



# Asking Friendly Strangers: Non-Semantic Attribute Transfer

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# Asking Friendly Strangers: Non-Semantic Attribute Transfer

Nils Murrugarra-Llerena and Adriana Kovashka

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## Introduction

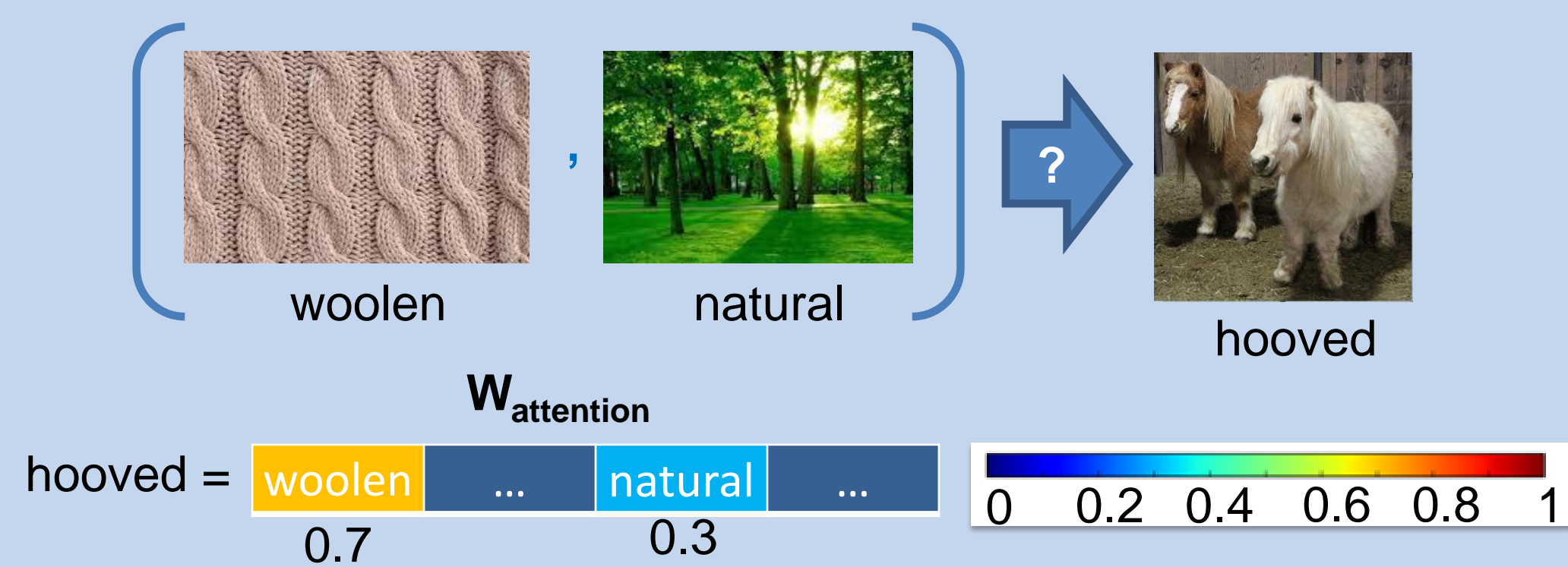
- We examine how to transfer knowledge from attribute classifiers on **unrelated domains**.
- We intelligently select how to weigh the contribution of the semantically unrelated source models using an attention-guided network.
- Employing this attention network, we outperform five different baselines.

## Motivation

- Traditional attribute transfer learning aims to transfer knowledge between attributes from the **same domain**, e.g. using “*has spots*”, “*has stripes*”, “*hooved*” as sources for the “*furry*” target attribute, in the animals domain.
- However, what can we do given **data scarcity**, i.e. **no semantically related categories**?

## Key idea

- Transfer knowledge from attribute classifiers on **unrelated domains**.

