

Selective Federated Transfer Learning using Representation Similarity

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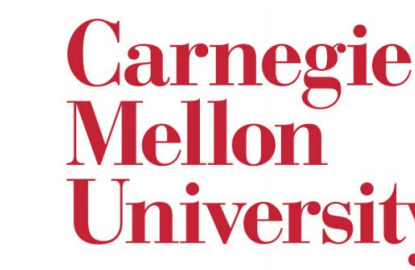
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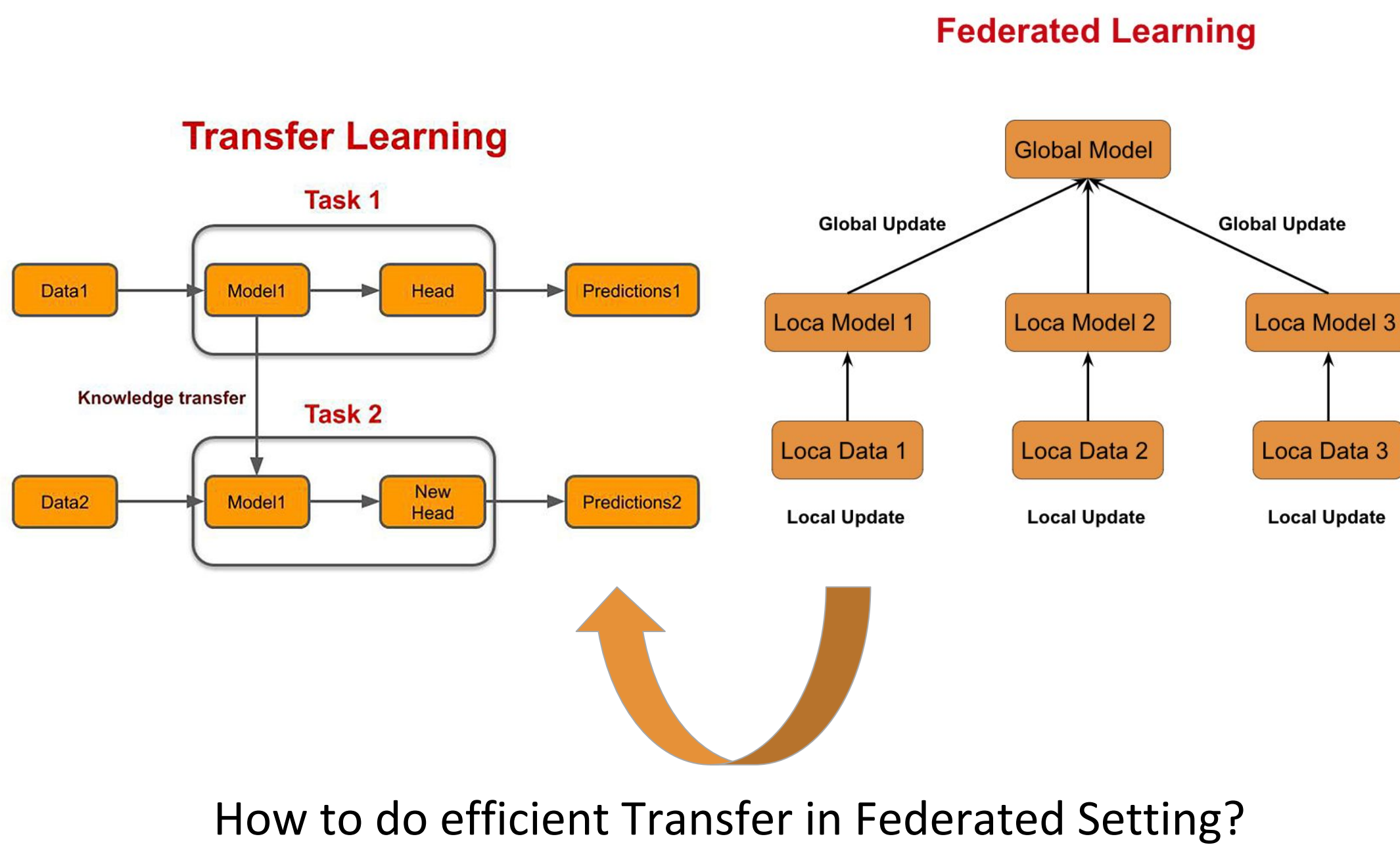
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Introduction



