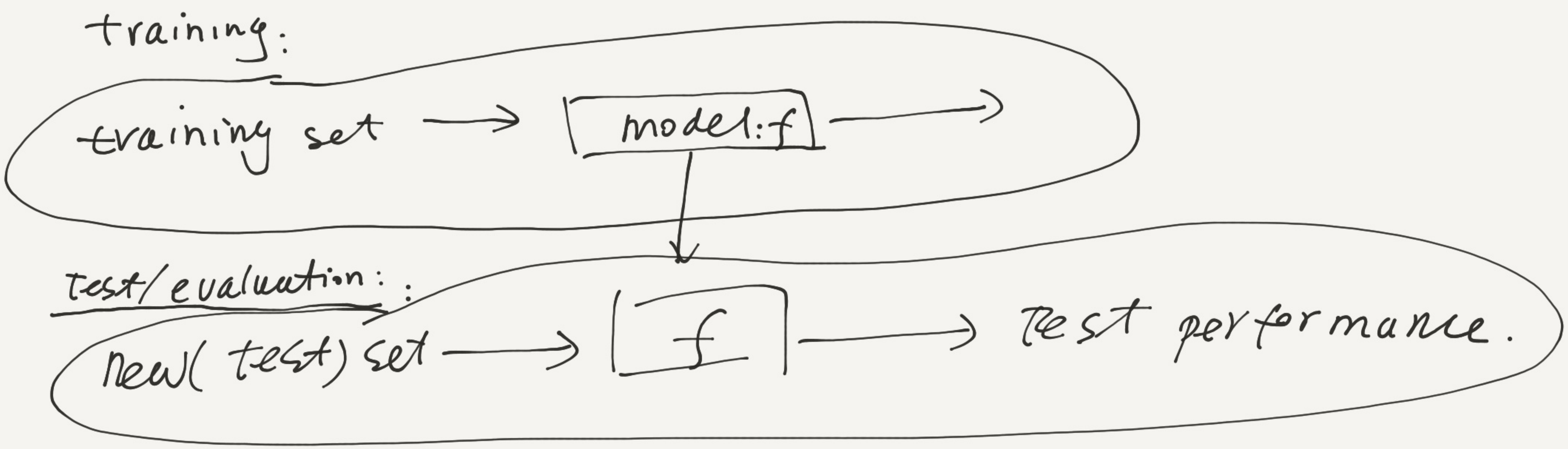
Lecture 25. Transfer learning

1. The assumption in our conventional training framework



Assumption: The training set and test set are drawn from the <u>same feature space</u> and the same distribution.

It is very challenge to the new data are from the same distribution of the training set.

2. Example of the challenge.

sentiment classification:

Task: Reviews $\longrightarrow$ f $\longrightarrow$ 0/neg or 1/positive.

Collect raw data: raw reviews. X

$\downarrow X$

Review annotation: Y
manually, expensive.
time-consuming

$\downarrow (X, Y)$

Data preprocessing:
remove noise.

$\downarrow$ Final dataset.

(X, Y) $\longrightarrow$ model training

For a different Task, e.g.

music reviews classification.

$(\bar{X}', \bar{Y}')$

How can we use knowledge from different tasks or ~~data~~ sources to reduce the efforts needed in our target task(s)?

3. Transfer Learning (TL)

(1) TL: aims to extract knowledge from one or more $\underbrace{\text{source tasks}}_{T_S}$

and applies to a $\underbrace{\text{target task}}_{T_T}$.