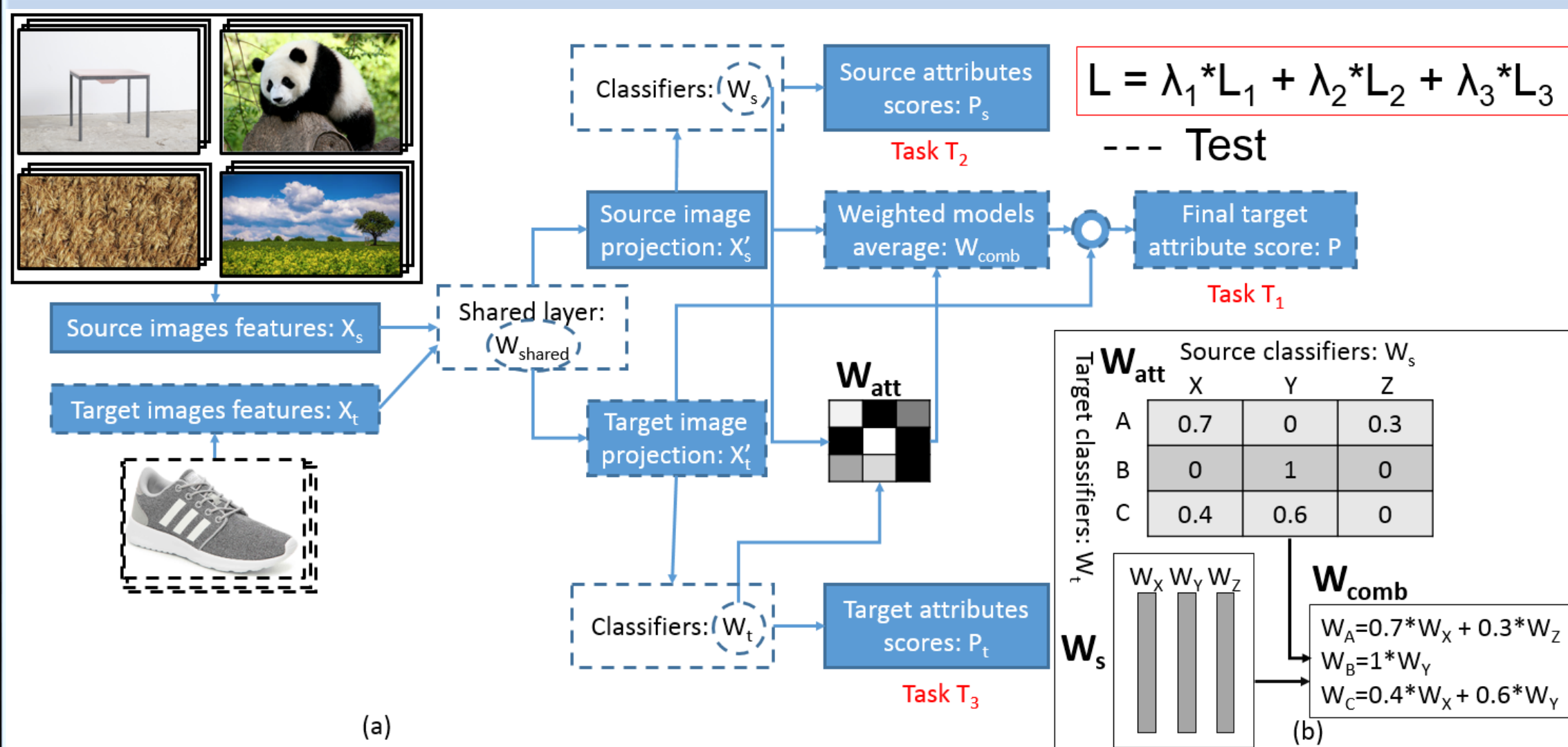


**Take away message:** Unrelated domains have valuable knowledge for learning attributes.

## Related work

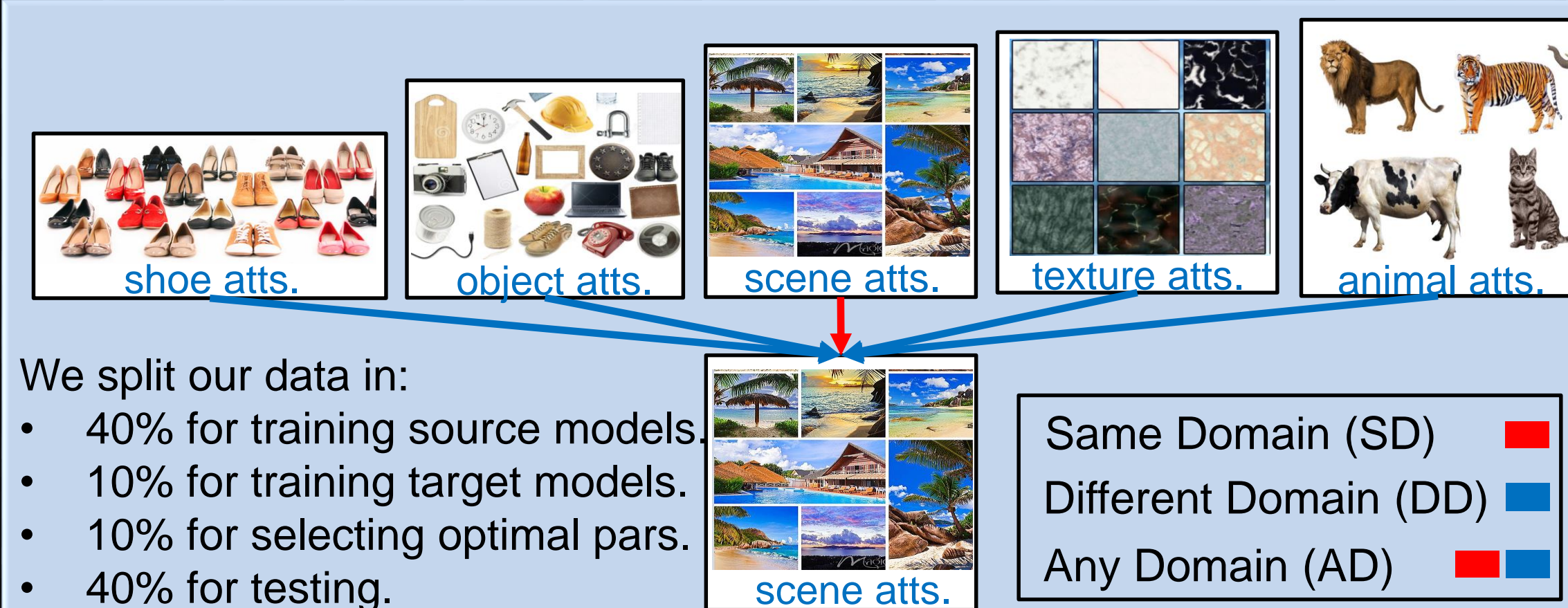
- We use **multi-task neural networks** for attribute transfer learning.
- Prior work only considers objects and attributes from the **same domain** (Chen and Grauman, CVPR 2014; Liu and Kovashka, WACV 2016). Our study differs in that we study if transferability of **unrelated attributes** (from **different domains**) is more beneficial.
- Attention networks are very common in question answering (Xu and Saenko, ECCV 2016; Shih et al., CVPR 2016). Instead of an image-text attention, we perform attention-guided transfer from source to target attribute classifiers.

## Approach



- We use an attention network to select relevant source models for our target attributes.
- We find a common feature space for source and target images via  $W_{\text{shared}}$ .
- In order to transfer knowledge between the source and target classifiers, we calculate normalized similarities  $W_{\text{att}}$  (attention weights).
  - $W_{\text{att}}$  employs cosine similarity and a RELU function to avoid negative transfer.
- We employ a loss composed of three terms. Our main task  $T_1$  predicts target attributes using our attention-guided transfer, and our side tasks  $T_2$  and  $T_3$  predict source and target attributes, respectively. All of them use a binary cross-entropy loss.