Challenges under Privacy Constraints

- Limited access to Target (client) data distribution
- Randomly transferring the source model
- Negative transfer



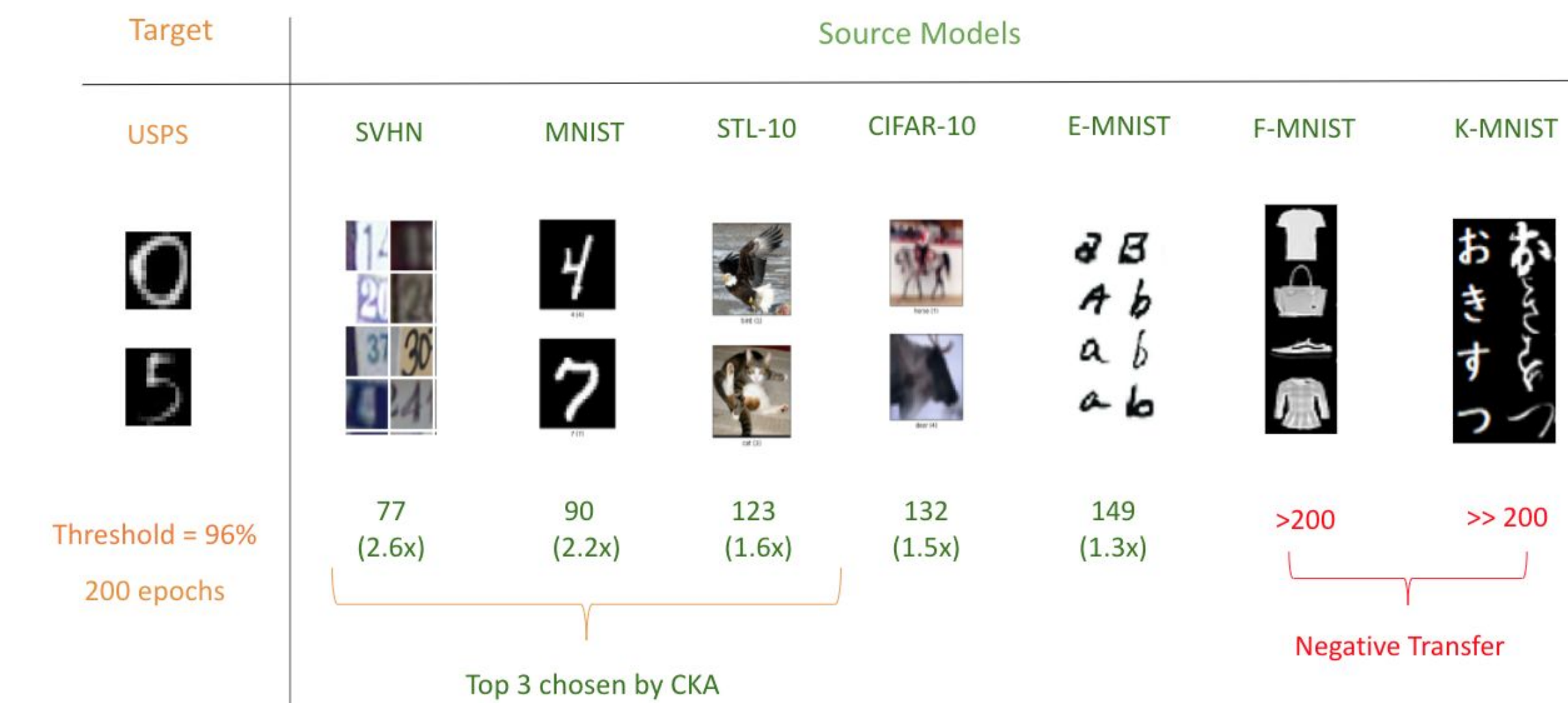
Q1: How to find a suitable Source model?

Q2: How to elect?

A1: Similarity Metric!
A2: Voting Scheme!