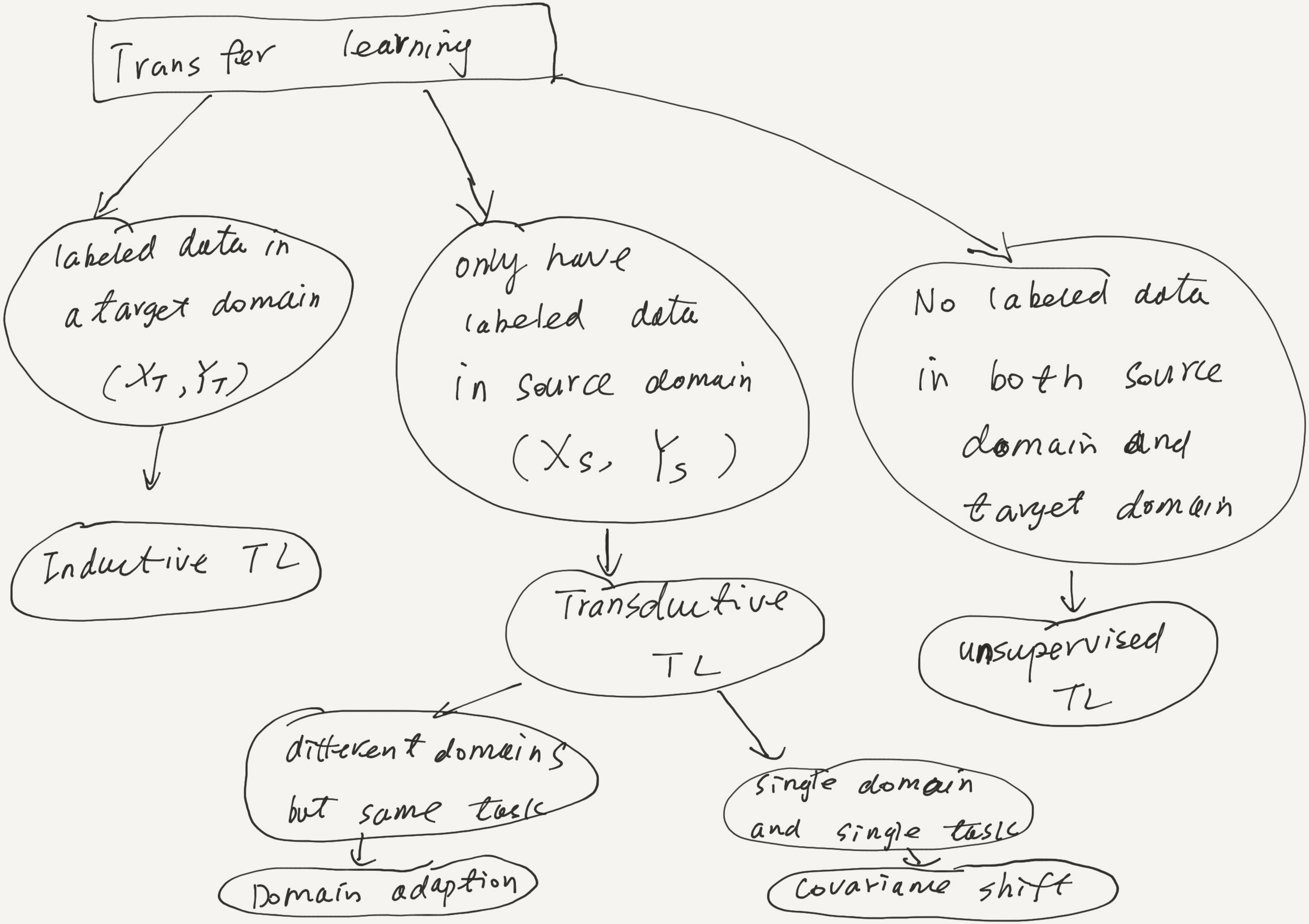
(2) Domain(s). $D = \{X, p(X)\}$

Task(s) : $T = \{\underbrace{Y}_{\text{label space}}, \underbrace{f(\cdot)}_{\text{model}}\}$

$T_S = \{Y_S, \underbrace{f_S(\cdot)}_{\text{model trained on the source domain}}\}$: source task

$T_T = \{Y_T, f_T(\cdot)\}$.

