Semisupervised Learning, Transfer Learning, and the Future at a Glance

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Machine Learning

Outline

1. **Semisupervised Learning**
   - Label Propagation
   - Semisupervised GAN
   - Semisupervised Clustering
2. **Transfer Learning**
   - Multitask Learning & Weight Initiation
   - Domain Adaptation
   - Zero Shot Learning
   - Unsupervised TL
3. **The Future at a Glance**

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  - E.g., drug design, medical diagnosis, etc.
- On the other hand, unlabeled data may be plentiful and cheap
- ***Semisupervised learning***: exploit the unlabeled data to improve the performance of a supervised learner
- Training set: $\mathbb{X} = \{(\boldsymbol{x}^{(i)}, y^{(i)})\}_{i=1}^{L} \cup \{\boldsymbol{x}^{(i)}\}_{i=L+1}^{N}$
  - Usually, $L \ll N$

Why Unlabeled Examples Help?

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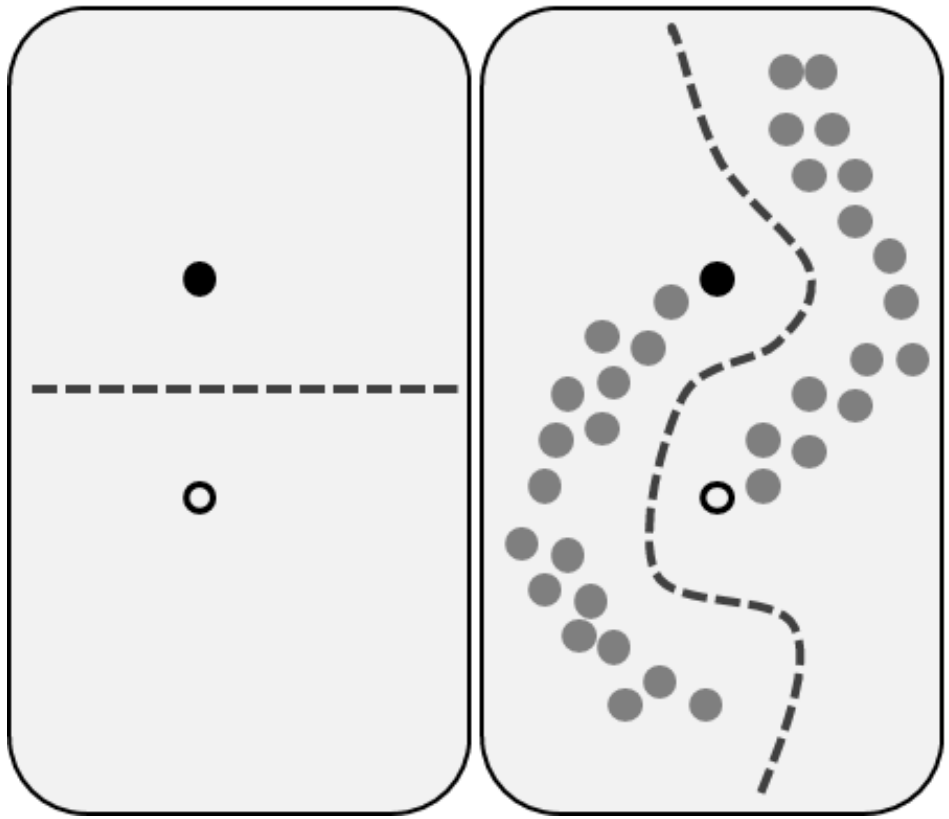
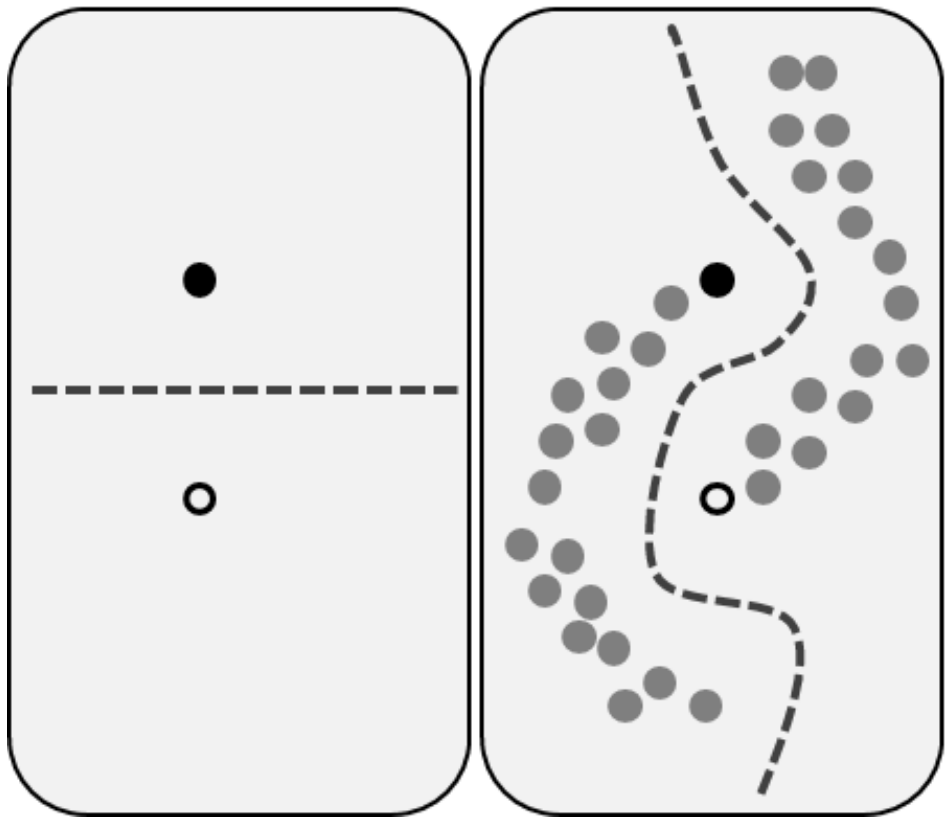


- Unlabeled examples help explain the marginal distribution of $\mathbf{x}$

Outline

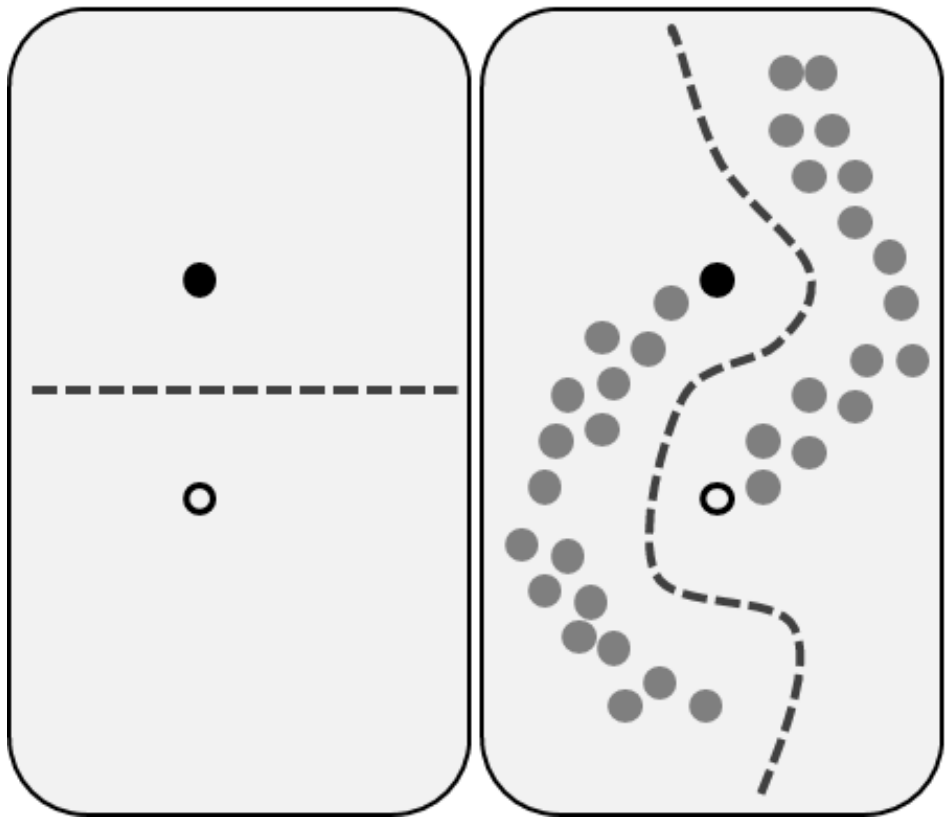
Label Propagation

- Assume that points of the same class reside in the same manifold



Label Propagation

- Assume that points of the same class reside in the same manifold
- So, the label should "propagate" along the local tangent spaces



Label Propagation along Local Similarity Graph

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   - E.g., K-NN graph, Parzen-Window graph, etc.
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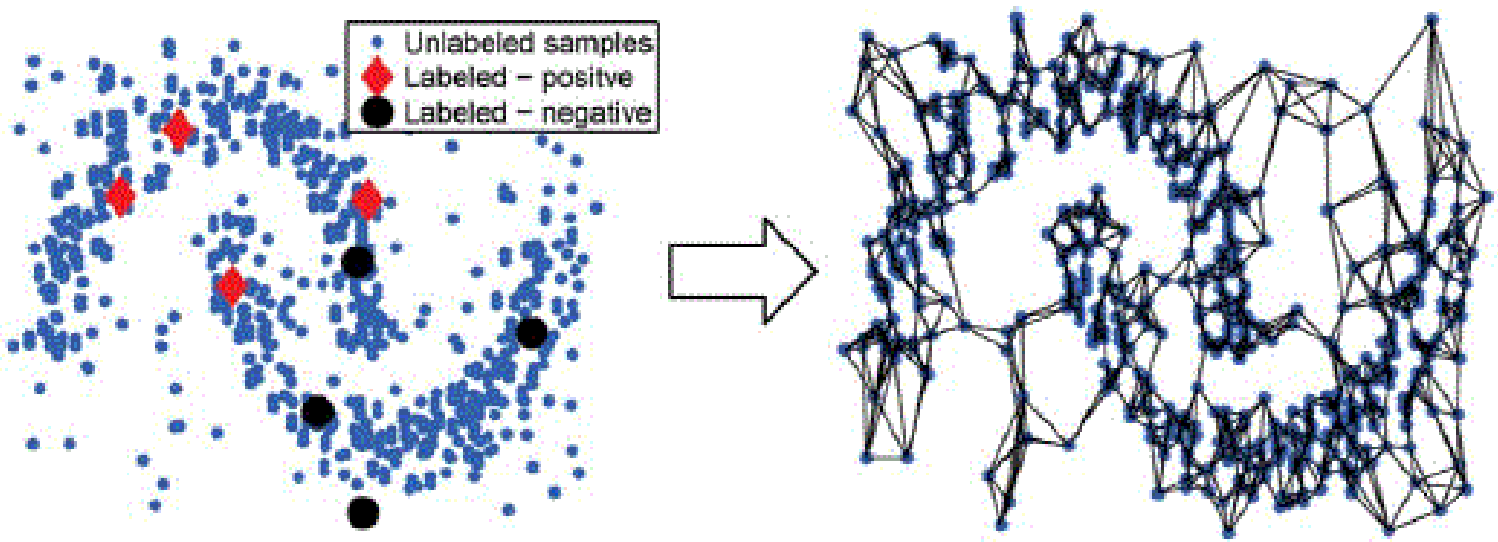

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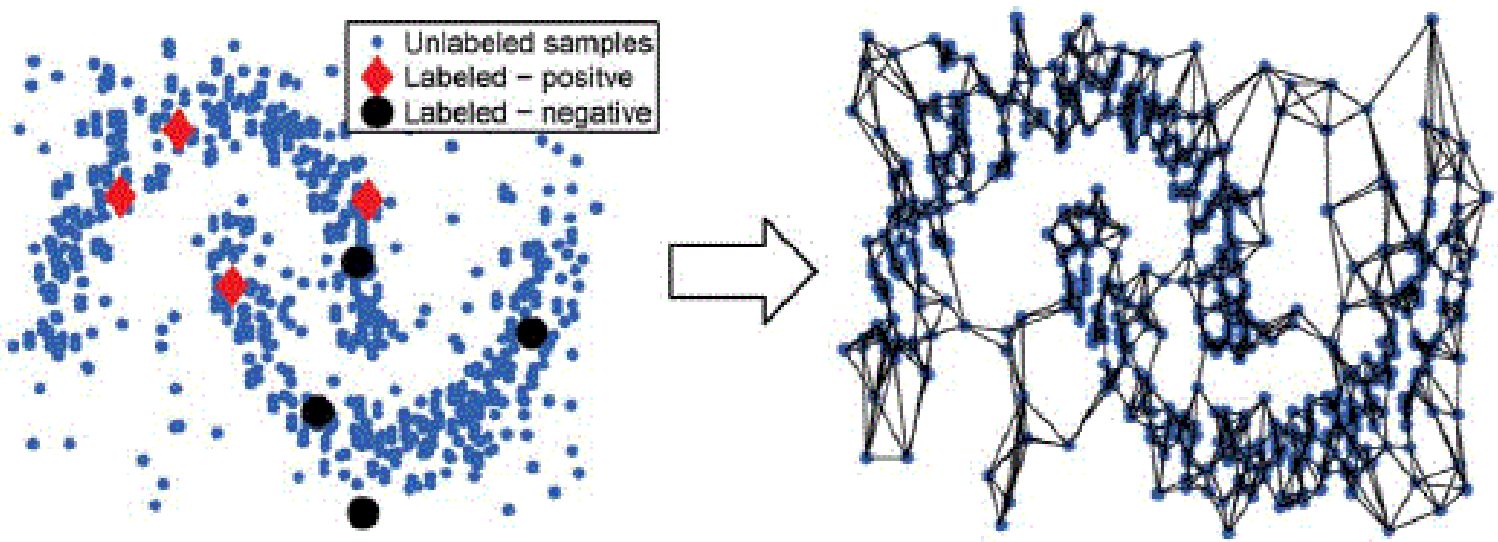

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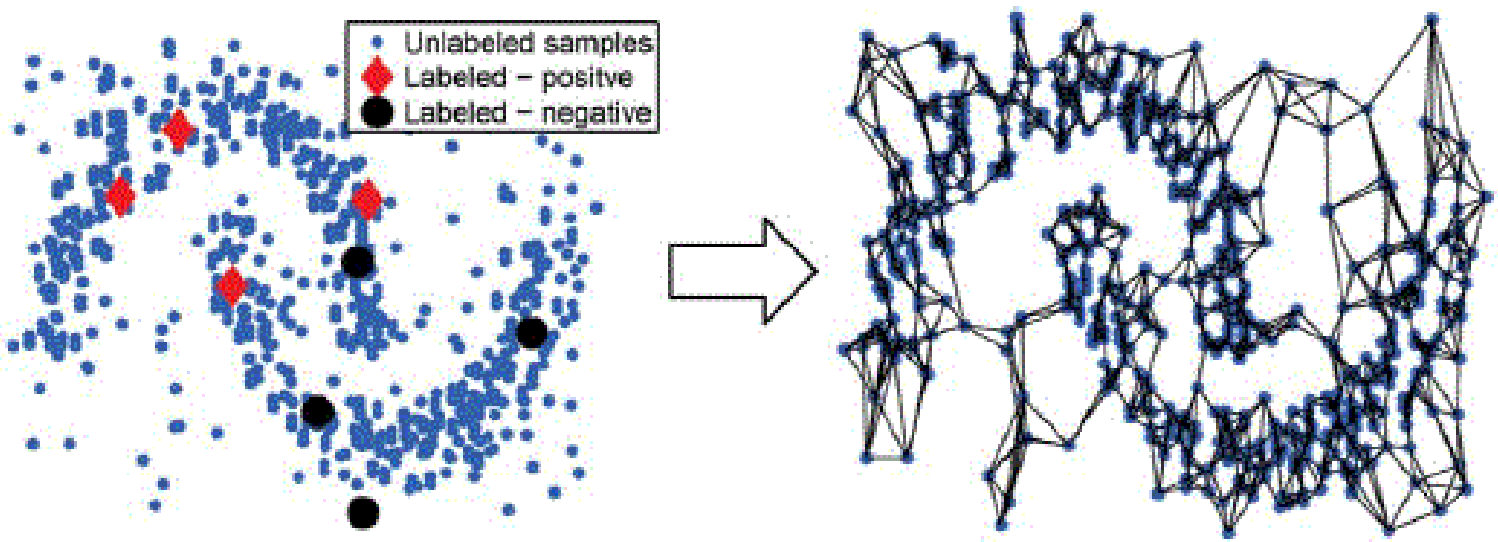
   - How?



Regularization using Graph Laplacian

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- Let $\boldsymbol{f} \in \mathbb{R}^N$ be the prediction vector, where $f_i = f(\boldsymbol{x}^{(i)})$
- The above penalty term can be simplified to

$$\Omega[f] = \boldsymbol{f}^\top \boldsymbol{L} \boldsymbol{f}$$

where $\boldsymbol{L} = \boldsymbol{D} - \boldsymbol{S}$ is called the ***graph Laplacian*** matrix [Proof]

- $D_{i,i} = \sum_j S_{i,j}$ the diagonal "degree" matrix

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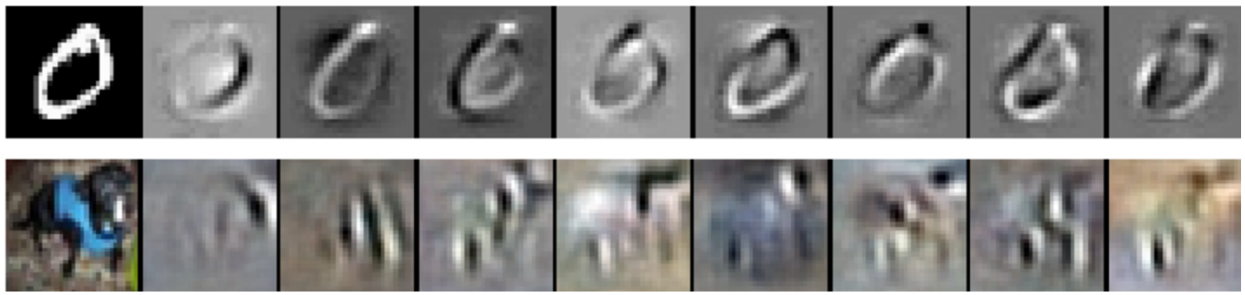

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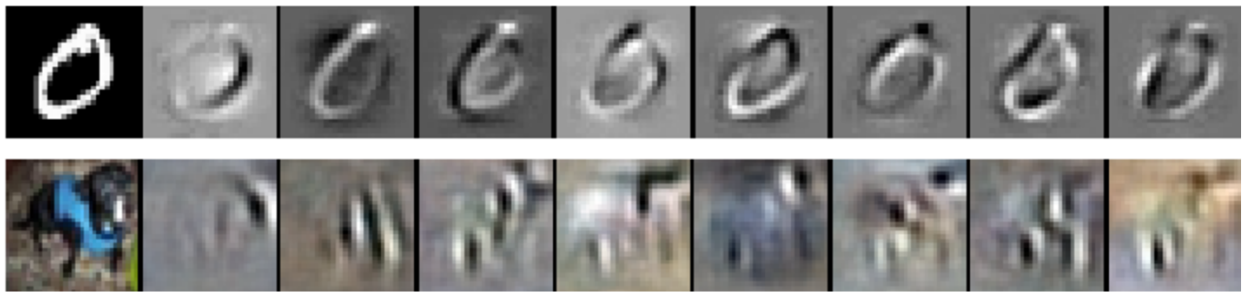

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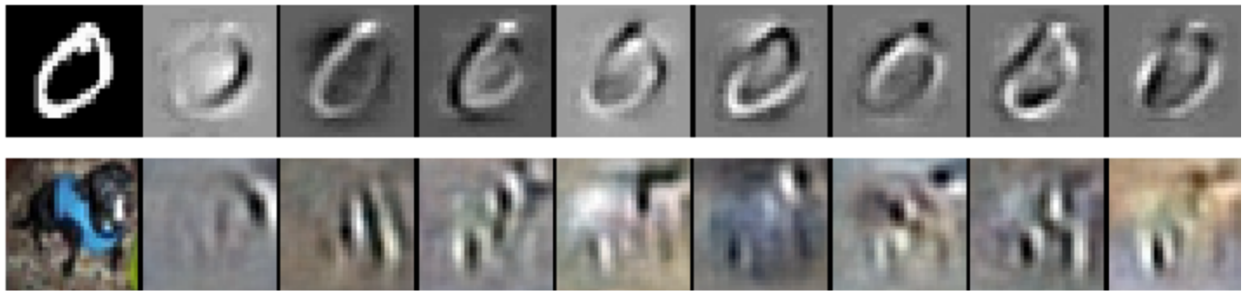

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- Points in the same manifold (backed by both labeled and unlabeled points) share the same label

