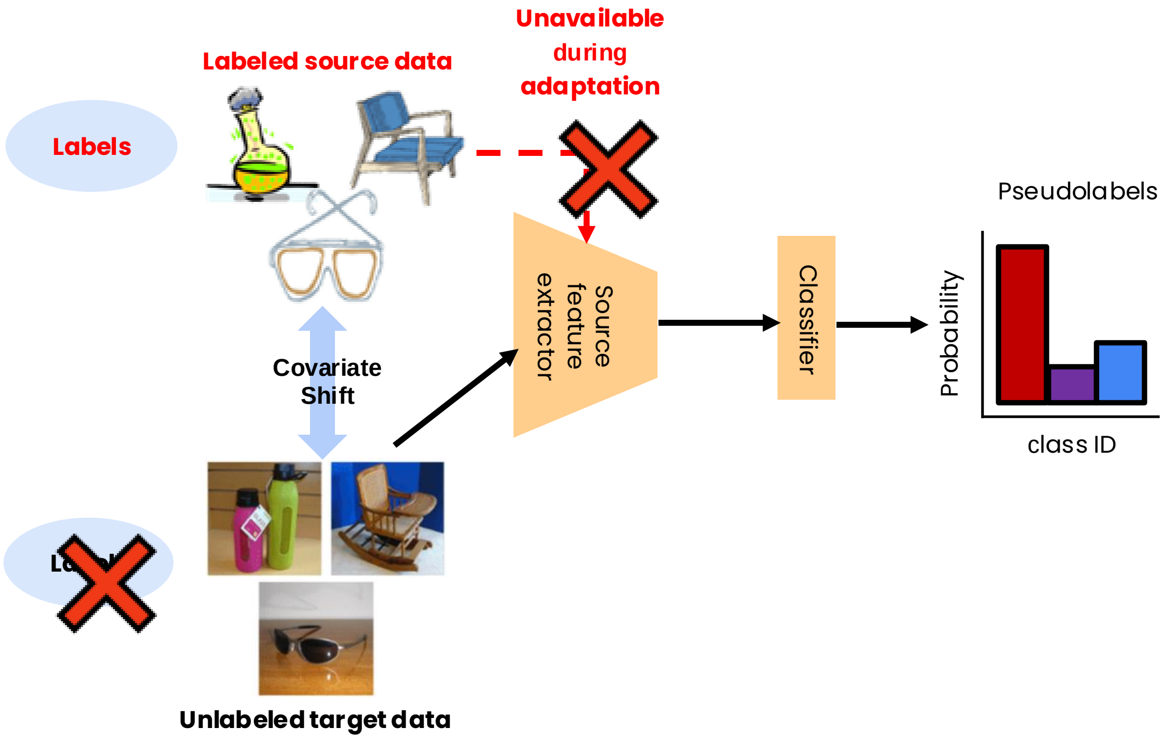
What is domain adaptation

- A way to mitigate the decrease in accuracy when the distributions of the source and target data are different (i.e., covariate shift)
  - Source data (labeled)
    - Used for training
    - Available during adaptation
  - Target data (unlabeled)
    - Used after deployment
    - Different "style" than source