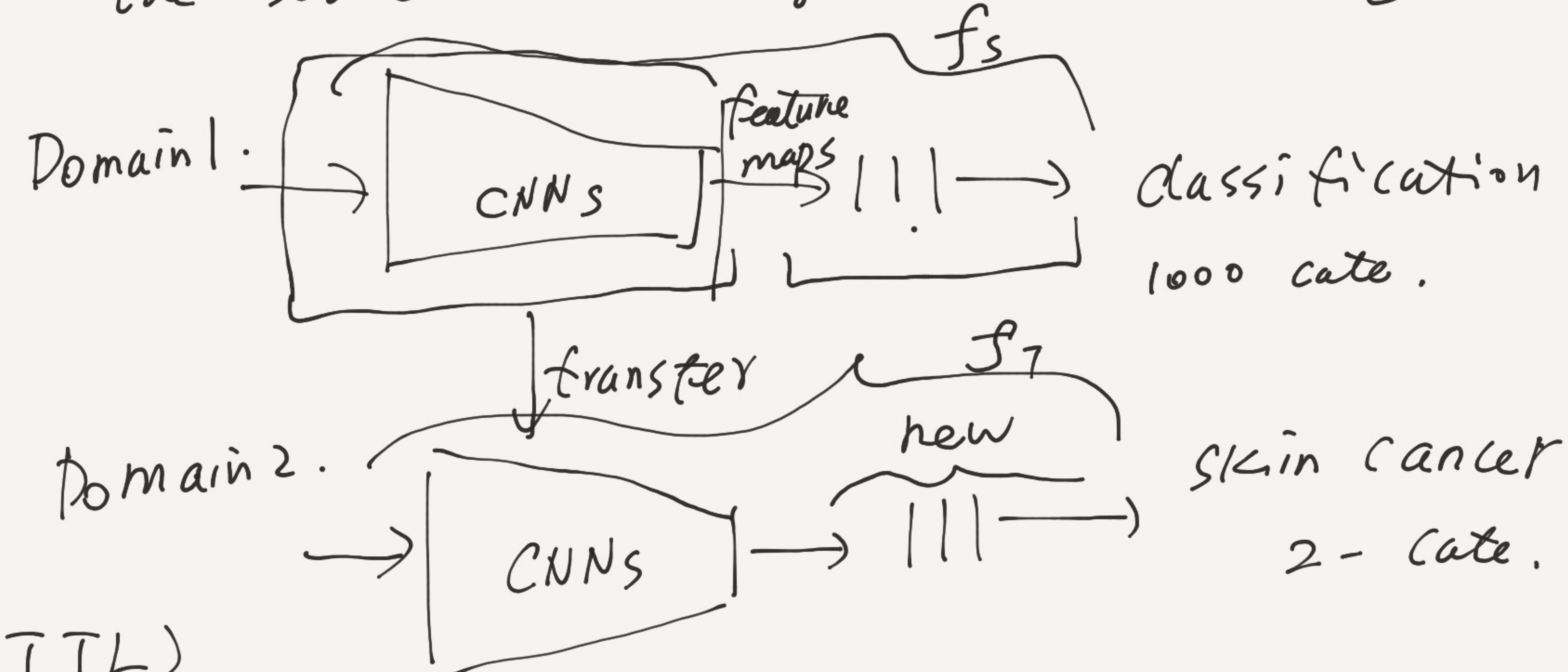
4 categorization of TL.



5 Inductive TL. (ITL)

aims to improve the target ML. $f_T(\cdot)$ in D_T using the knowledge in D_S and T_S, where $T_S \neq T_T$.

(1) parameter transfer: Discover shared (ITL) parameters between the source and target models. ($f_S(\cdot)$ and $f_T(\cdot)$)



(ITL)
(2) Relational-Knowledge transfer: build mapping of relational knowledge between the $\underbrace{\text{source domain}}_{D_S}$ and $\underbrace{\text{target domain}}_{D_T}$.

(3) feature-representation transfer.

(4) Instance transfer.

→ can be used for both Transductive and Inductive. TL.