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- Discriminator learns one extra class "fake" in addition to K classes
  - Softmax output units $\boldsymbol{a}^{(L)} = \hat{\boldsymbol{\rho}} \in \mathbb{R}^{K+1}$ for $\mathrm{P}(\mathbf{y} \mid \mathbf{x}, \boldsymbol{\Theta}) \sim \text{Categorical}(\boldsymbol{\rho})$

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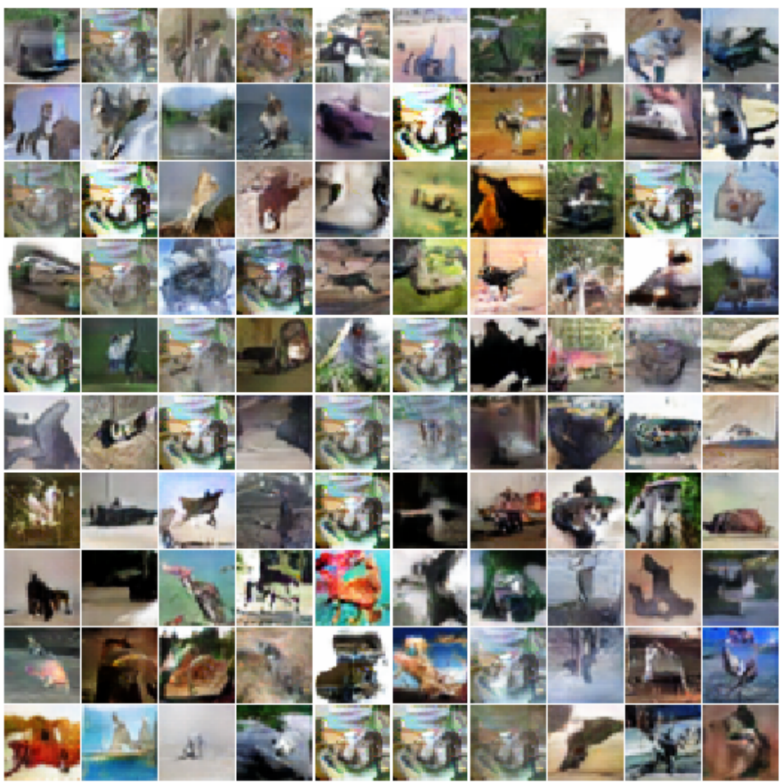
- Generated point should be identified as fake
- Real, unlabeled points can be in any class except $K+1$

Performance

- State-of-the-art classification performance given:
  - 100 labeled points (out of 60K) in MNIST
  - 4K labeled points (out of 50K) in CIFAR-10
- With generators:



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Clustering

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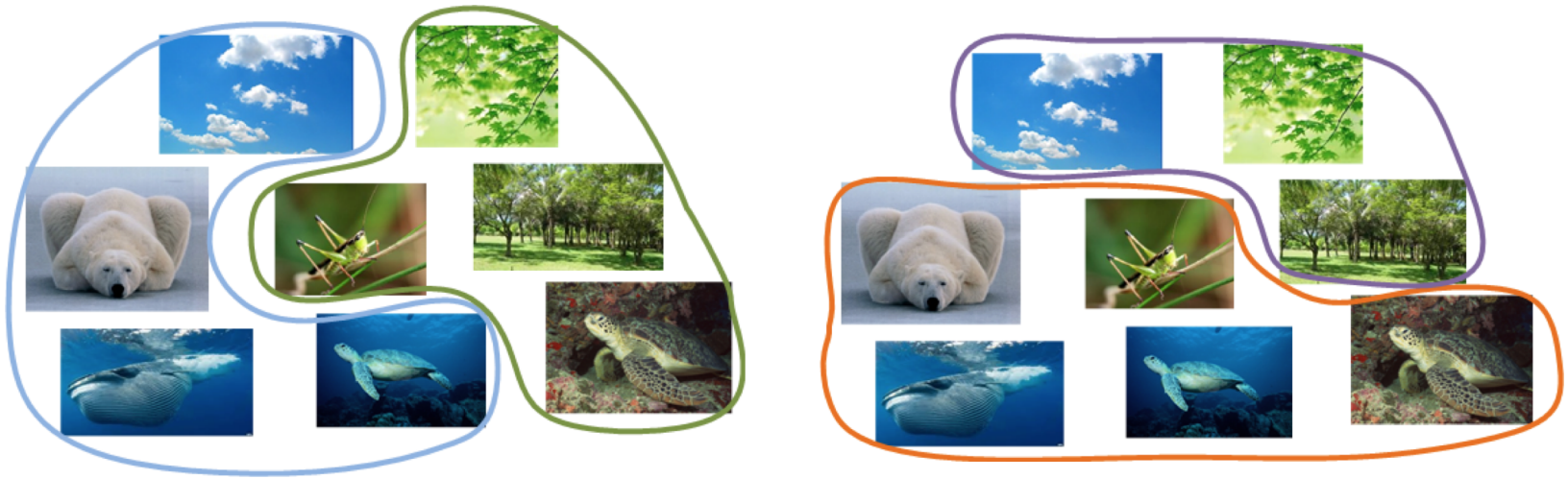
- E.g., how to cluster the following images into two group?

Semisupervised Clustering

- Different users may have different answers:



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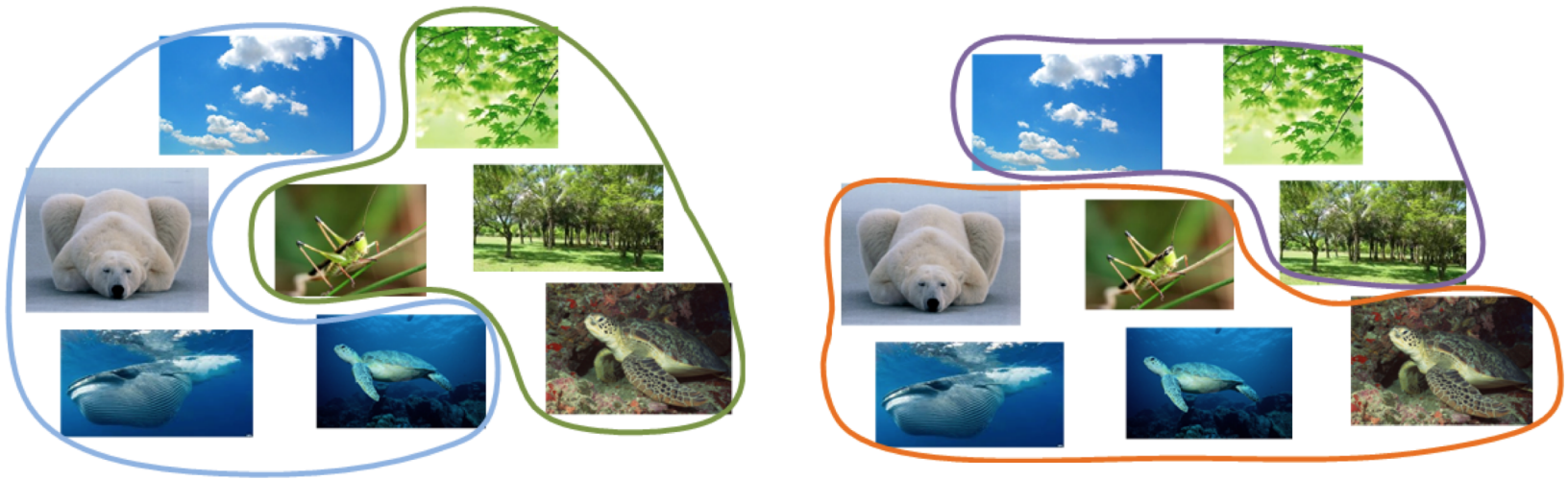

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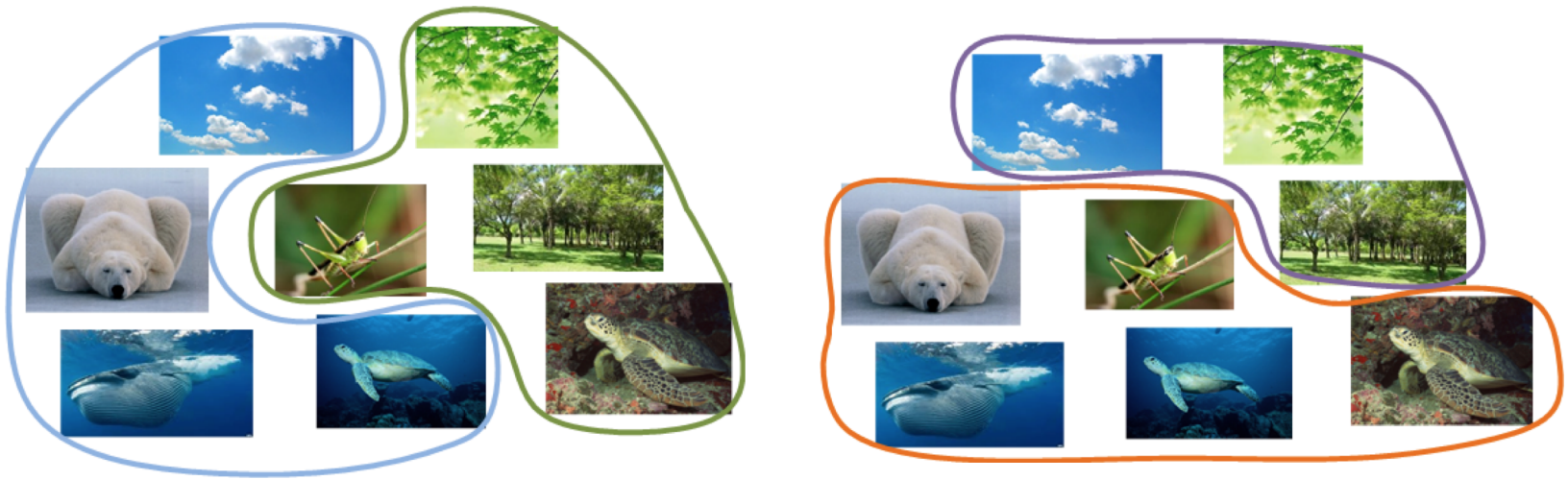

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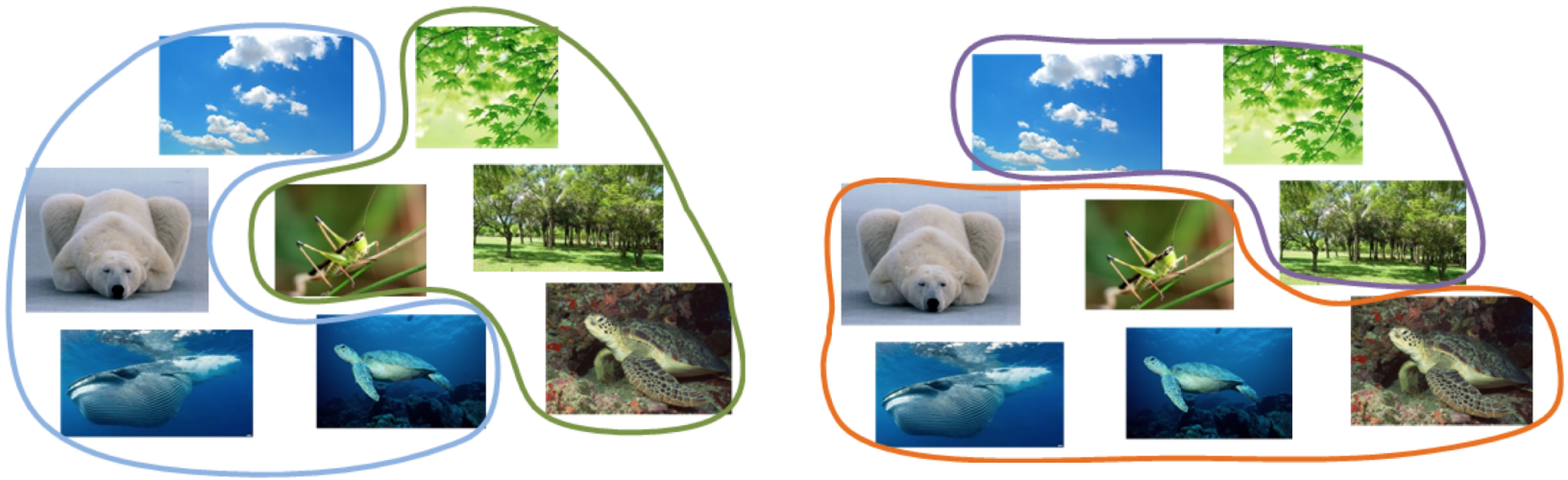

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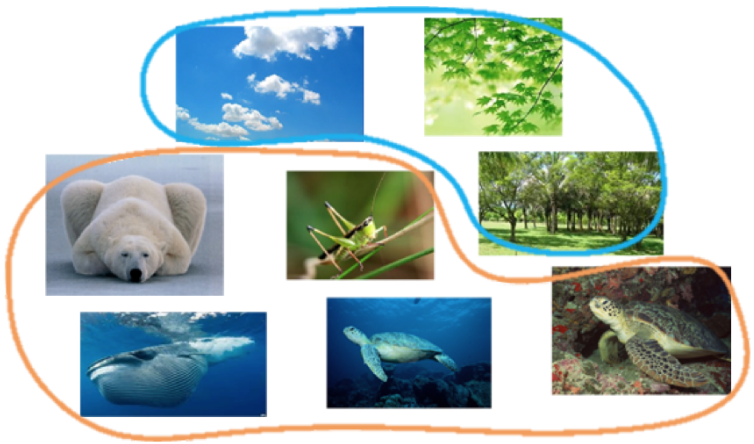
  - In what form?

Point-Level Supervision

- Side info: must-links and/or cannot-links



User-perceived Clusters

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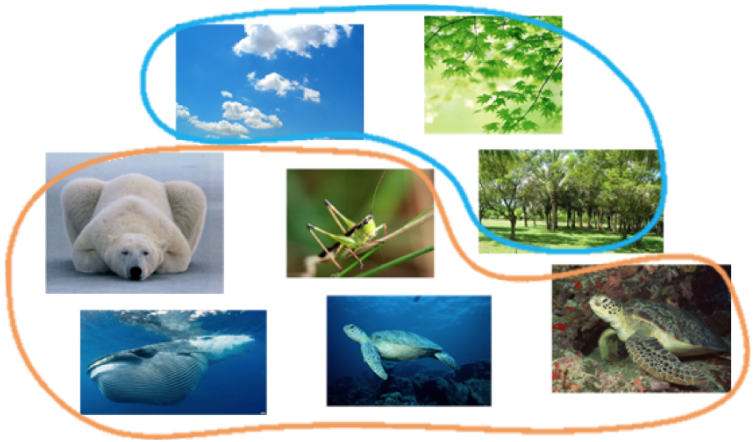

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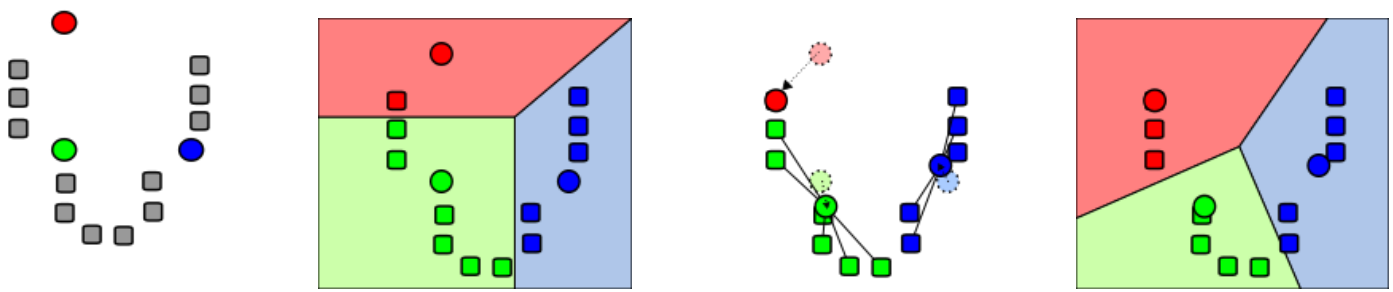
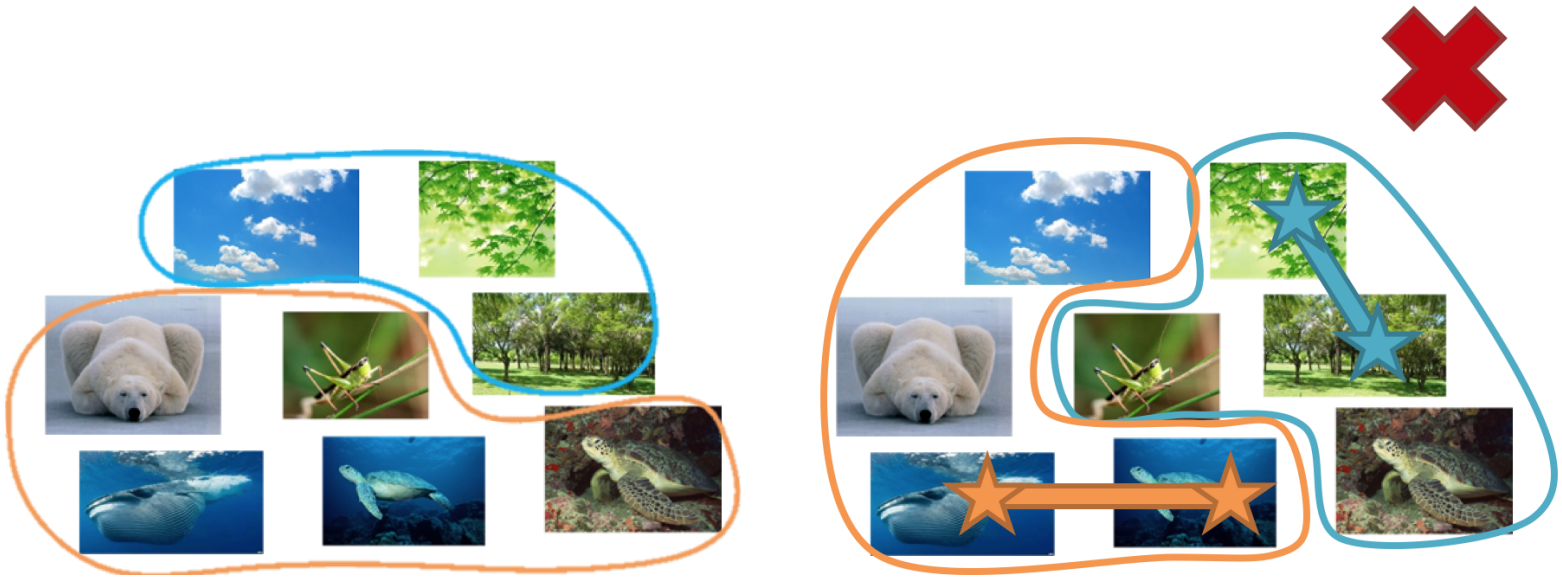
Data-driven Clusters

- Constrained K-means [13]: to assign points to clusters without violating the constraints



Sampling Bias

- Sampling of pairwise constraints matters:



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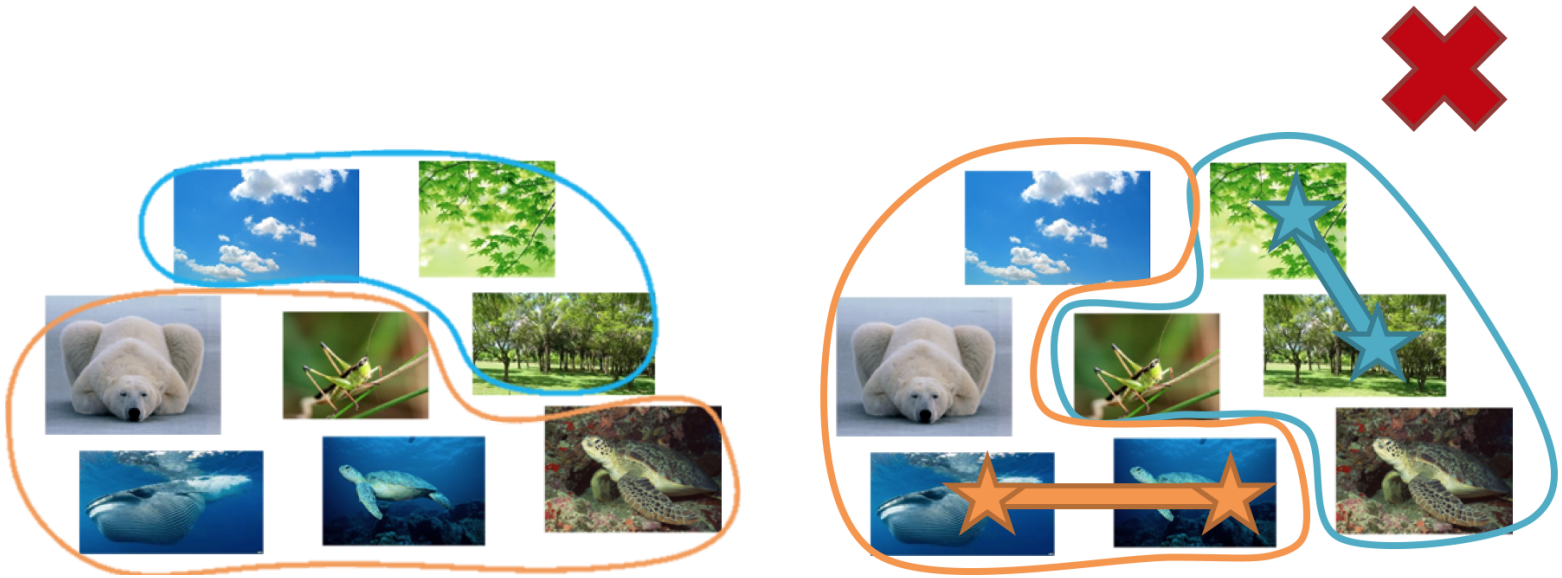