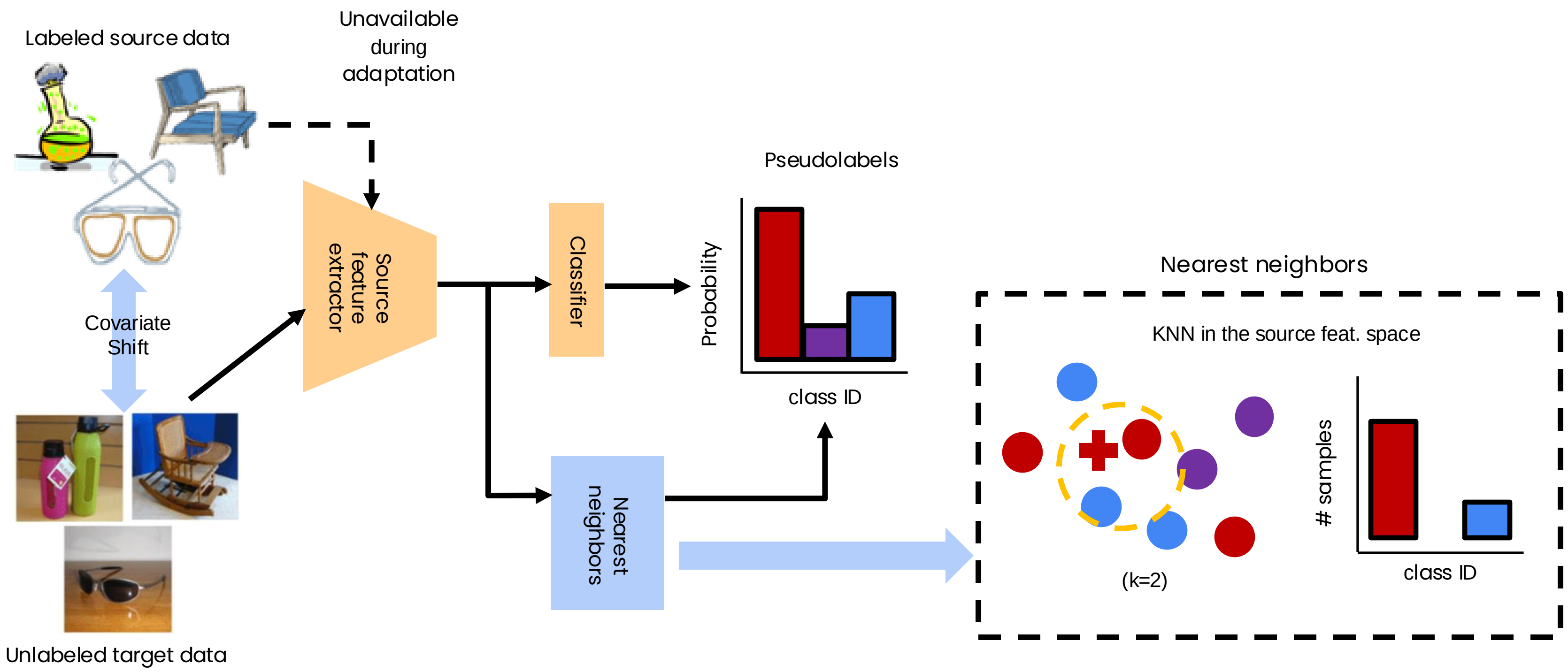
What is source-free domain adaptation (SFDA)

- In some cases, the source data is unavailable after the source model is deployed (e.g., for privacy issues)
  - Given the lack of labels, pseudolabels are used instead



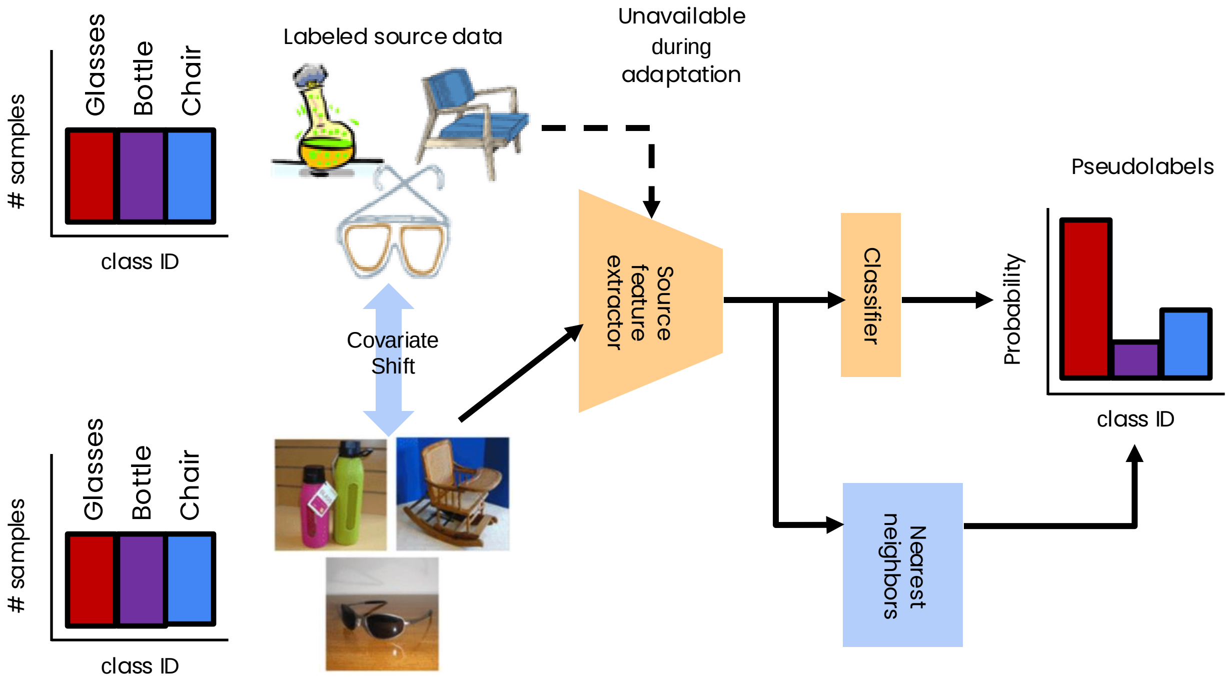
What is source-free domain adaptation (SFDA)