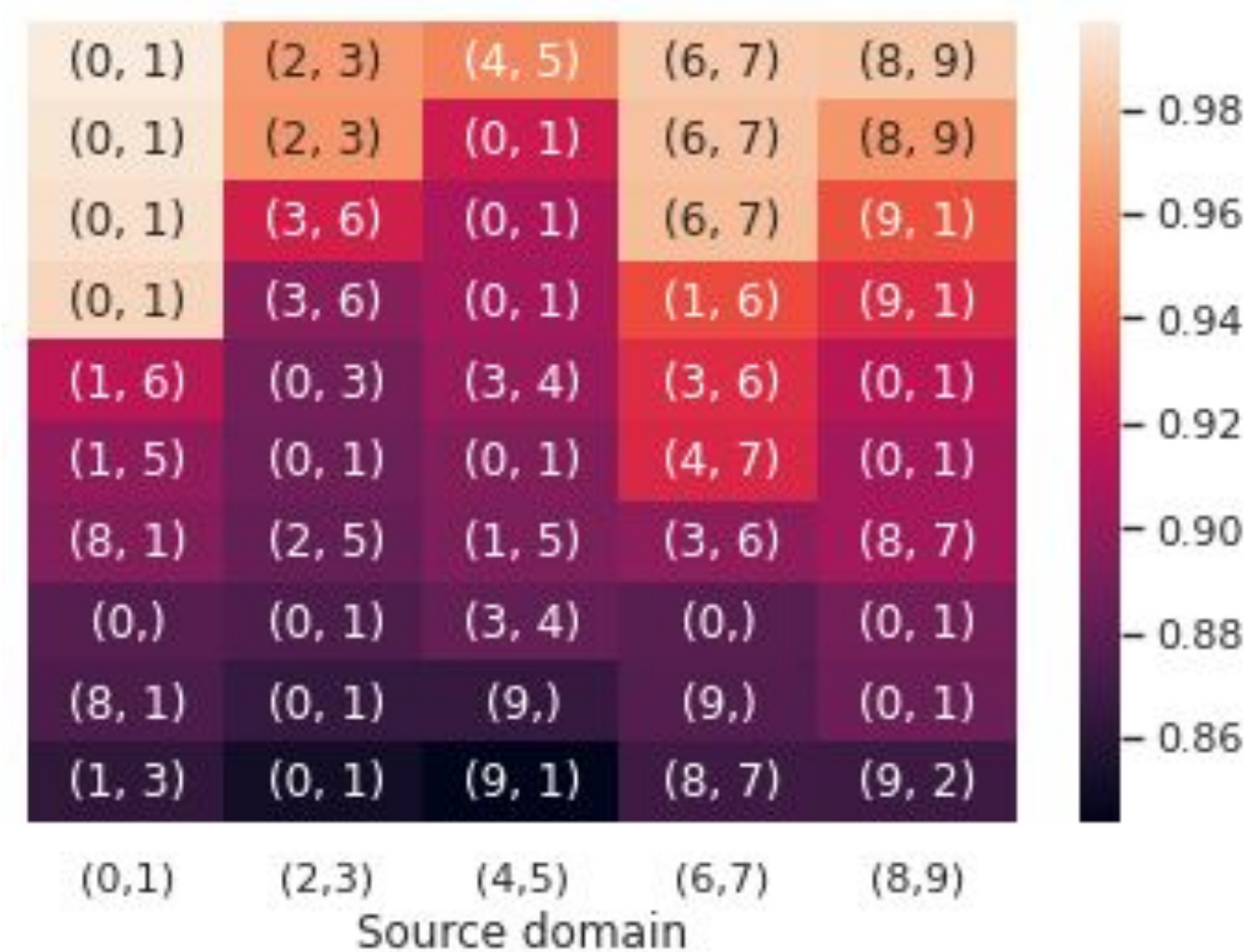


Experimental Results



Motivation

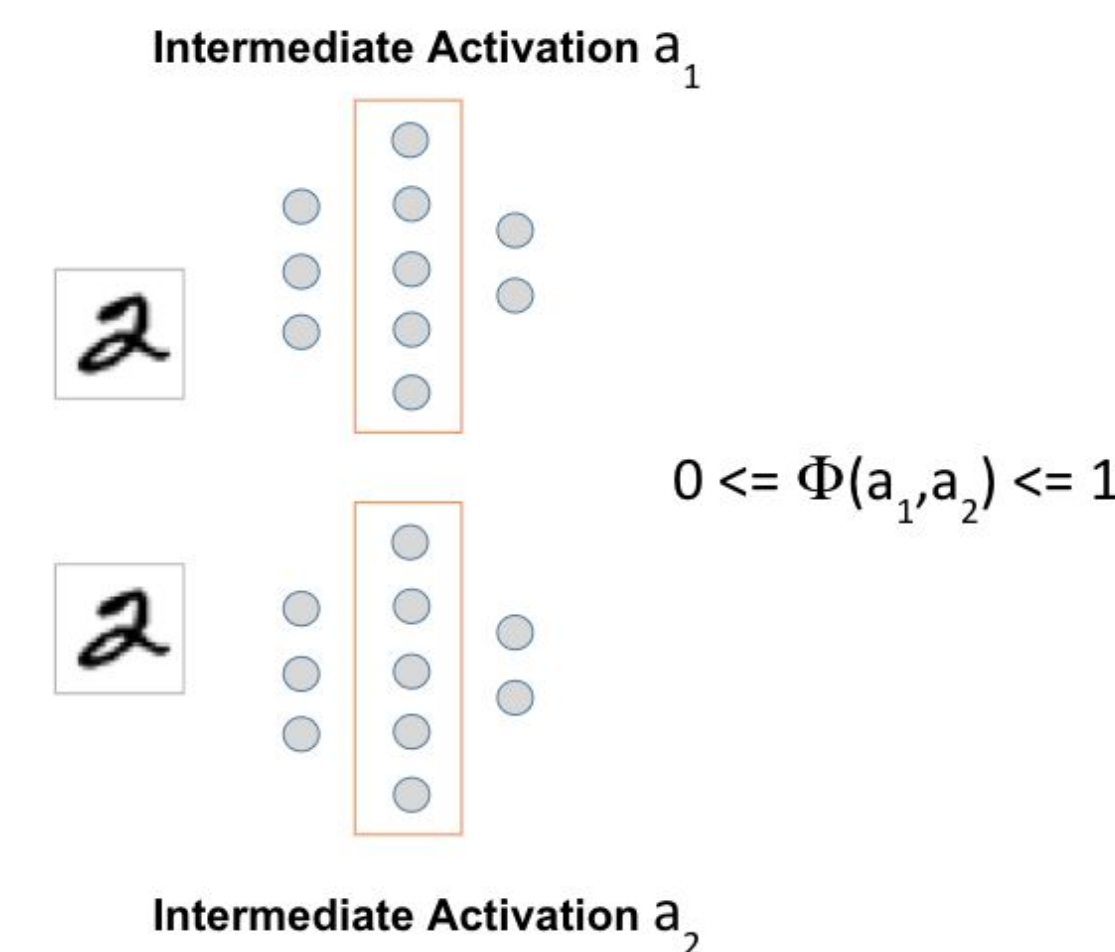
- Given a pool of already trained *source* models
- Match the most similar source model to a *target* model in a federated manner
- Transfer the model parameters and then continue with the federated training
- We use the concepts of “similarity representations”
- **Final aim:** Reach a desired accuracy at a lower number of communication rounds
- Selective Transfer



Selective Mechanism

Similarity Metric

- SVCCA (Raghu et al. (2017))
- PWCCA (Morcos et al. (2018))
- Centered Kernel Alignment (CKA) (Kornblith et al. (2019))



Federated Voting

- Transfer the source models to the selected clients
- Each client does a CKA on the available source models and global model
- Using their own dataset (thereby adhering to the privacy)
- Each clients votes for the source model with maximum CKA value
- Works well for similar/highly similar source and target datasets

TABLE I
SOURCE DOMAIN IDENTIFICATION ACCURACY

Similarity Metric	Accuracy
CCA (R^2_{CCA})	20
SVCCA	19
PWCCA	20.5
EMD	15
Naïve Histogram bin matching	21
CKA	79