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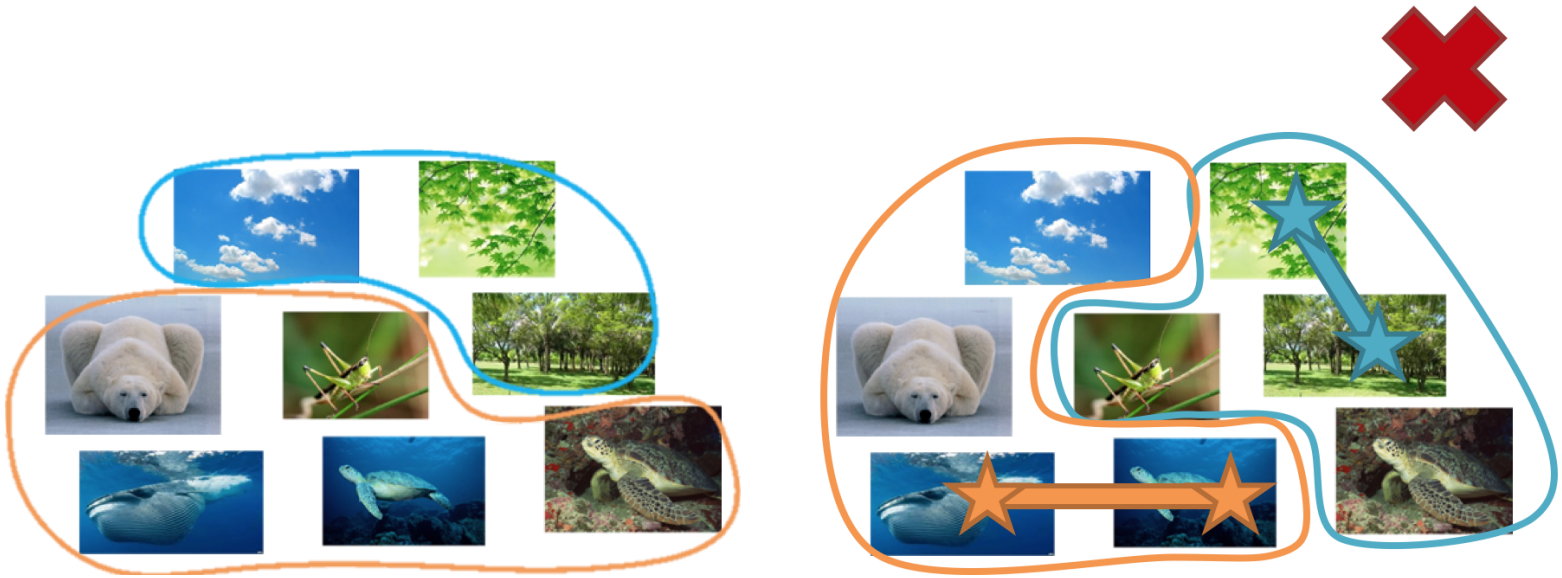

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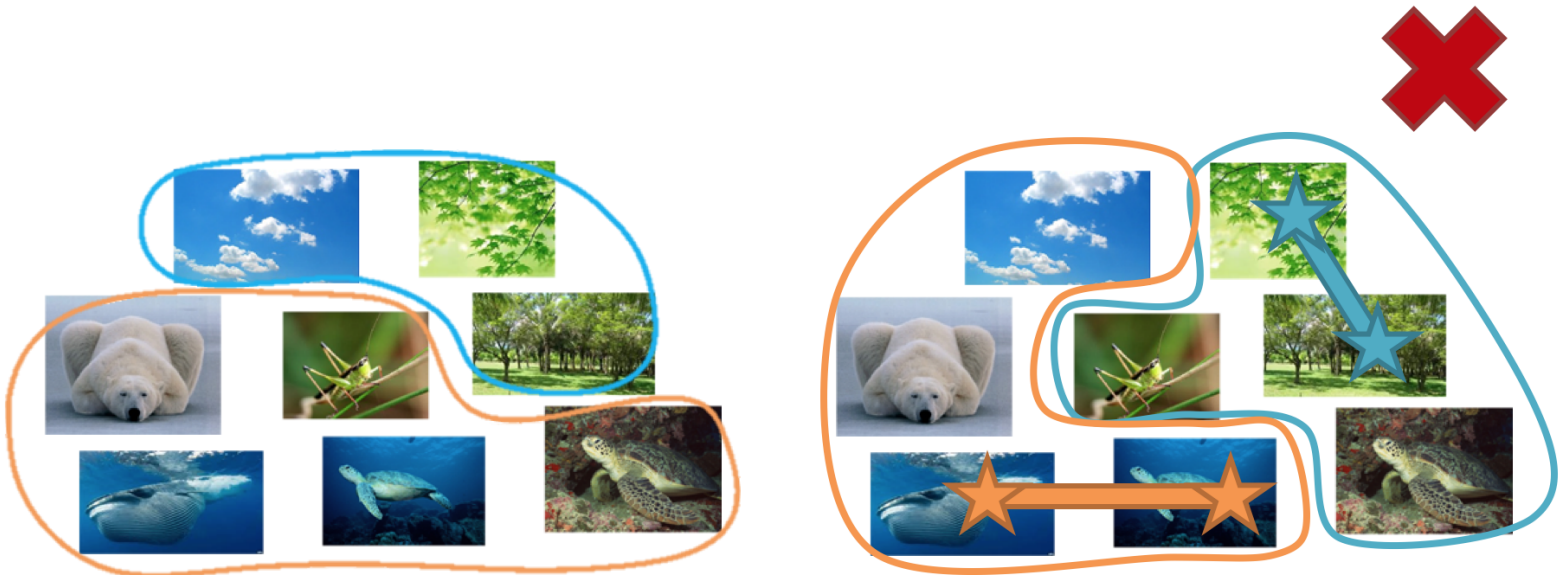

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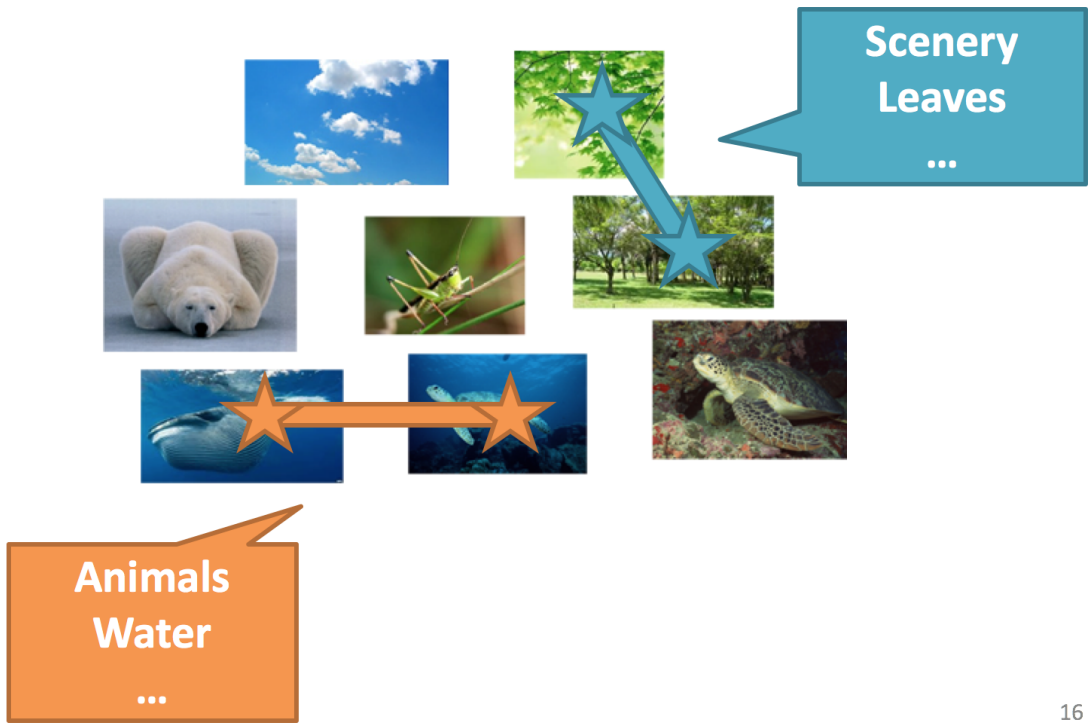
- E.g., suppose we want to cluster products in an e-commerce website
  - Use click-streams provided by the user to get must-links implicitly
- User not likely to click products uniformly
  - Instead, e.g., clicks products with the lowest prices

Feature-Level Supervision I

- Side info: perception vectors $\{\boldsymbol{p}^{(n)} \in \mathbb{R}^B\}_{n=1}^N$
  - E.g., bag-of-word vectors of the "reasons" (text) behind must-/cannot-links
  - B the vocabulary size
  - $\boldsymbol{p}^{(n)} \neq \mathbf{0}$ if point n is covered by a must-/cannot-link



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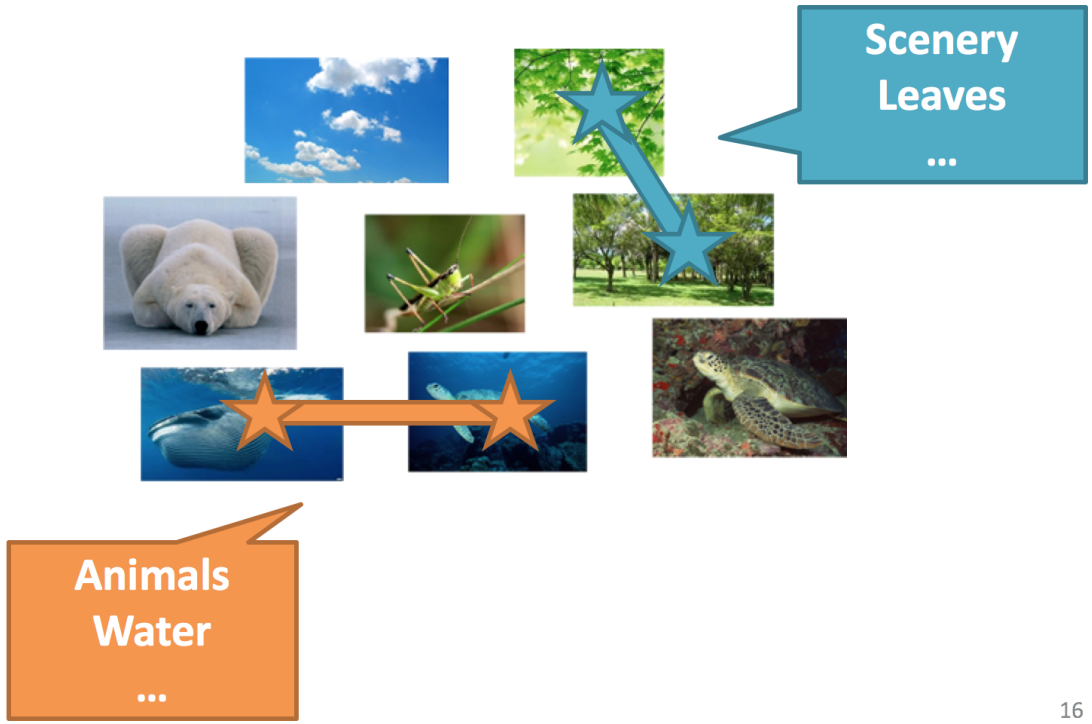
Feature-Level Supervision II



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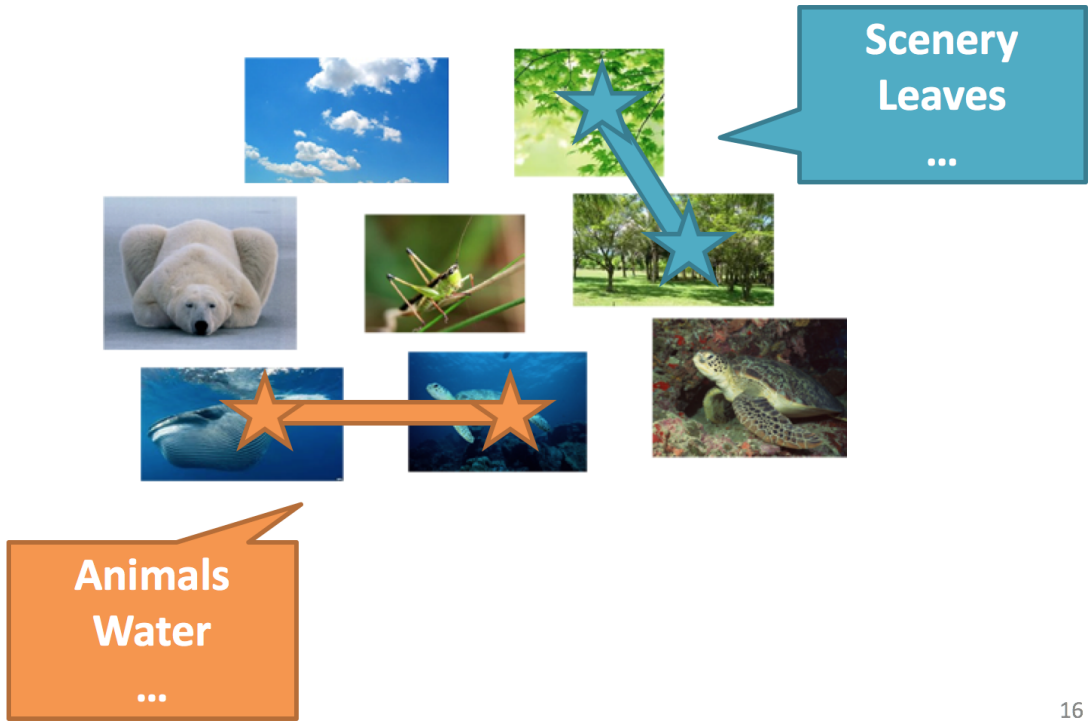

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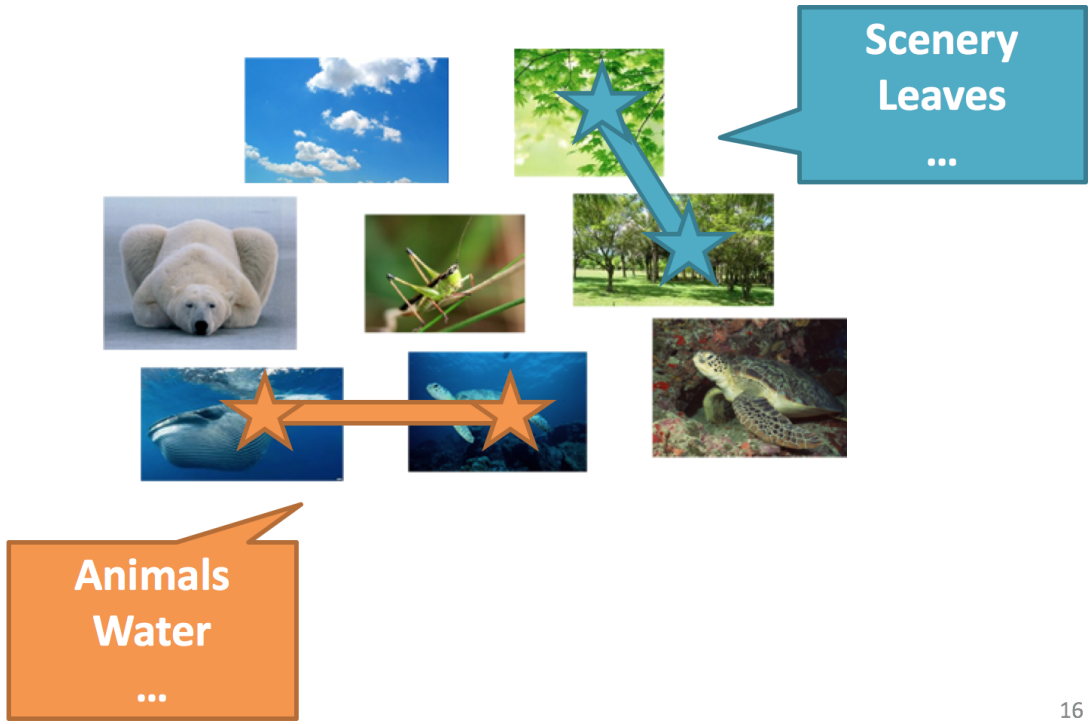

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  - Use click-streams provided by the user as must-links
  - Use the ***query*** that triggers clicks as the perception vector
- How to learn form the perception vectors?

Perception-Embedding Clustering

- Perception-embedding clustering [4]: to map every $\boldsymbol{x}^{(n)} \in \mathbb{R}^D$ to a dense $\boldsymbol{f}^{(n)} \in \mathbb{R}^B$ and cluster based on $\boldsymbol{f}^{(n)}$'s

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- Cost function for mapping function:

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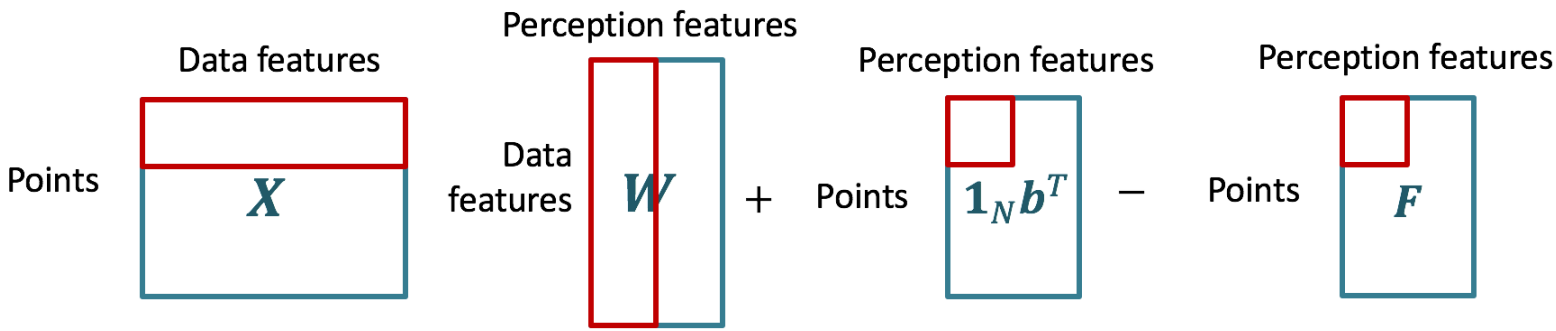
  - $\boldsymbol{X} \in \mathbb{R}^{N\times D}$, $\boldsymbol{W} \in \mathbb{R}^{D\times B}$, $\boldsymbol{b} \in \mathbb{R}^B$, $\boldsymbol{S} \in \mathbb{R}^{N\times N}$, and $\boldsymbol{F}, \boldsymbol{P} \in \mathbb{R}^{N\times B}$



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1	0	0
0	**0**	0
0	0	**1**

$\boldsymbol{S}$: row selector

$\times$

	Animal	Leaves	Nature
$\boldsymbol{x}_1$	0.85	0.78	0.22
$\boldsymbol{x}_2$	0.75	0.91	0.36
$\boldsymbol{x}_3$	0.15	0.94	0.82

$-$

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$\boldsymbol{P}$: feature-level supervision

Perception-Embedding Clustering

- Perception-embedding clustering [4]: to map every $\boldsymbol{x}^{(n)} \in \mathbb{R}^D$ to a dense $\boldsymbol{f}^{(n)} \in \mathbb{R}^B$ and cluster based on $\boldsymbol{f}^{(n)}$'s
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- The embedding (parametrized by $\boldsymbol{W}$ and $\boldsymbol{b}$) applies to ***all*** points, thereby avoiding sampling bias