- Pseudolabels are normally calculated via nearest neighbors
  - Nearby samples in the feature space refine the predictions



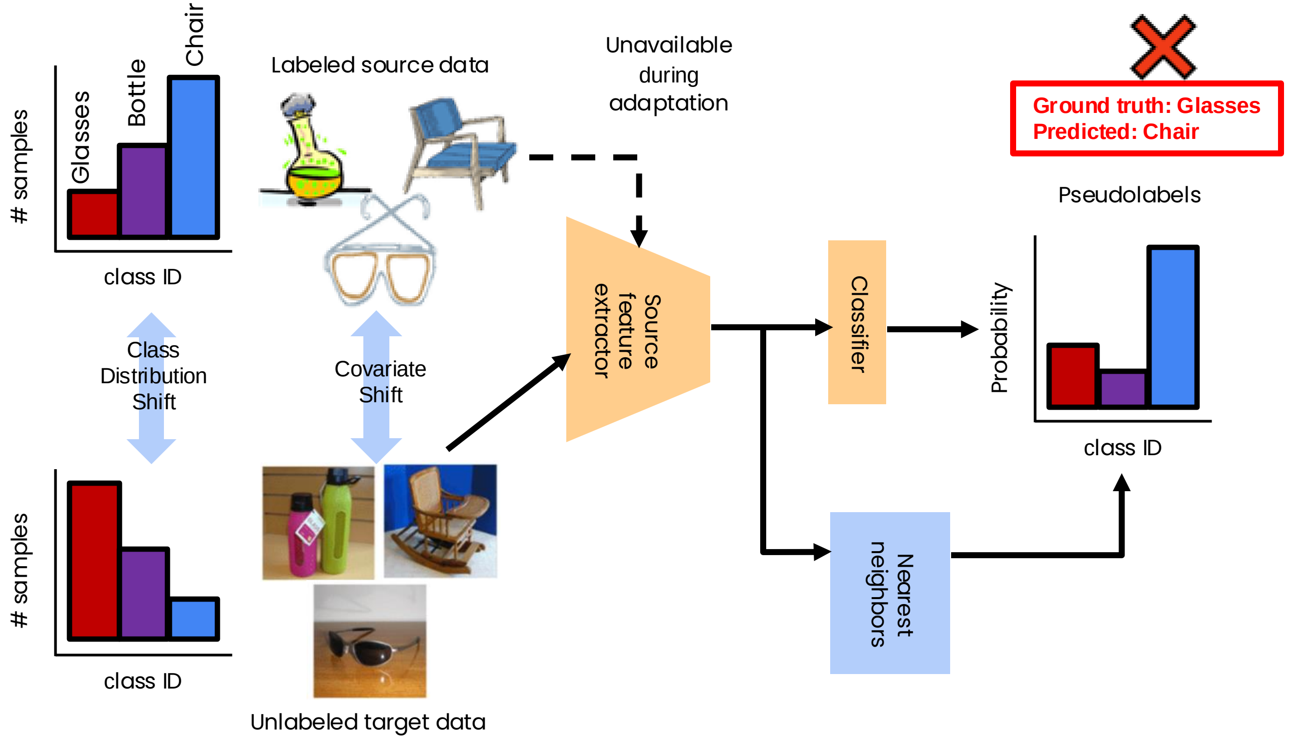
What is source-free domain adaptation under class distribution shift (SFDA-CDS)