## Experimental setup



## Evaluation

We compare our methods:

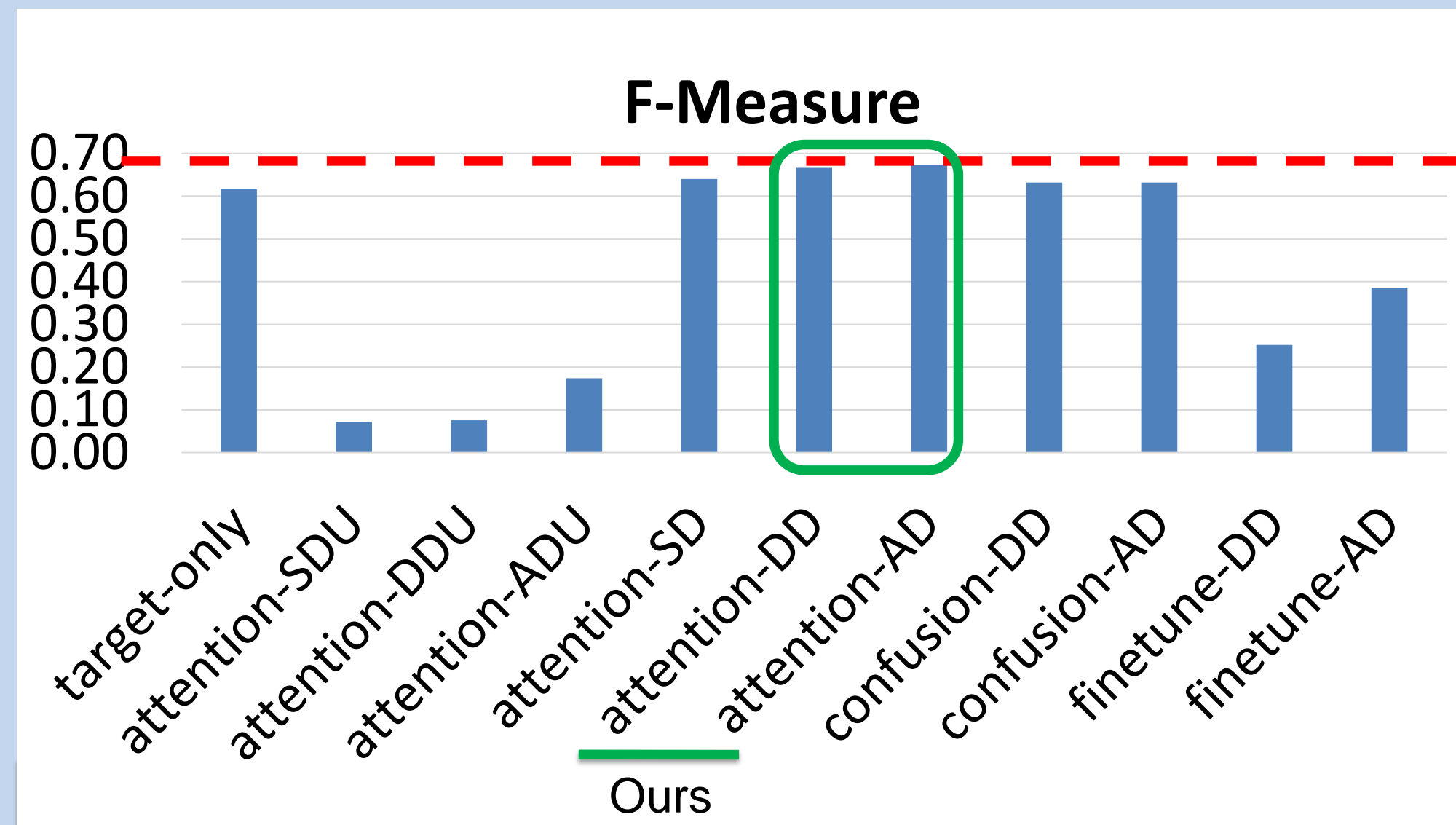
- Attention – Different Domain (ours)*, which uses  $D_i$  as target domain and  $D/D_i$  as source domains.
- Attention – Any Domain (ours)*, which uses  $D_i$  as target domain and  $D$  as source domains.