Outline

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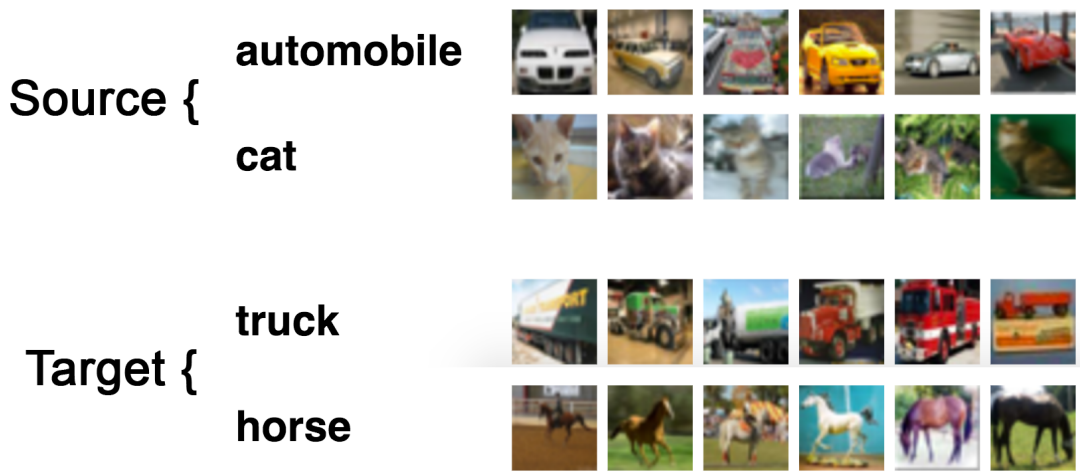

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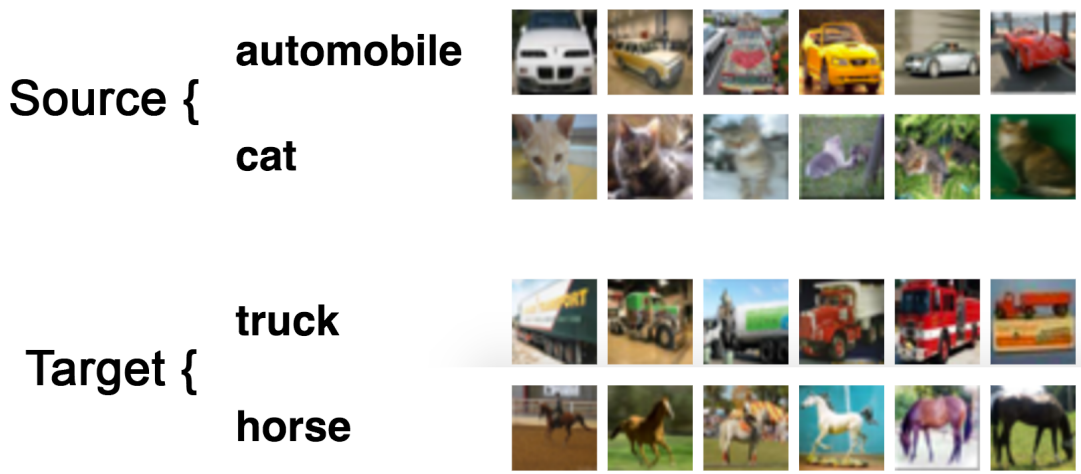

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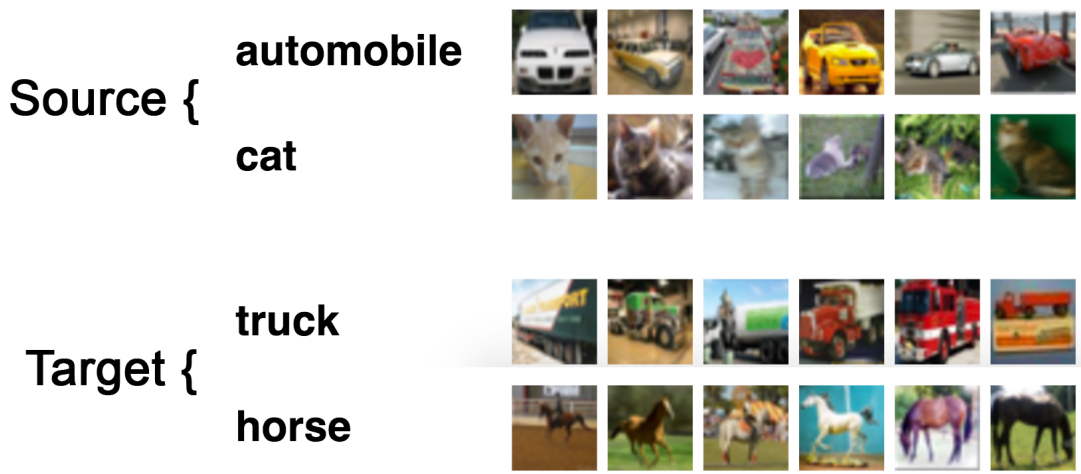

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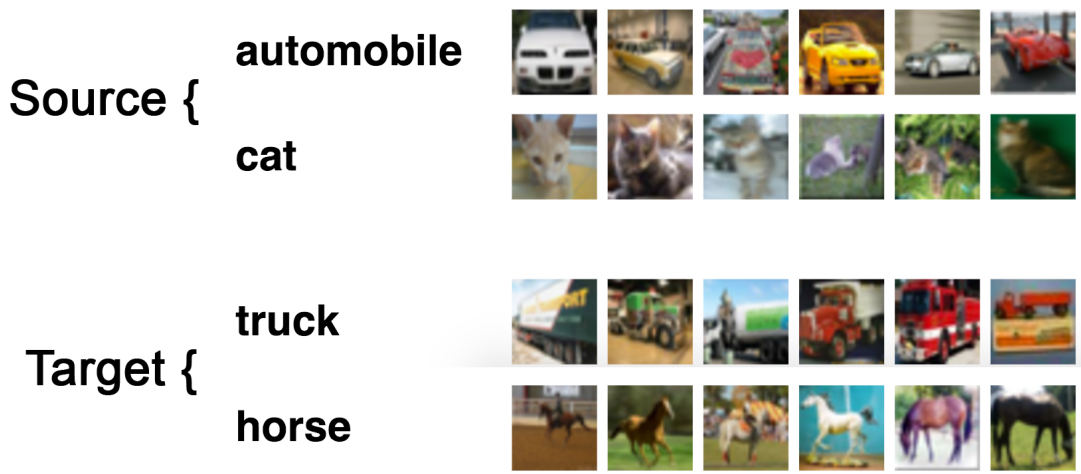

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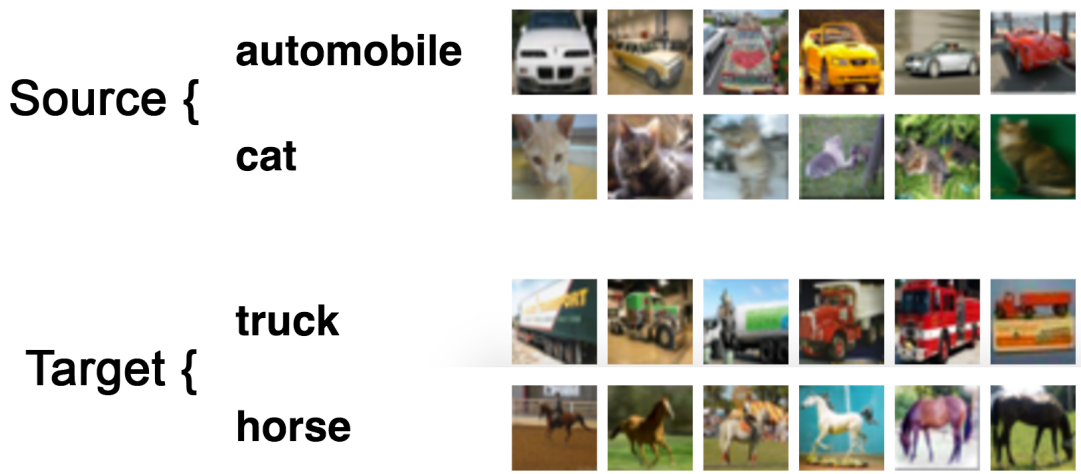
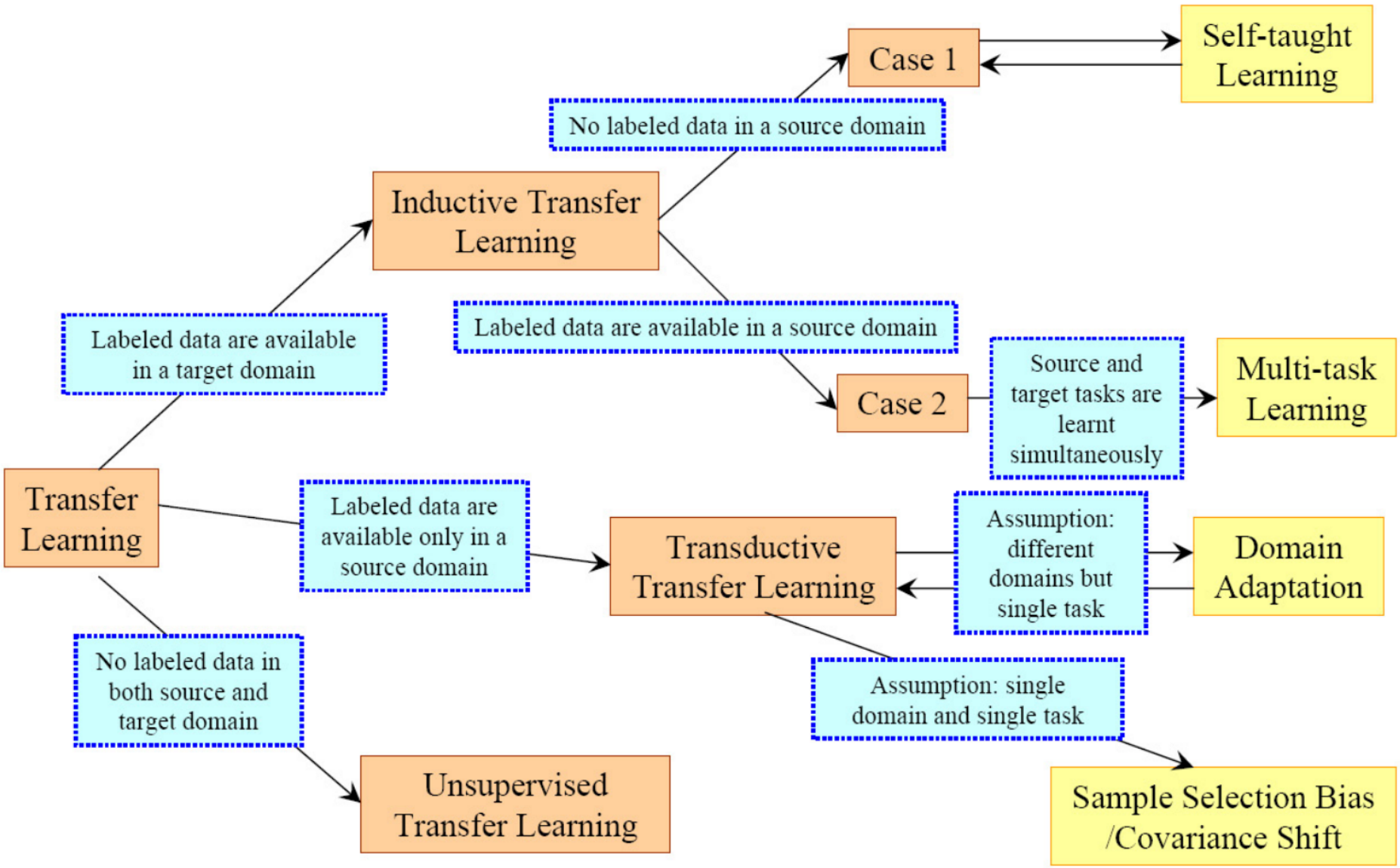


Branches [10]


Transfer Learning
Labeled data are available in a target domain
Inductive Transfer Learning
No labeled data in a source domain
Case 1
Self-taught Learning
Labeled data are available in a source domain
Case 2
Source and target tasks are learnt simultaneously
Multi-task Learning
Labeled data are available only in a source domain
Transductive Transfer Learning
Assumption: different domains but single task
Domain Adaptation
No labeled data in both source and target domain
Unsupervised Transfer Learning
Assumption: single domain and single task
Sample Selection Bias /Covariance Shift

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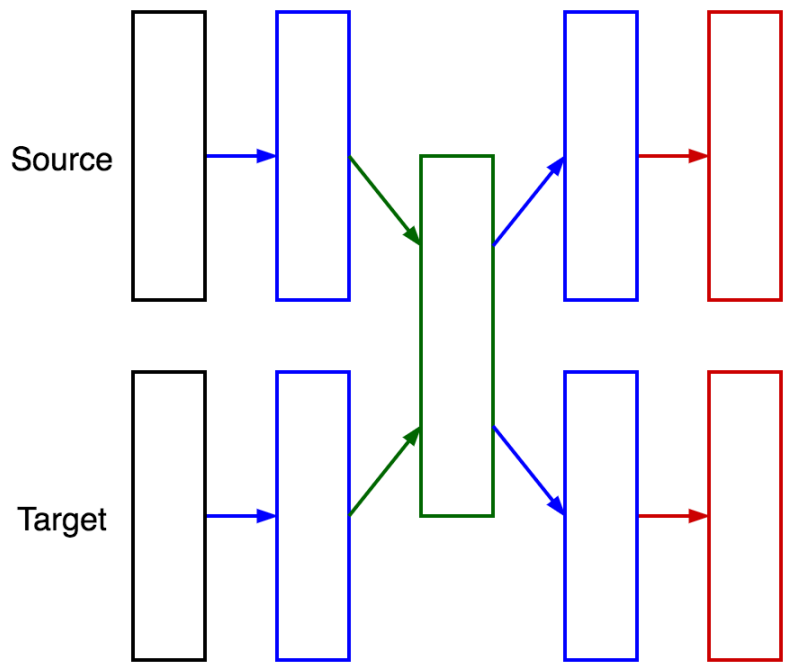

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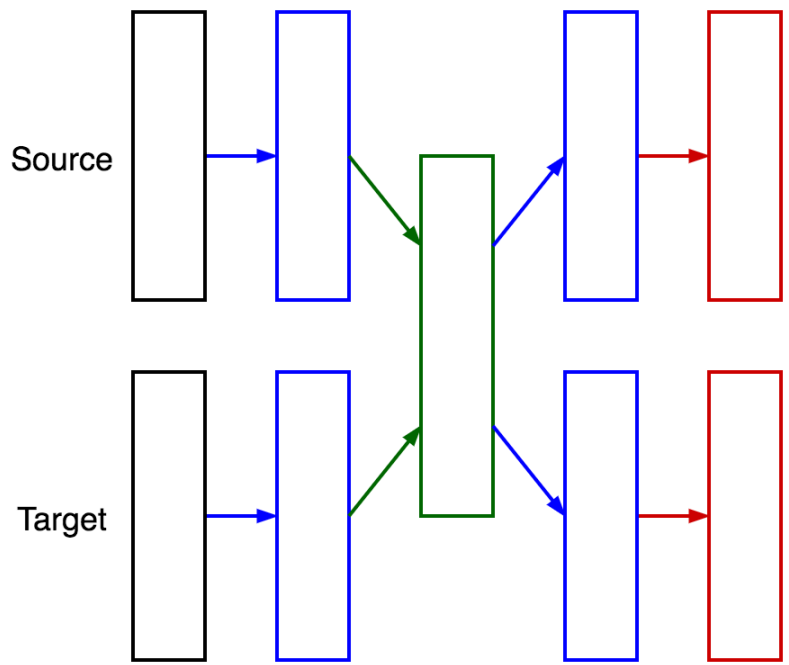

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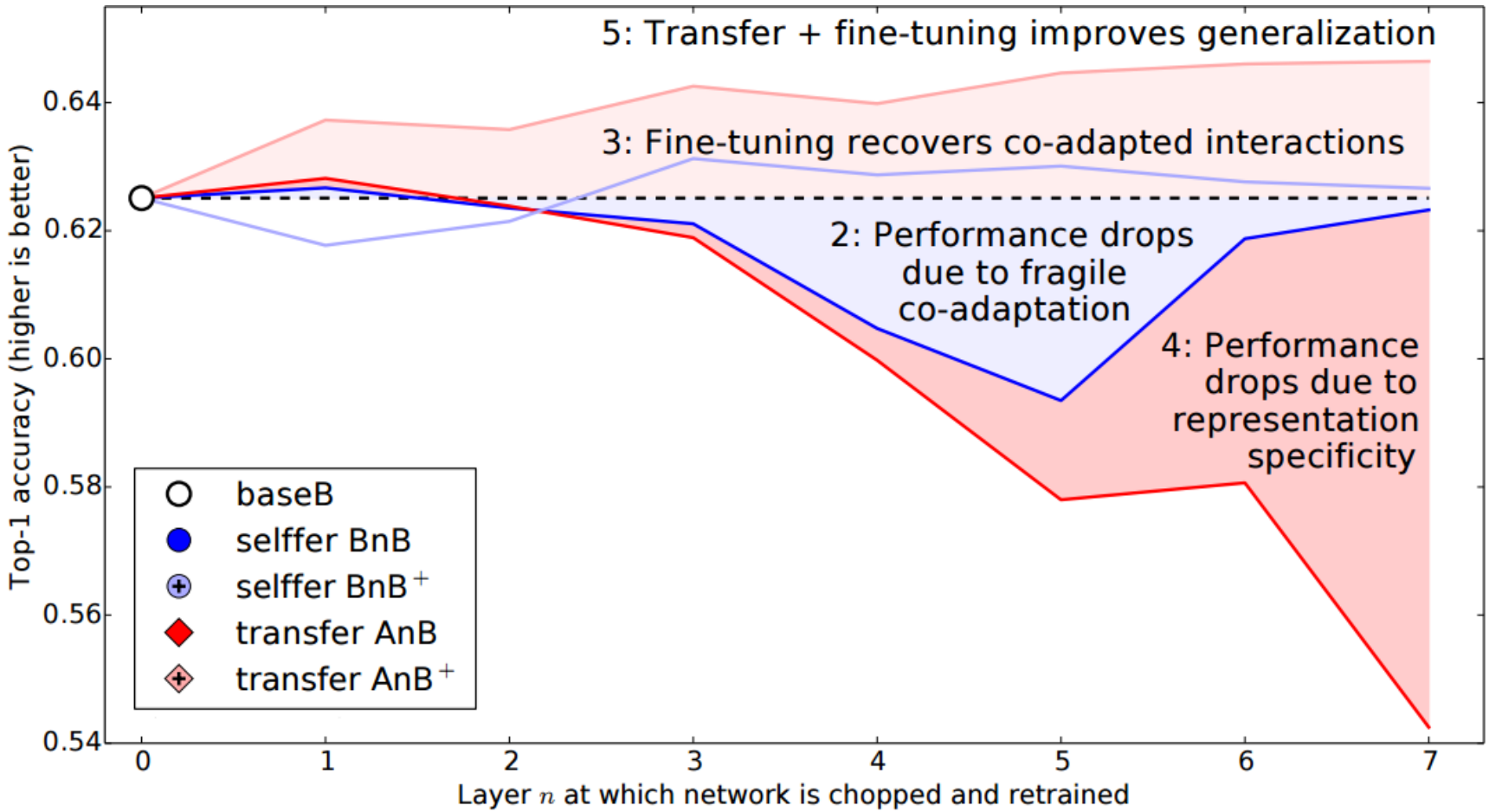
- Results from 2 CNNs (A and B) over ImageNet [14]:



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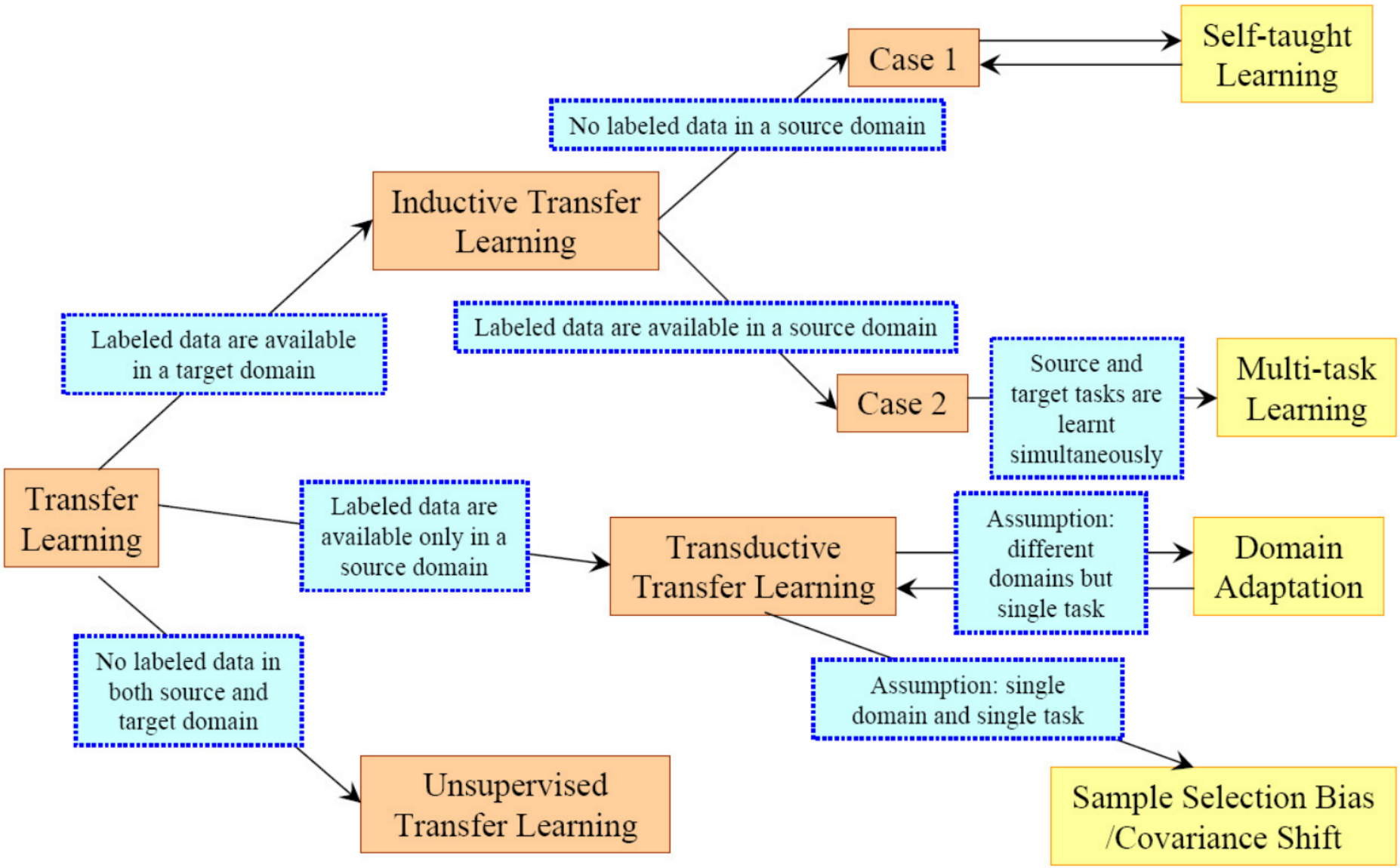
  - Instead prepend/append ***simple weight rewriter*** (e.g., linear SVM)

Outline

Domain Adaptation



Domain Adversarial Networks

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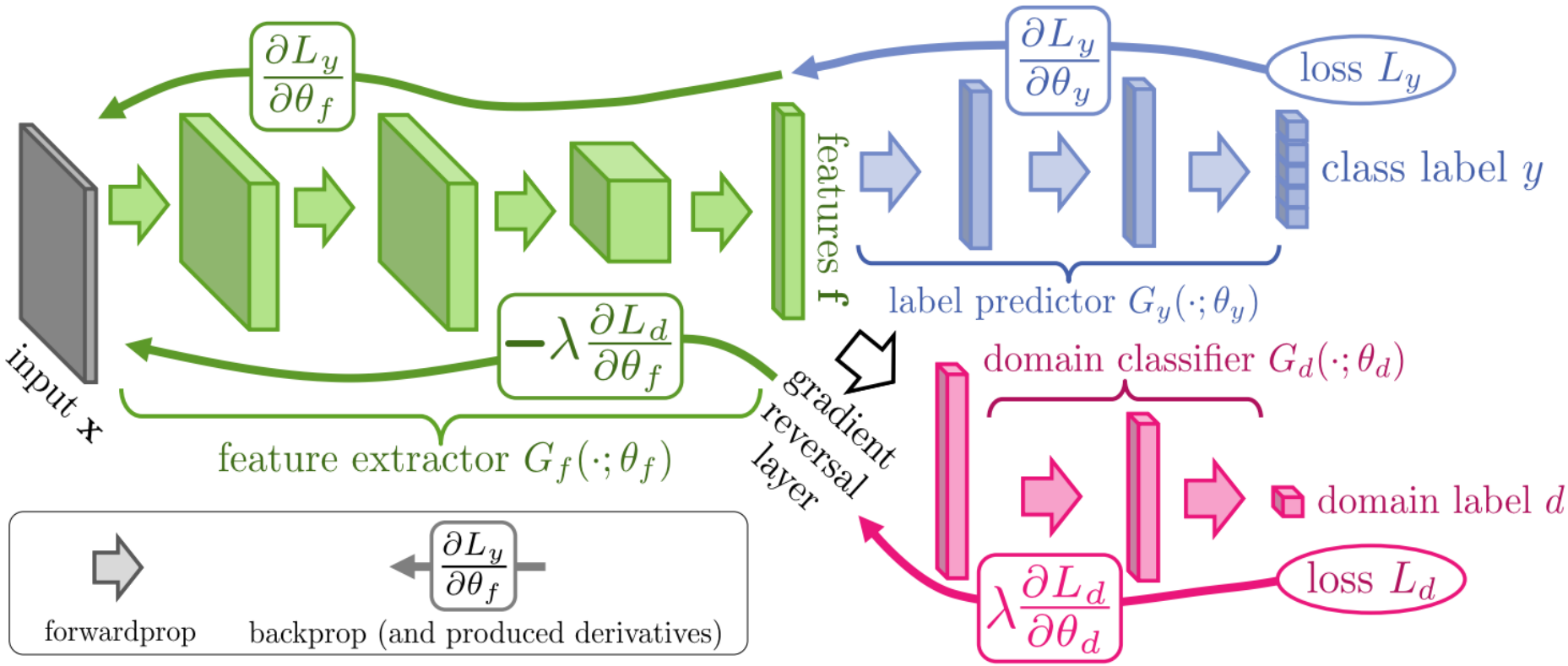
- Domain classifier + gradient reversal layer [7]



Outline

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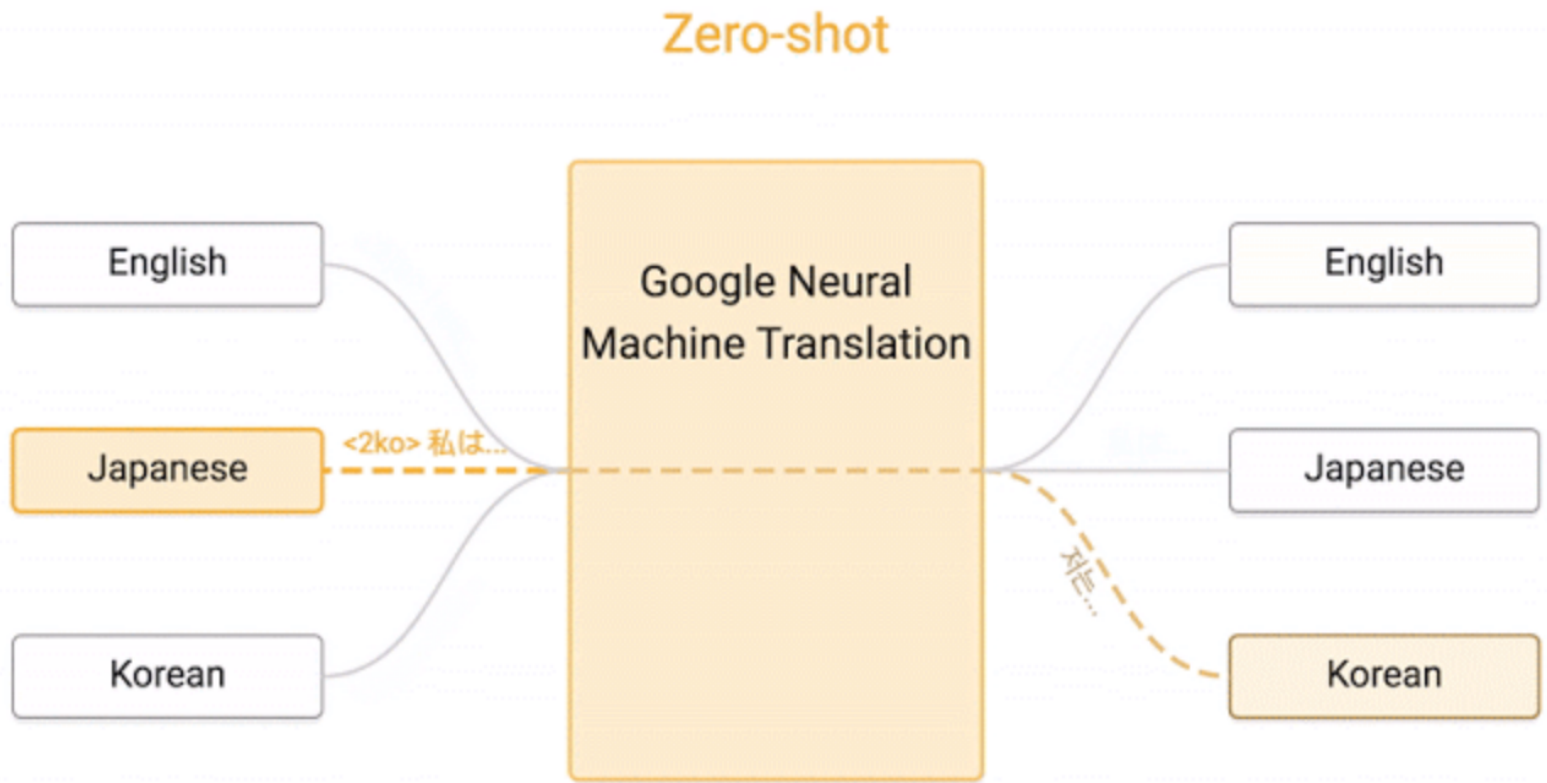

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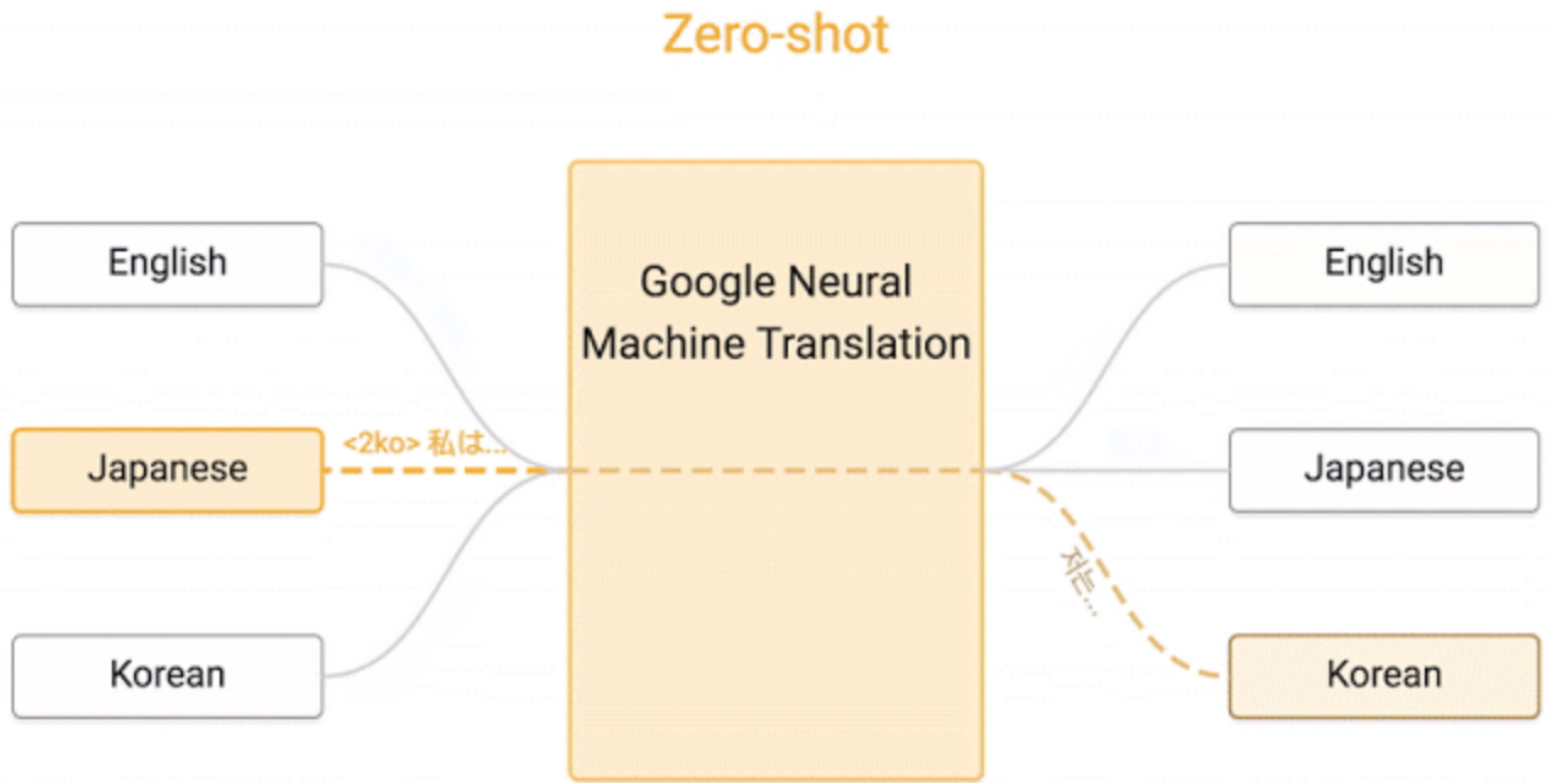
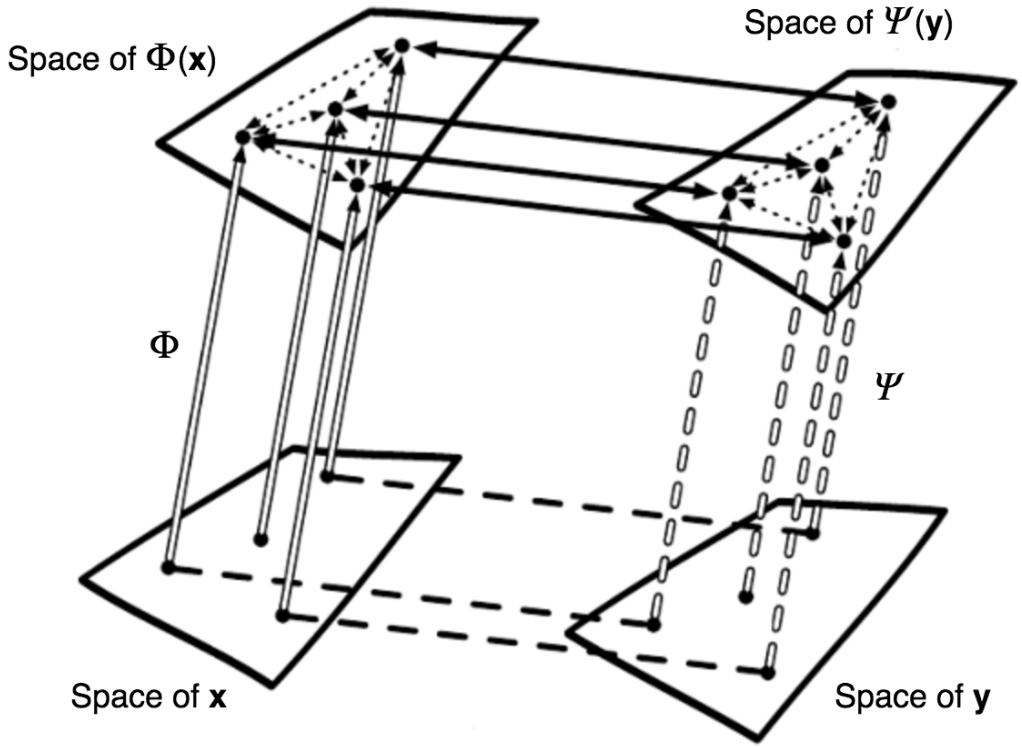


- How is that possible?

Label Representations

- Side information: the ***semantic representations*** $\Psi(\mathbf{y})$ of labels
  - E.g., "has paws," "has stripes," or "is black" for the "animal" class



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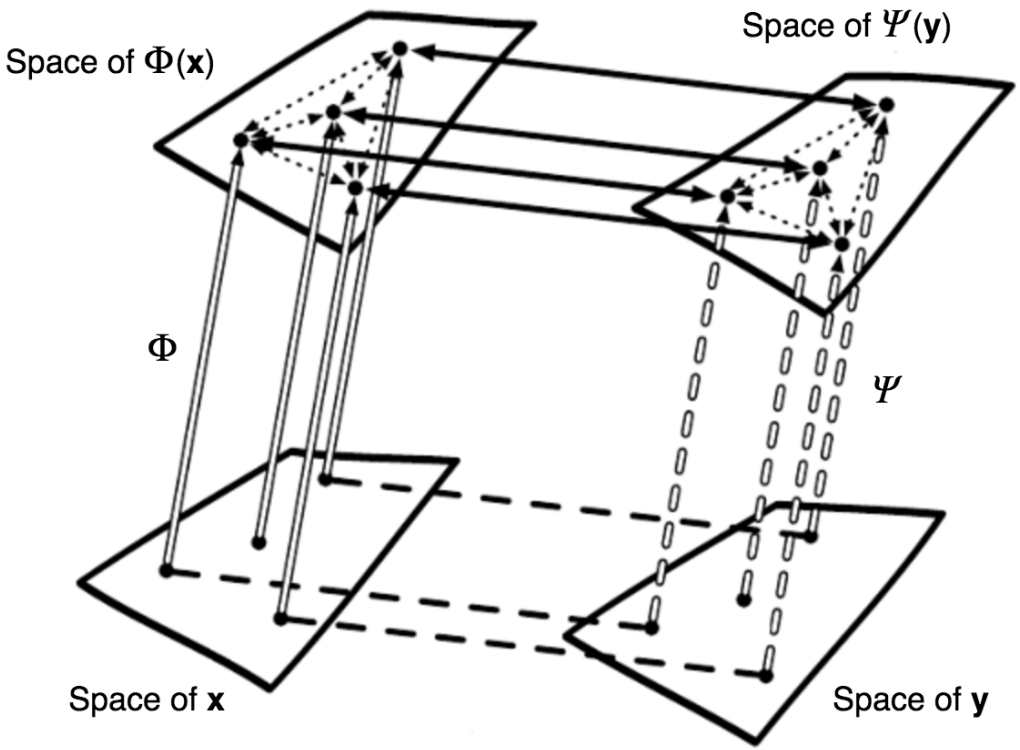

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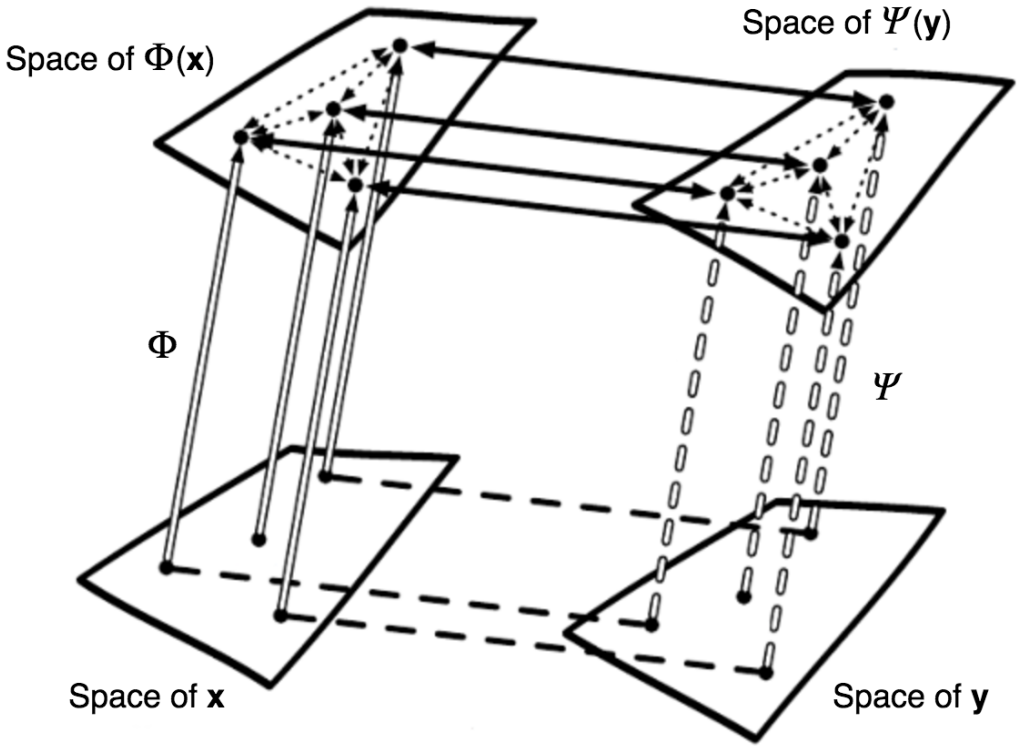
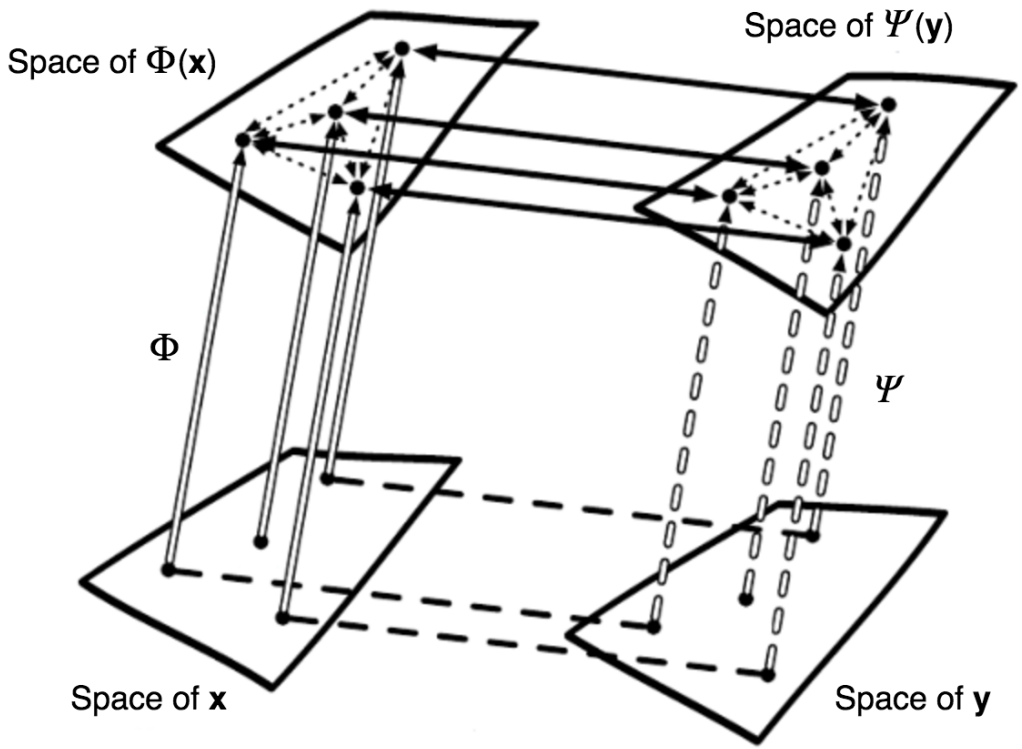
- Embedding function Ψ can be learned
  - jointedly with the model (e.g., in Google Neural Machine Translation)
  - or separately (e.g., in [1])



Why Does Zero Shot Learning Work?