- SFDA methods assume matching class distributions among domains



What is source-free domain adaptation under class distribution shift (SFDA-CDS)

- However, in real scenarios, the number of samples per class differs between source and target (i.e., class distribution shift)



- This causes a drop in performance due to the majority/minority bias

What is source-free domain adaptation under class distribution shift (SFDA-CDS)

- This difficult scenario presents a number of problems
  - Standard CDS mitigation methods require labels
  - However, we only have a CDS-biased source model and label-less target data
- → **This makes estimating the CDS impossible**
  - Majority and minority classes cannot be determined
  - Misclassifications may be due to both either the bias of the source model or the target data

02

Our proposal: Robust nearest neighbors for SFDA-CDS

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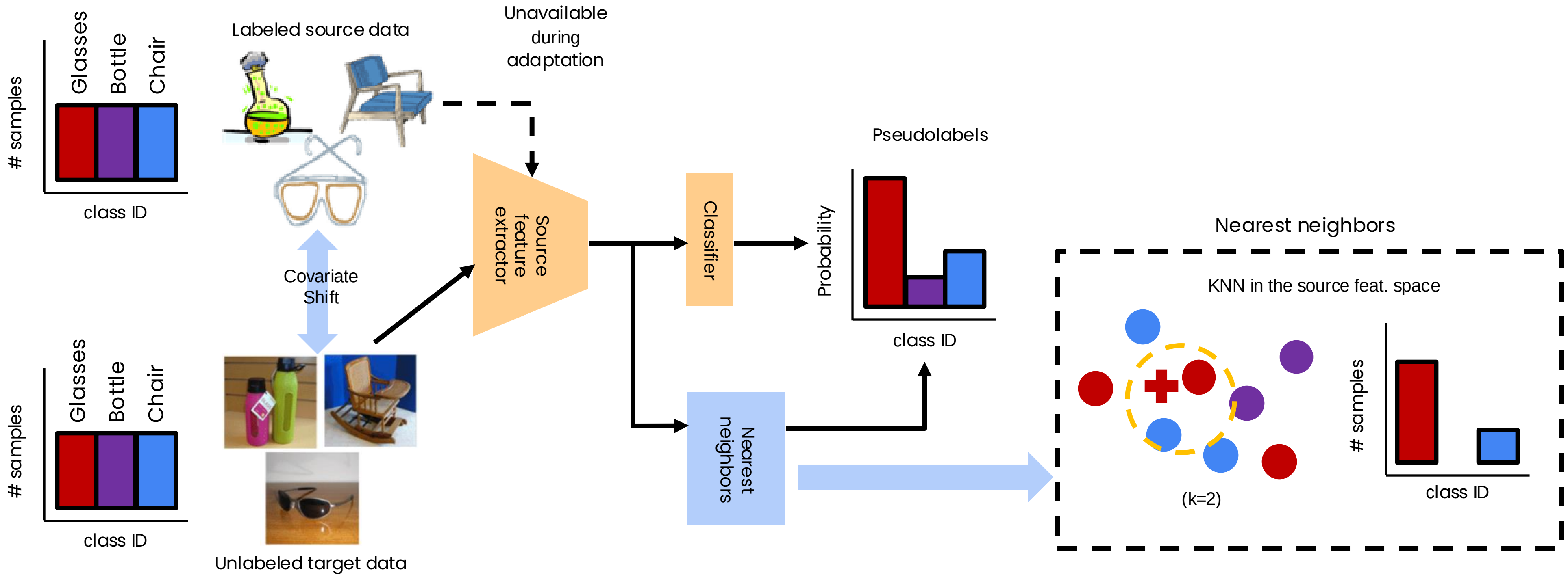
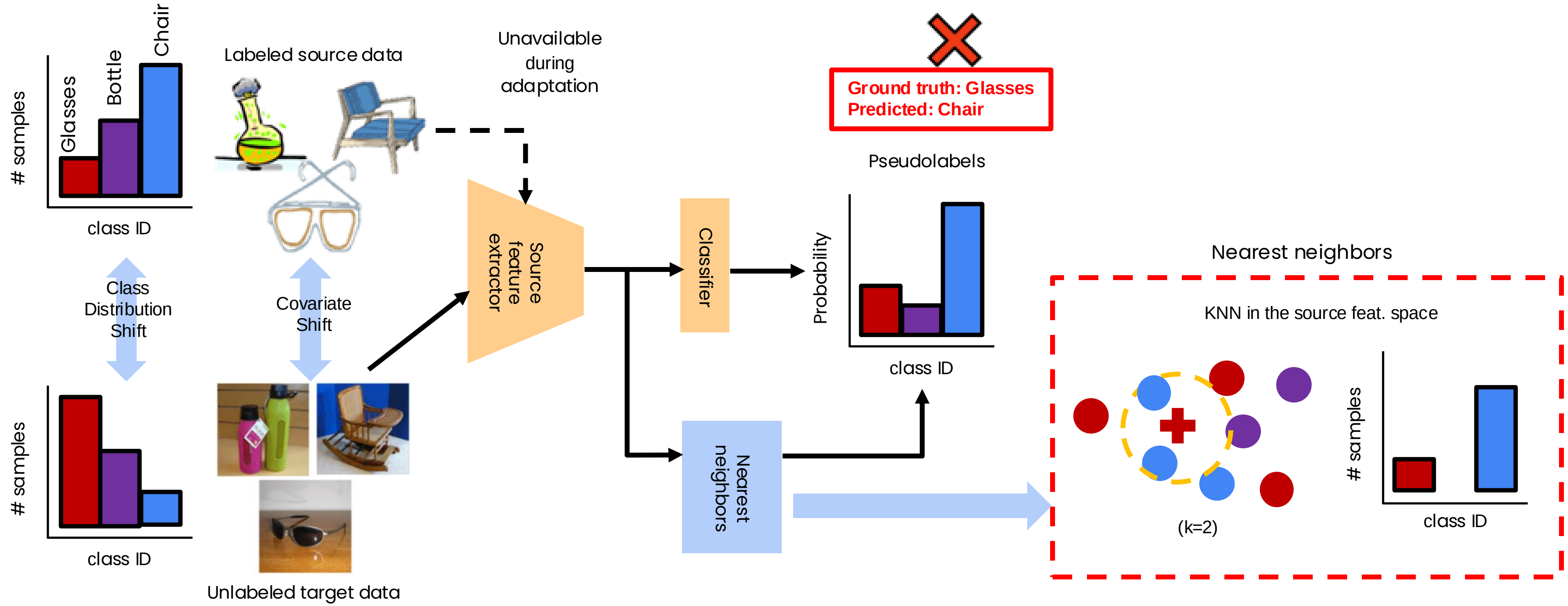
The effect of CDS in the nearest neighbors algorithm