- In task A, a model uses labeled pairs $(\boldsymbol{x}^{(i)}, \boldsymbol{y}^{(i)})$'s to learn the map between spaces of $\Phi(\mathbf{x})$ and $\Psi(\mathbf{y})$



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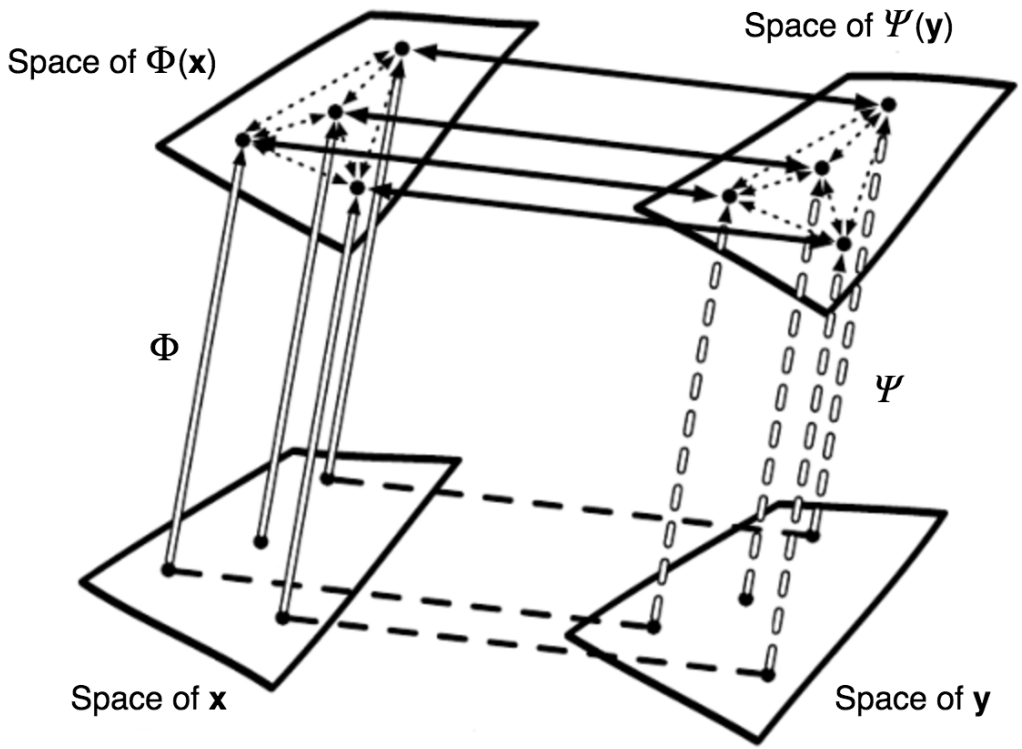
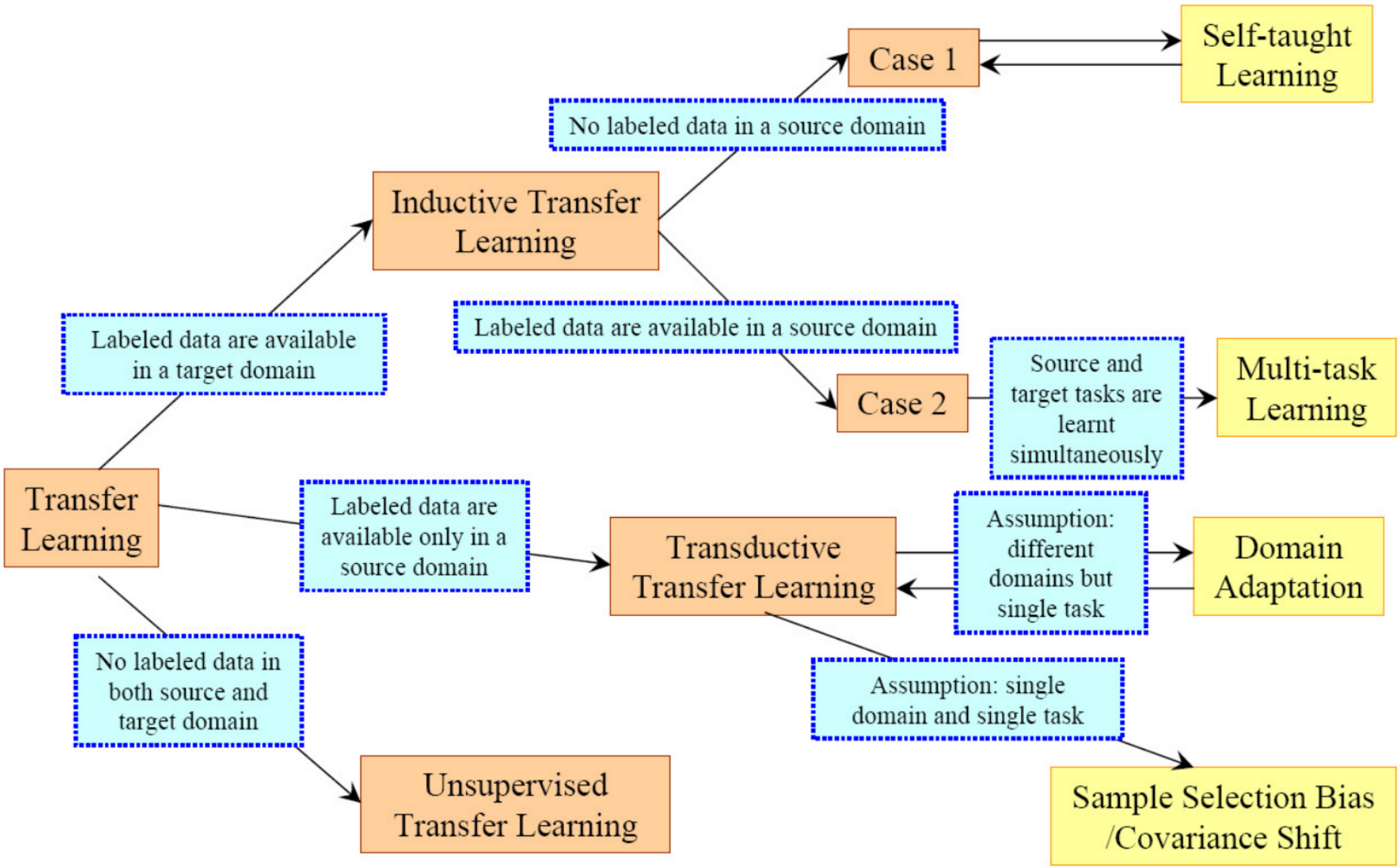
- In task B (with zero shot), the model predicts label of point $\boldsymbol{x}'$ by
  1. First obtaining $\Phi(\boldsymbol{x}')$
  2. Then following the map to find out $\Psi(\boldsymbol{y}')$



Outline

Unsupervised TL



Cross-Domain Recommendation

- Data (rating matrix) in a domain may be too sparse
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  - Cannot be factorized well
- Can we exploit rating matrices from other domains?

$X^{(source)}$ (Movies)

?	?	?	3	?
?	5	?	1	?
?	2	?	?	?
?	?	?	1	?

$X^{(target)}$ (Books)

?	?	?	?	?
?	?	2	?	?
5	?	?	?	3
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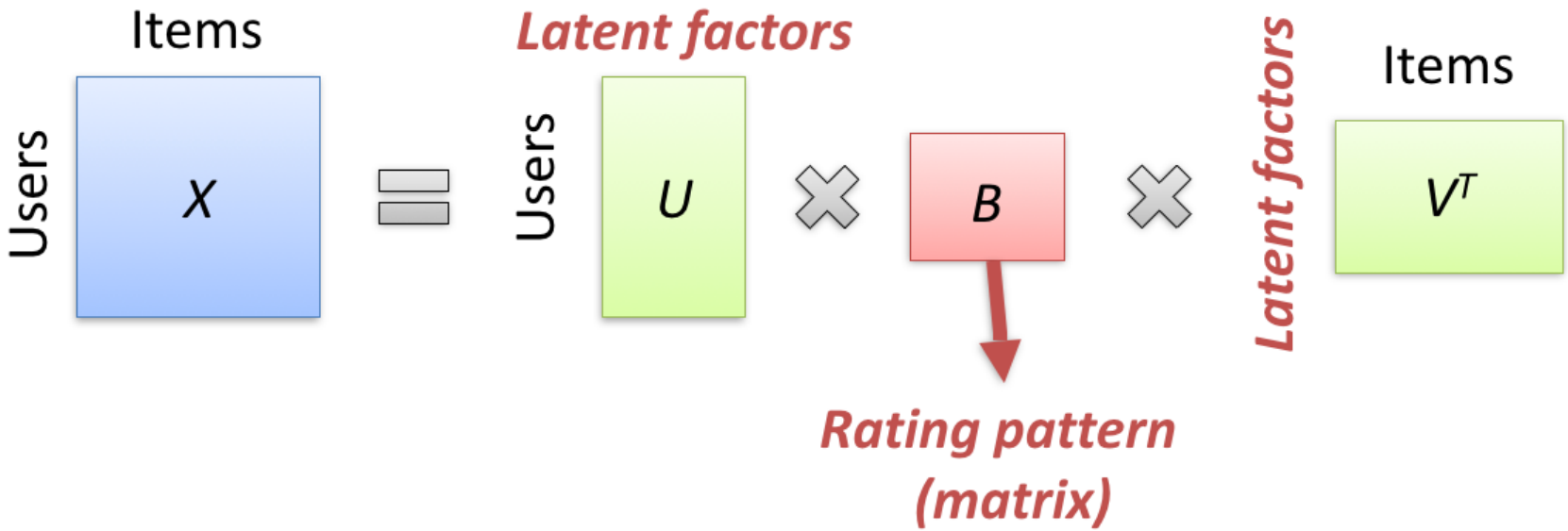
Nonnegative Matrix Tri-Factorization

$$\arg\min_{\boldsymbol{U},\boldsymbol{B},\boldsymbol{V}>\boldsymbol{O}} \|\boldsymbol{X}-\boldsymbol{U}\boldsymbol{B}\boldsymbol{V}^\top\|_F^2$$



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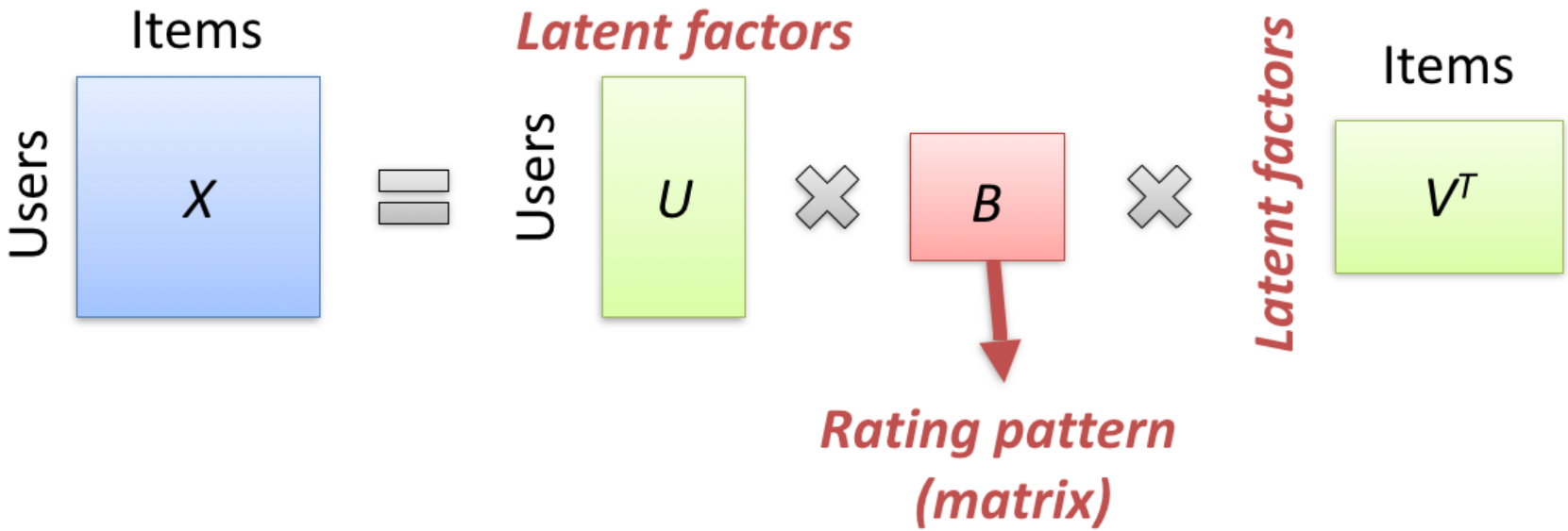
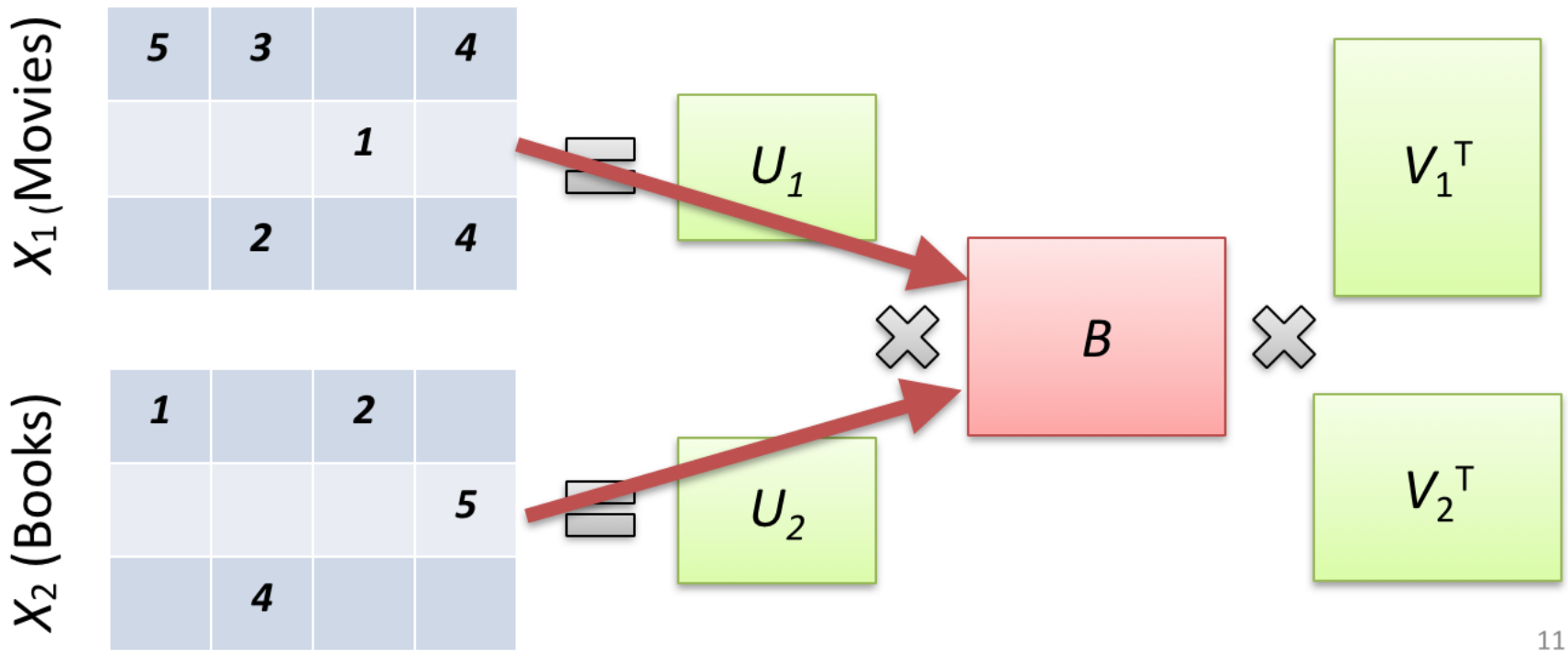


- Has a clustering interpretation [6]

Collective NMTF [9]

$$\arg \min_{\boldsymbol{U}^{(k)},\boldsymbol{B},\boldsymbol{V}^{(k)}>\boldsymbol{O}} \sum_k \|\boldsymbol{X}^{(k)} - \boldsymbol{U}^{(k)}\boldsymbol{B}\boldsymbol{V}^{(k)\top}\|_F^2$$



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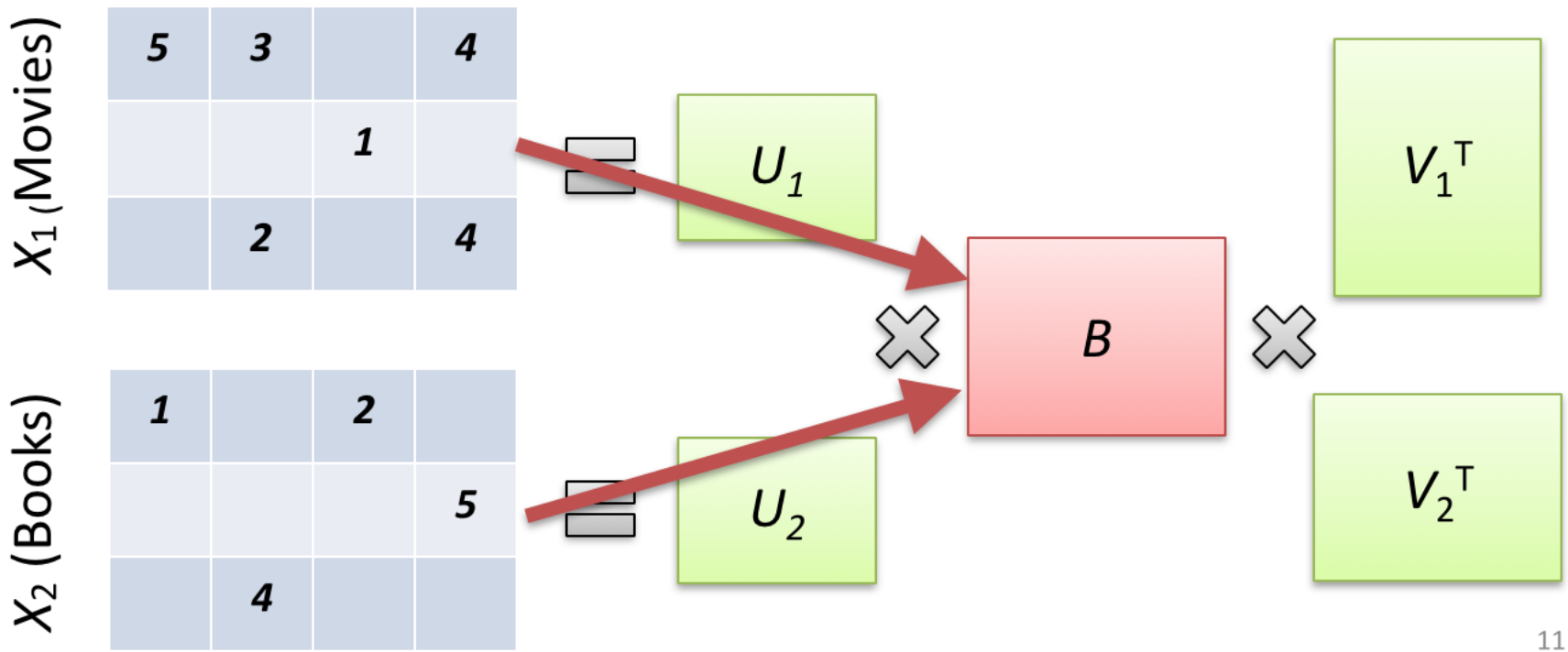
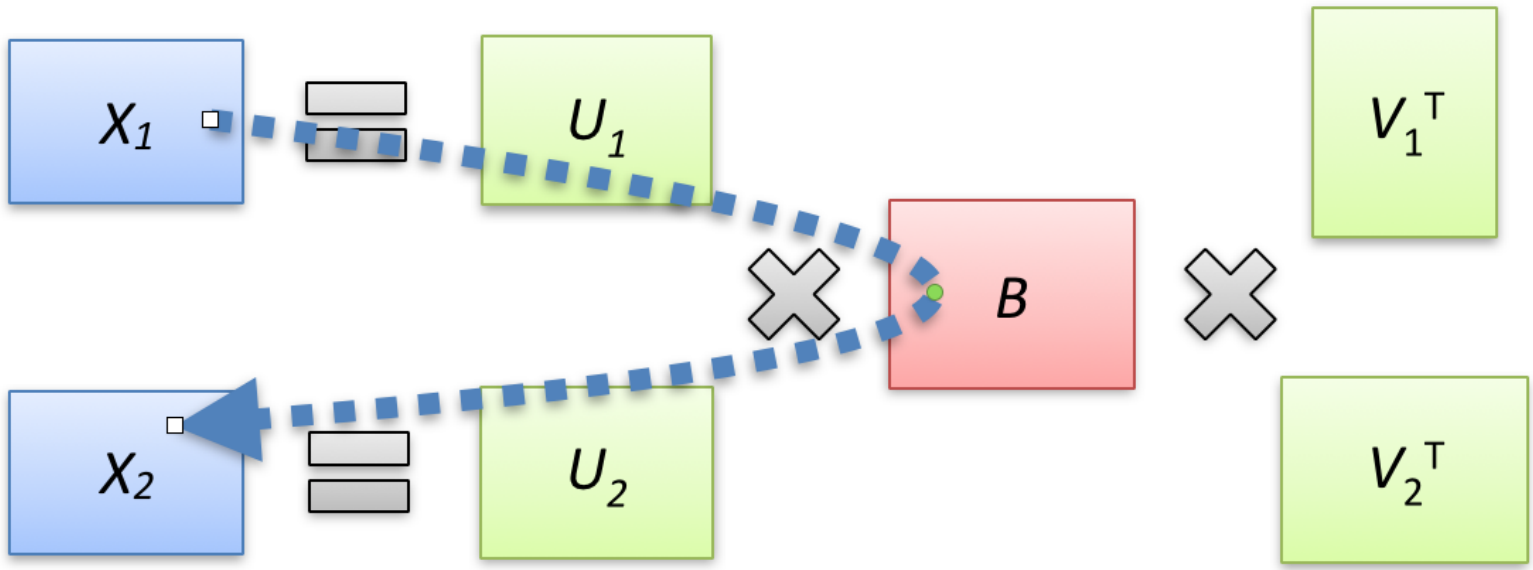


- More ratings help find better $\boldsymbol{B}$ (and recommendations)

Limitation

- Can only transfer ***linearly*** correlated knowledge



Limitation

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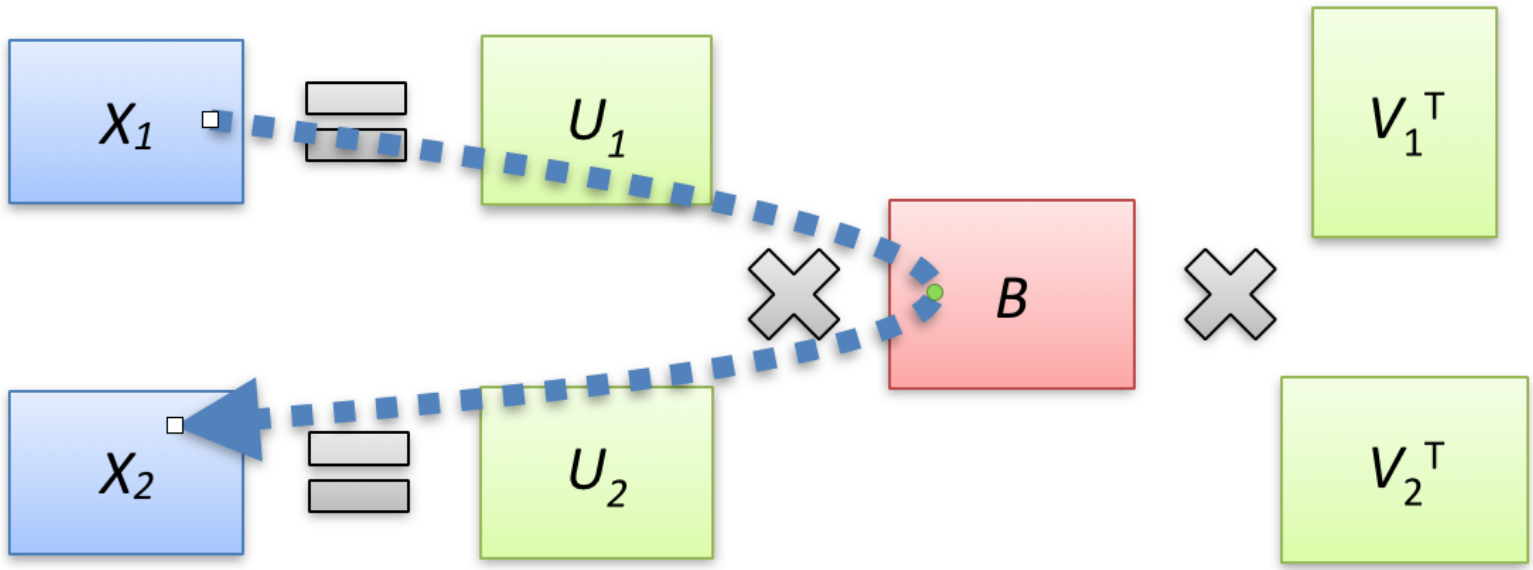
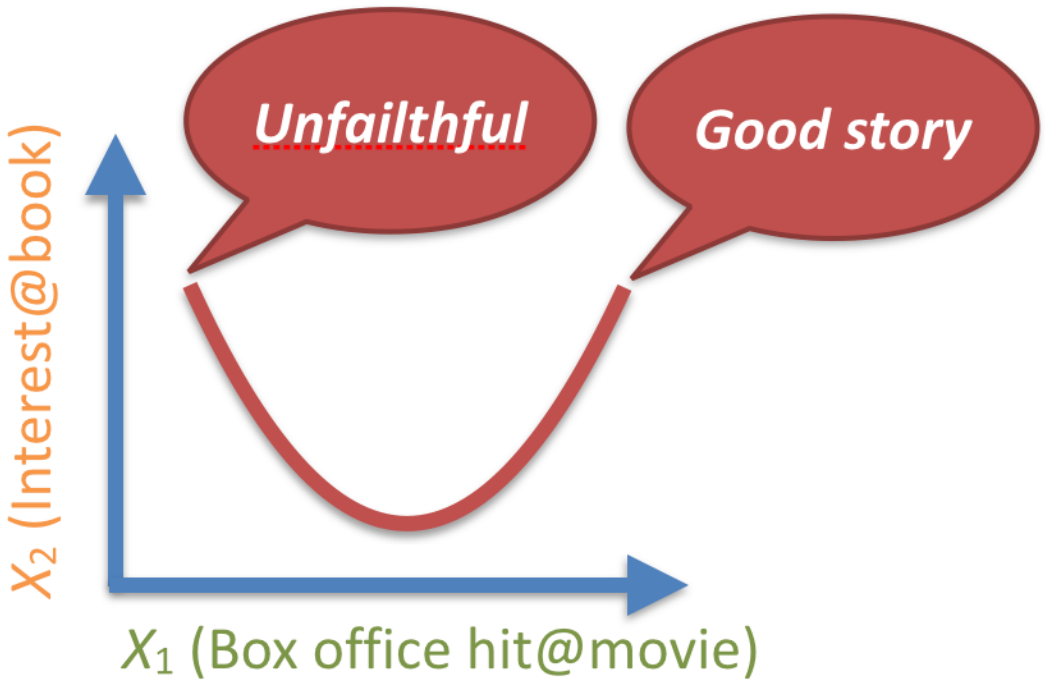


- In many case, $\boldsymbol{X}^{(\text{source})}$ and $\boldsymbol{X}^{(\text{target})}$ are not linearly correlated

Nonlinearly Correlated Domains

- E.g., suppose we have latent factors:
  - Source (movie): box office hit
  - Target (book): user interests



Nonlinearly Correlated Domains

- E.g., suppose we have latent factors:
  - Source (movie): box office hit
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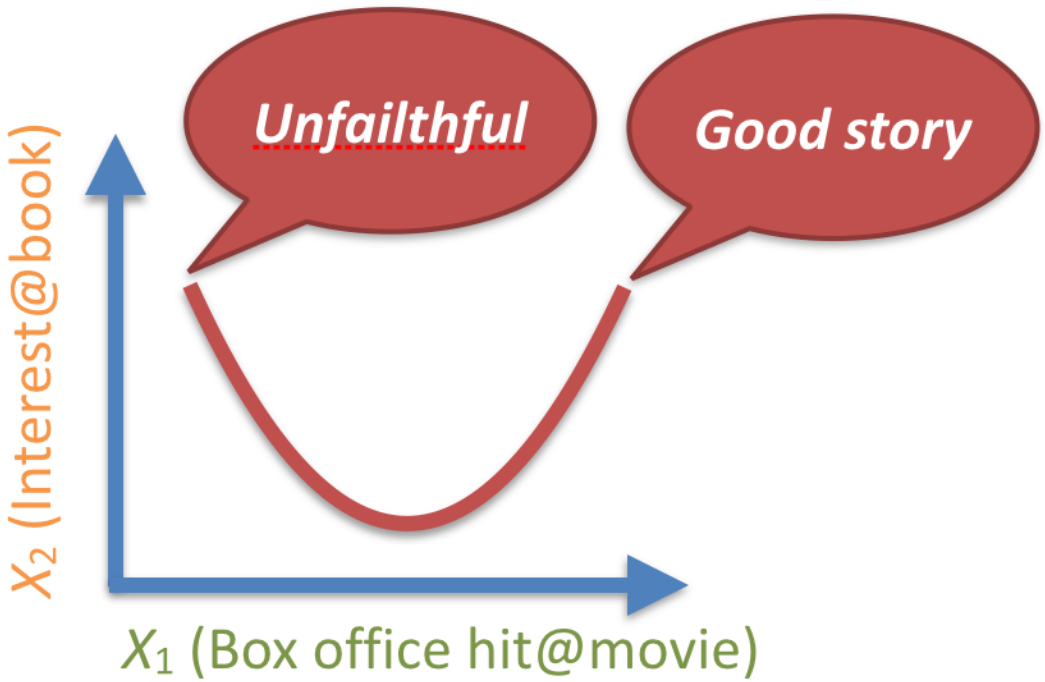
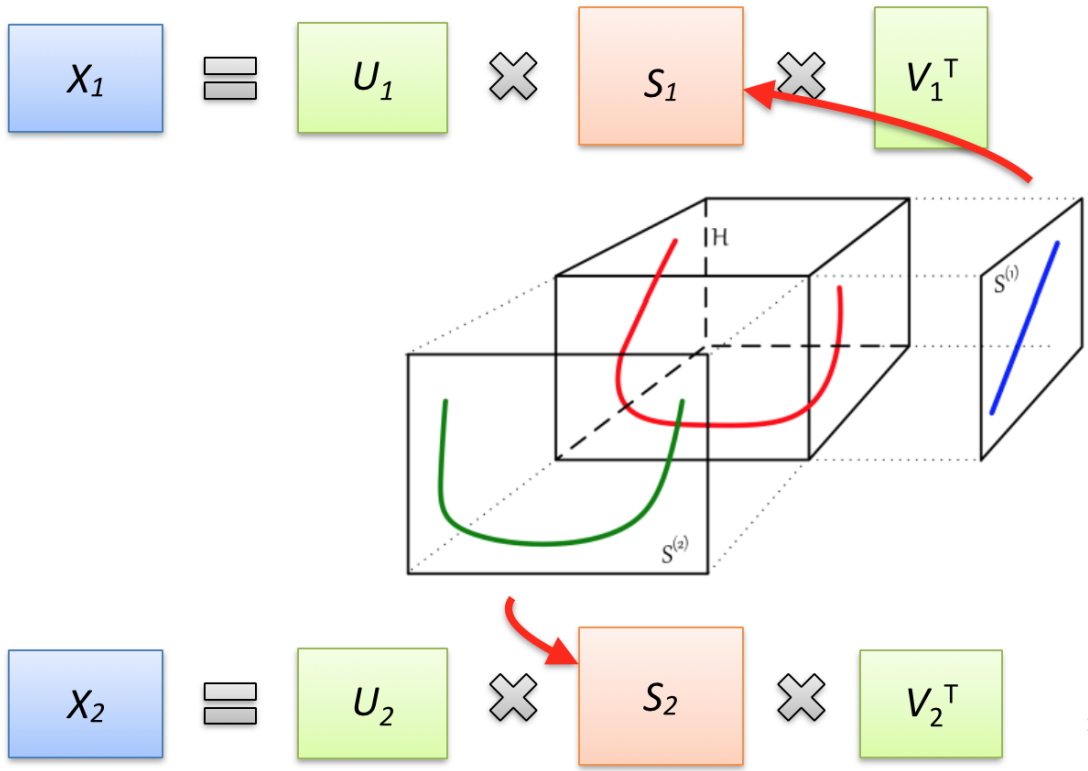
- How to transfer nonlinearly correlated knowledge?



Hyper Structure Transfer

- Idea: to let $S^{(k)}$'s be *projections of a shared tensor* H [8]:

$$\arg \min_{U^{(k)},\mathbf{H},V^{(k)}>O} \sum_k \|X^{(k)} - U^{(k)} \text{proj}^{(k)}(\mathbf{H}) V^{(k)\top}\|_F^2$$



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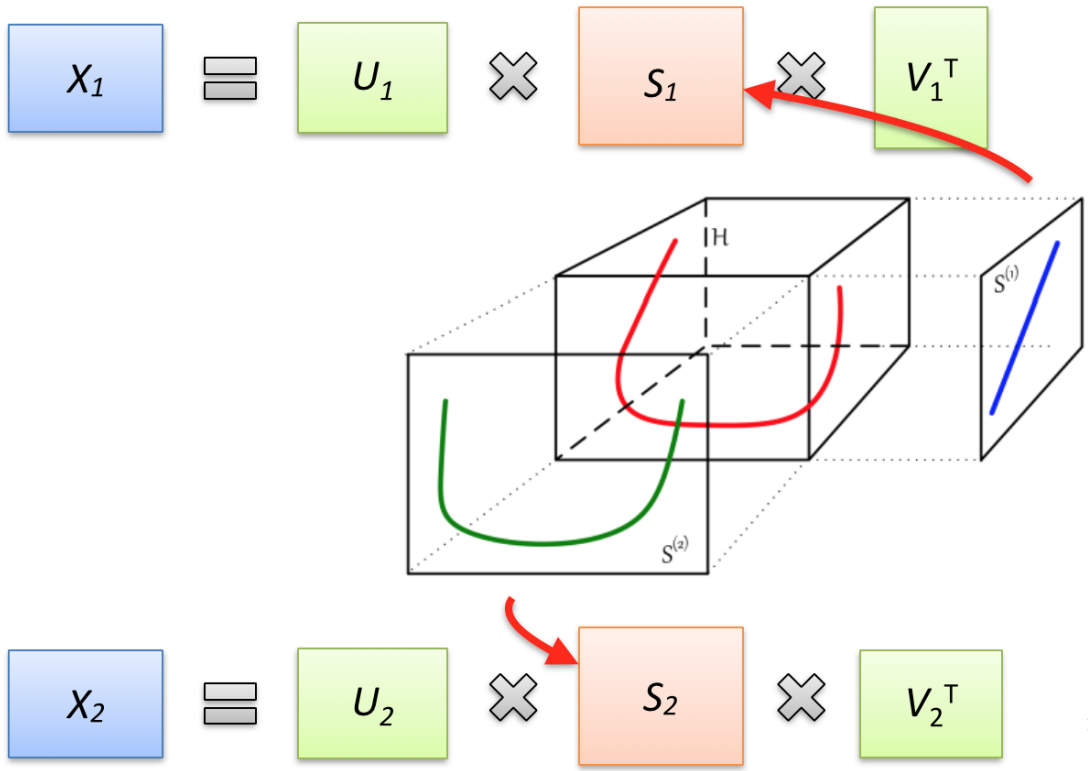
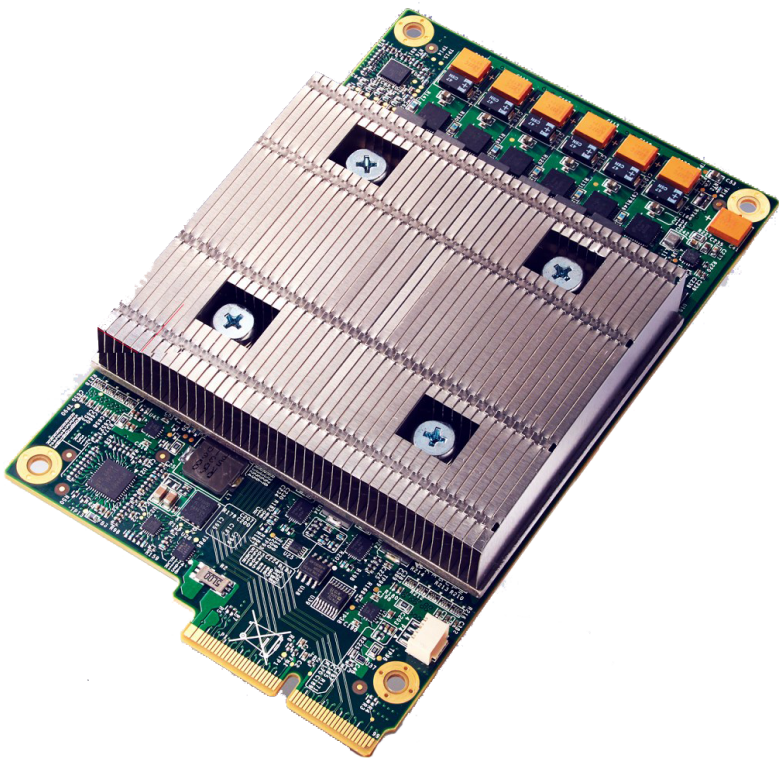
- $\boldsymbol{S}^{(k)} = \text{proj}^{(k)}(\mathbf{H})$'s can be nonlinearly correlated



Outline

ML-Driven Computers

- Tensor processing units (TPUs) designed by Google:
  - Reduced precision (16- or 8-bit floats)
  - Support TensorFlow
- In Google Photos, each TPU can process 100+ million photos a day



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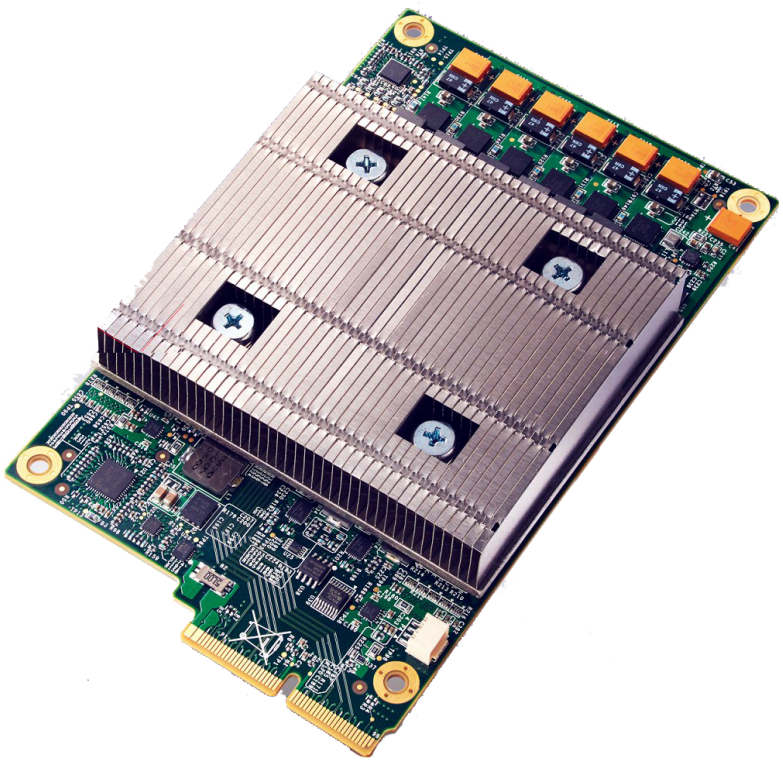

"... performance roughly equivalent to fast-forwarding 7 years into the future (3 gens of Moore's Law)..."