- The nearest neighbors algorithm is reliable without CDS



The effect of CDS in the nearest neighbors algorithm

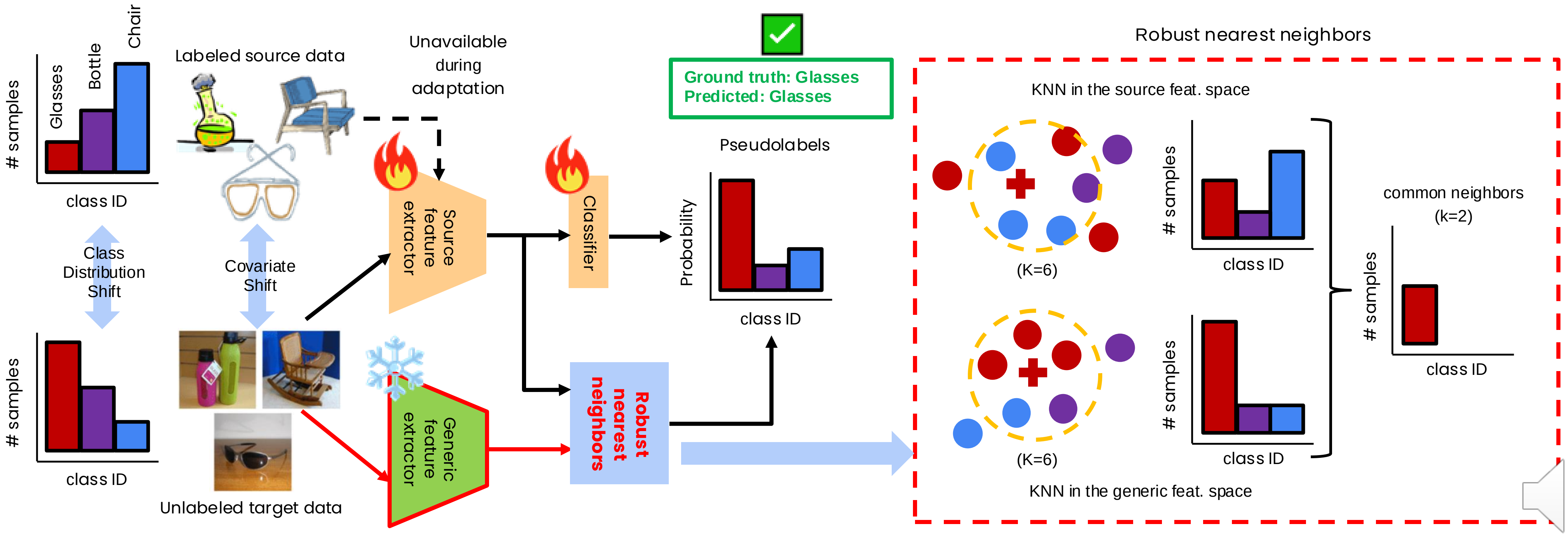
- However, it is sensitive to the majority-minority bias in CDS
    - But in this setting bias cannot be eliminated



- **Leveraging "generic" features free of the source bias for a "second opinion"**

Proposed method: Robust nearest neighbors

- **Finding common nearest neighbors between the source and the generic feature spaces**



Proposed method: Robust nearest neighbors

- Since our framework does not require additional training, it provides several advantages
  - Generic features are only calculated once at the beginning (no extra cost)
  - It can also be applied to the setting of test-time adaptation (TTA)
    - Running on evaluation mode (no weight update)

Main results

- Our robust nearest neighbors outperform previous methods in both SFDA and TTA tasks under CDS

Method (SFDA)	VisDA-C	Office-Home	DomainNet
ISFDA	76.69	<u>65.36</u>	79.58
PL base	81.01	56.82	79.48
+ Ours (ResNet)	83.85	55.47	70.28
+ Ours (ViT-B)	83.88	58.71	<u>82.51</u>
+ Ours (Swin-B)	86.64	64.64	78.95
PL guided	83.59	61.05	80.12
+ Ours (ResNet)	86.6	59.67	72.74
+ Ours (ViT-B)	<u>86.72</u>	62.31	**83.9**
+ Ours (Swin-B)	**88.84**	**69.04**	81.4

Method (TTA)	VisDA-C	Office-Home	DomainNet
TENT	48.68	51.15	70.34
+ Shift adapter	**72.97**	52.78	<u>71.63</u>
Pseudolabel	47.12	52.34	67.06
+ Ours (ResNet)	50.07	52.83	63.01
+ Ours (ViT-B)	49.60	<u>53.95</u>	**73.23**
+ Ours (Swin-B)	<u>52.49</u>	**60.16**	70.59

Conclusions

- Nearest neighbors used in SFDA pseudolabeling is sensitive to CDS: Minority target samples are misclassified as majority source classes
- We proposed a method with no additional training cost to calculate robust nearest neighbors via features free from the source bias
- Our robust nearest neighbors outperform previous methods in both SFDA and TTA tasks under CDS

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10/01 16:30~18:30