Single "Brain" behind a Corporate?

- Currently, different models for different tasks
  - Inefficient in data collection, computation, and human resource

[1] Google Brain, https://openreview.net/pdf?id=B1ckMDqlg

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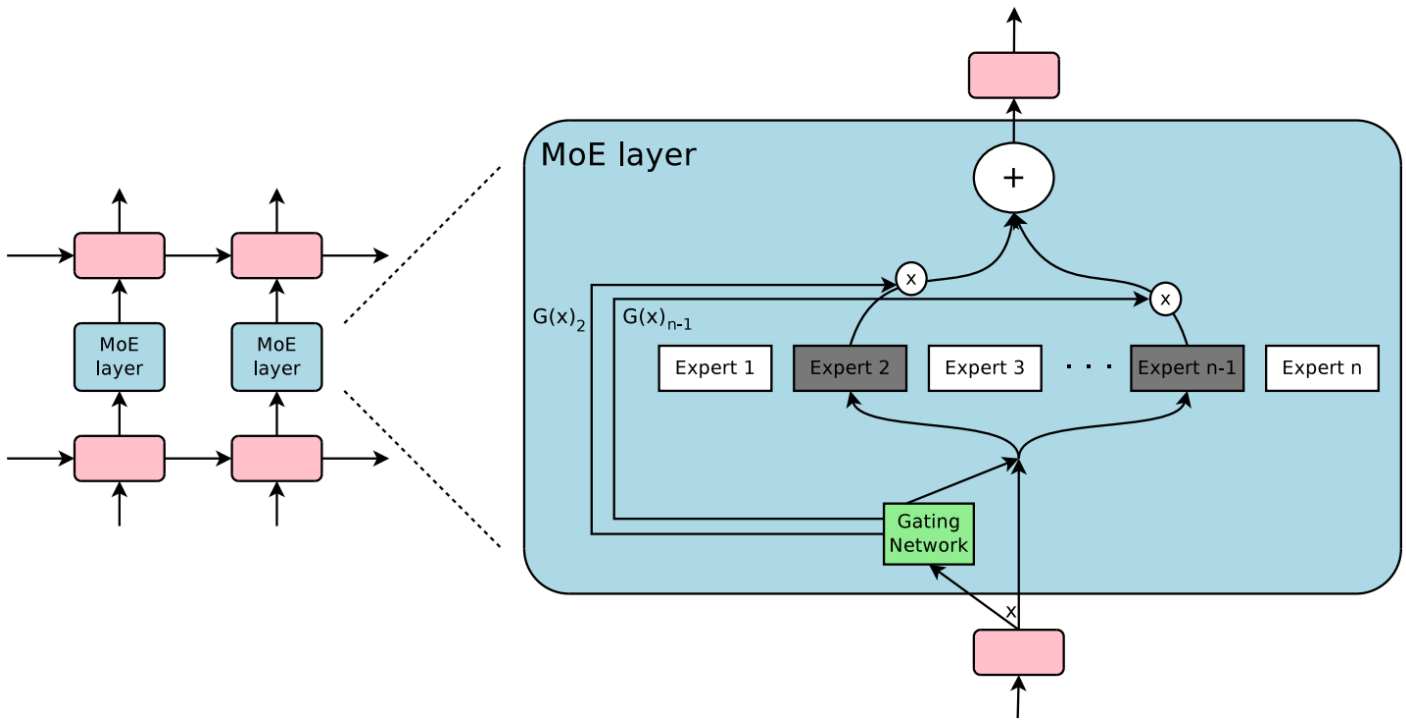
Single "Brain" behind a Corporate?

- Currently, different models for different tasks
  - Inefficient in data collection, computation, and human resource
- Idea: bigger and unified model, but sparsely activated
- E.g, ***mixture of experts layer***[1] embedded within language model
  - Sparse gating function selects two experts to perform computations
  - Outputs are modulated by the outputs of the gating network



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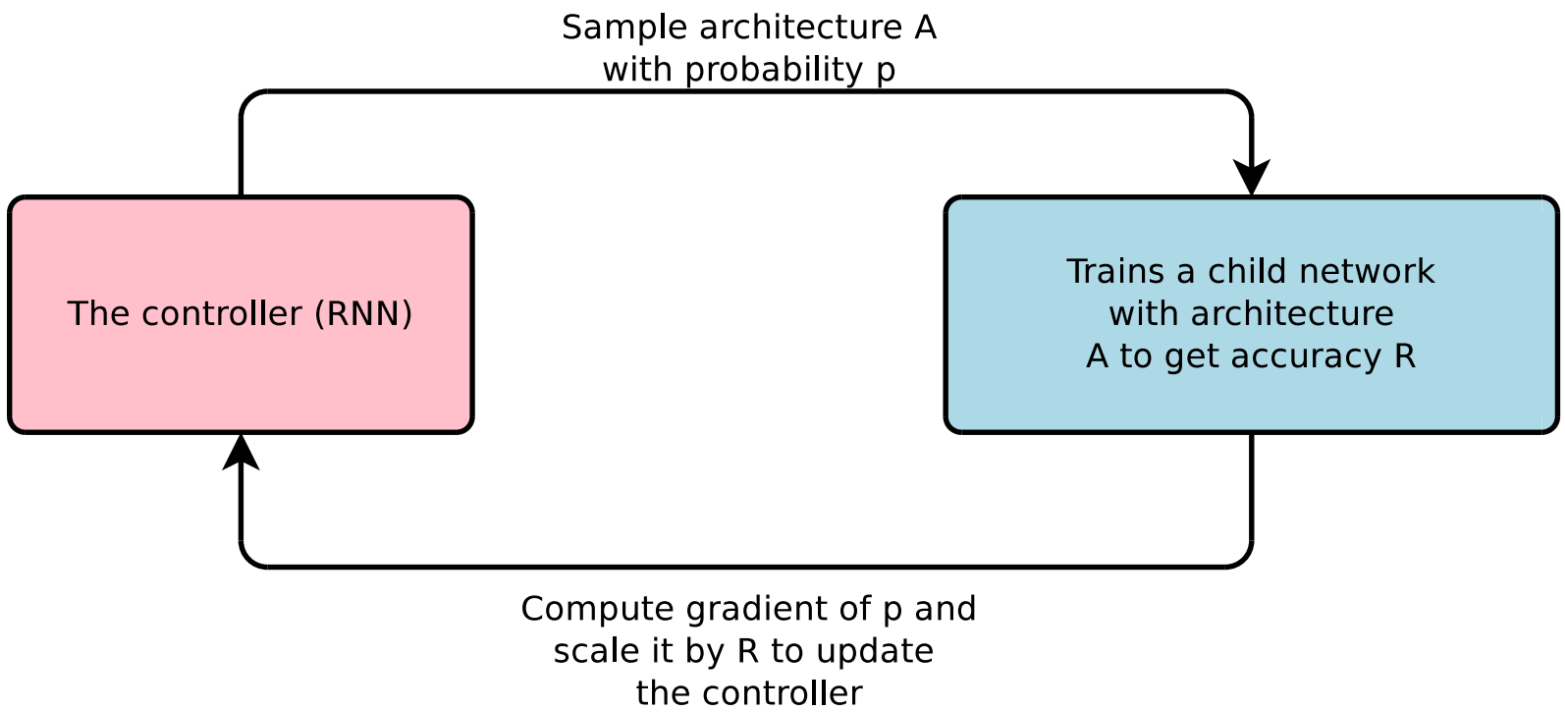
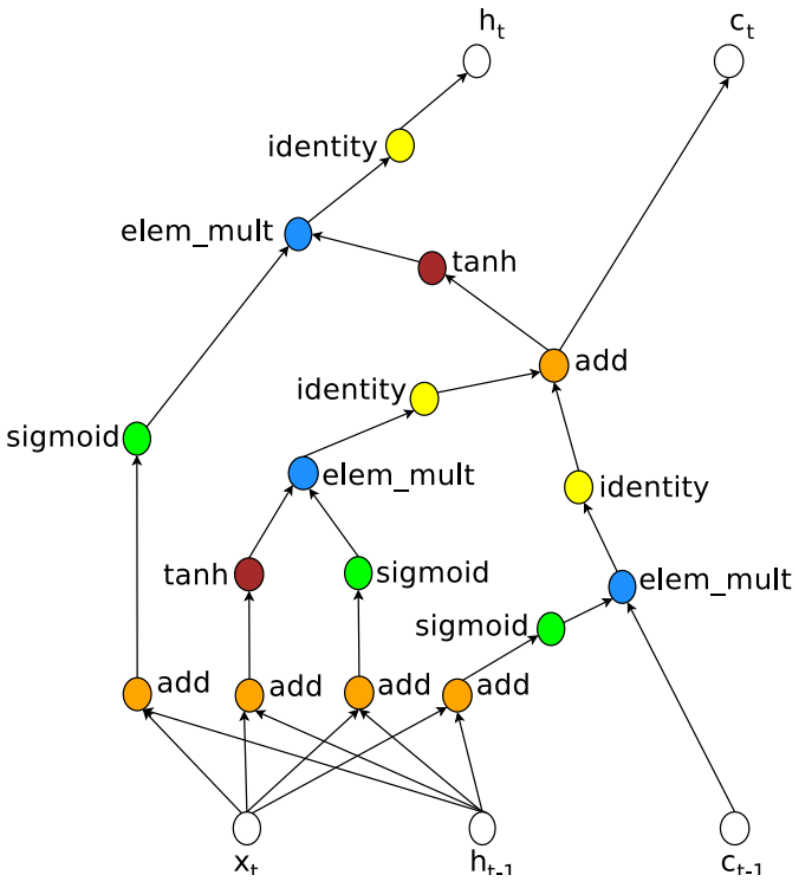
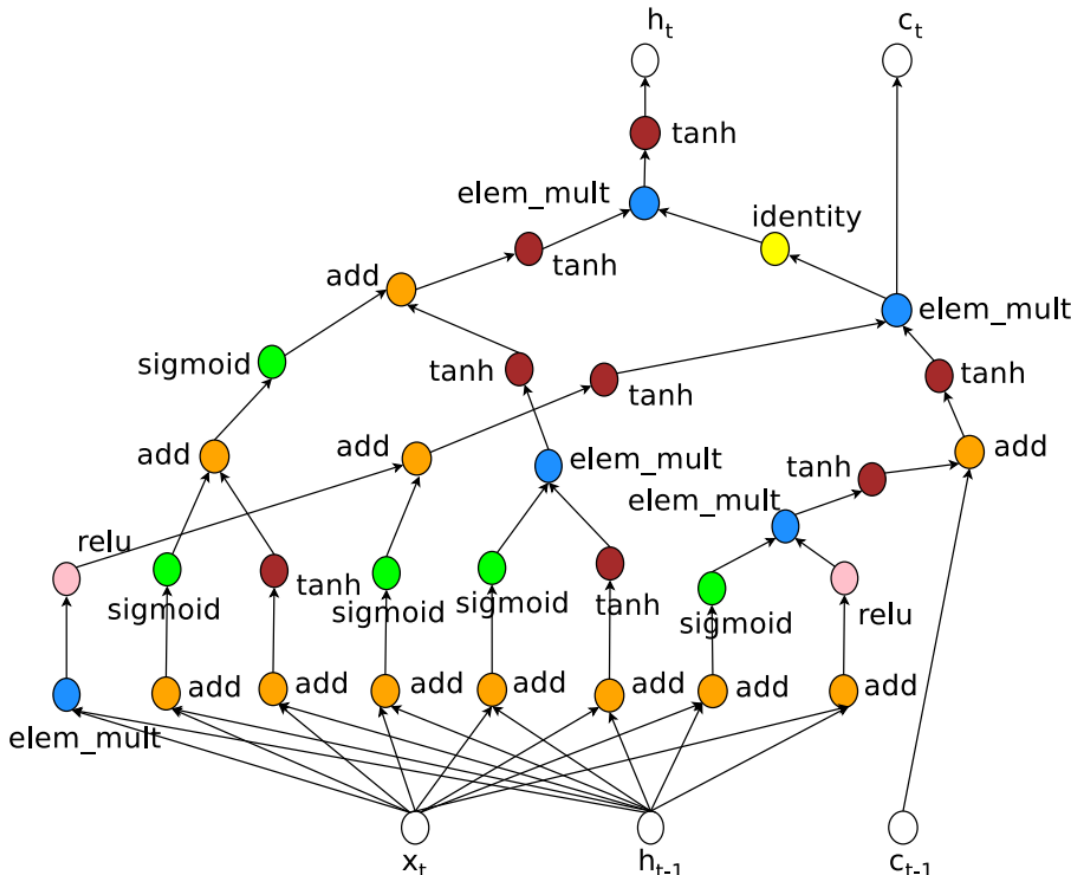
- Can we turn this into: solution = data + 100X computation?
- ***Learning to learn***
- E.g., use ***reinforcement learning*** to search for the best architecture [15]



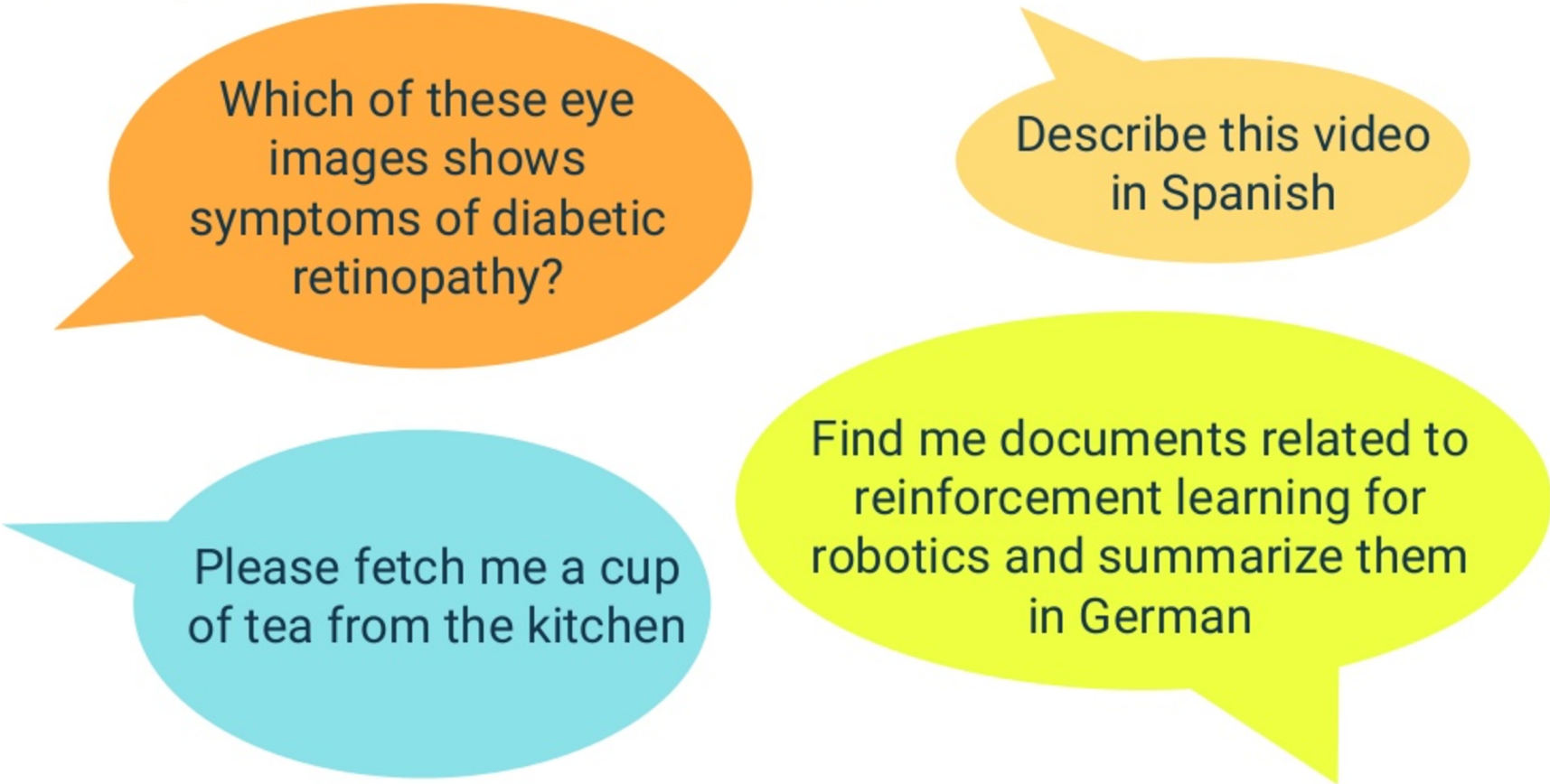
LSTM vs Learned Unit

- Computation graphs



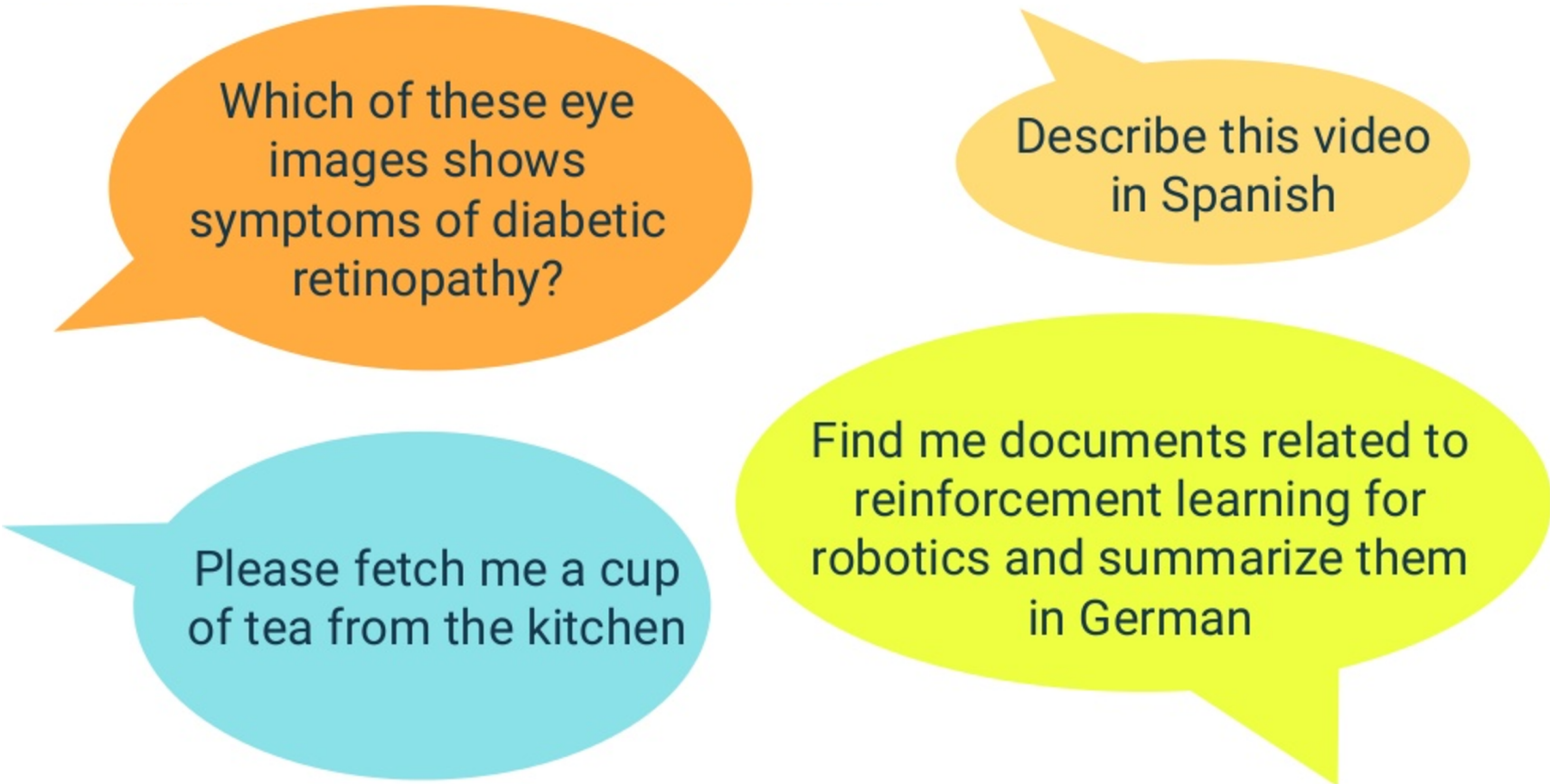


Human-Computer Interaction in the Future



Human-Computer Interaction in the Future

- Or at least how you can query Google in the future...



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