$D_i$  : domain (instances + attributes)

$$D = \bigcup_{i=1}^5 D_i$$

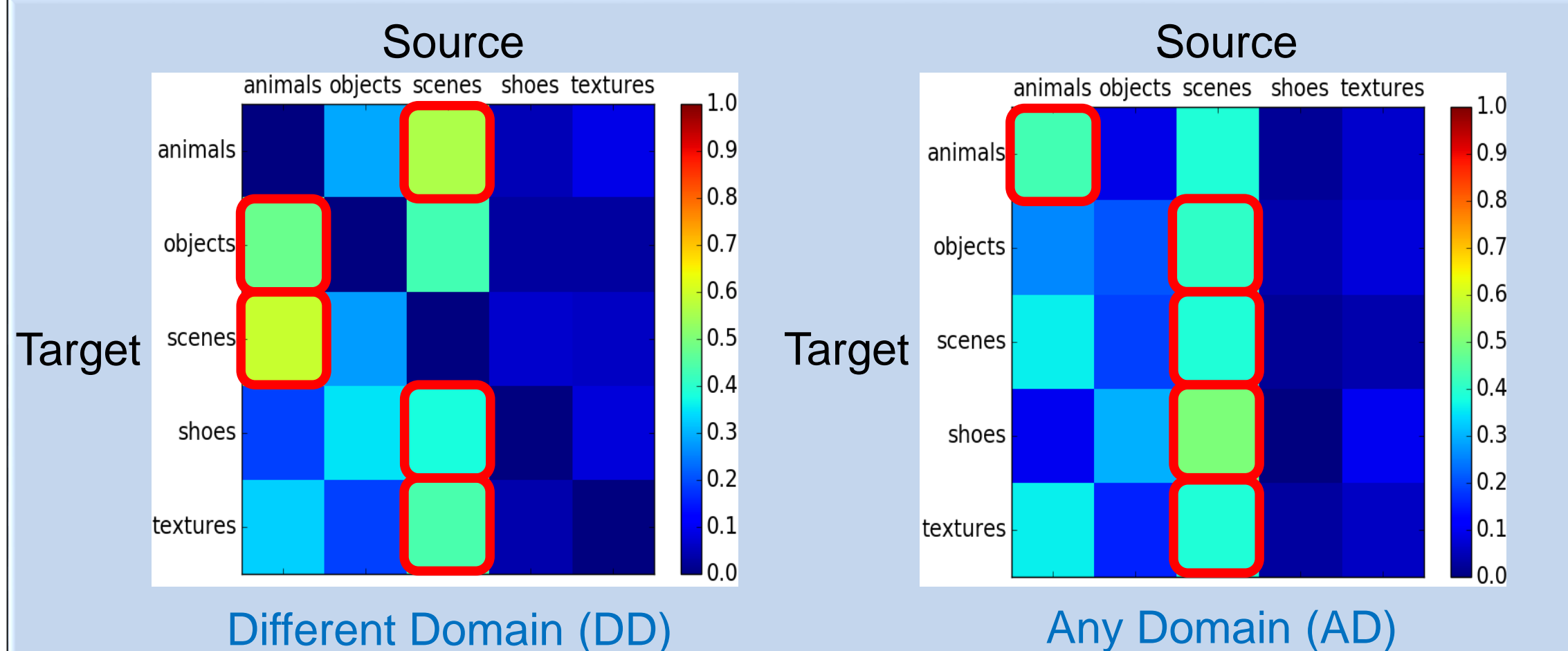
with five different baselines using **F-measure**:

- Attention – Same Domain*, which uses  $D_i$  as target domain and  $D_i$  as source domain.
- Target-only*, which performs no transfer.
- Attention-SDU*, *Attention-DDU*, and *Attention-ADU*, which replace our attention weights ( $W_{\text{att}}$ ) with uniform weights.
- Confusion – Different Domain* and *Confusion – Any Domain*, which use a transfer learning approach with invariant feature representation (Tzeng et al., ICCV 2015).
- Finetune – Different Domain* and *Finetune – Any Domain*, which finetune an AlexNet with source data, and then with target data (Oquab et al., CVPR 2014).



- We believe the success of our method is due to a common feature representation (**shared layer:  $W_{\text{shared}}$** ) and parameter transfer (**attention weights:  $W_{\text{att}}$** ).

## Qualitative results



- The most relevant domain for animals, shoes, and textures is scenes, and **scenes is not closely related to any of these domains**.
- Similarly, the most meaningful domain for objects and scenes is animals, **another semantically unrelated source domain**.
- Shoes and textures attributes **do not benefit almost at all** from other attributes in the same domain.
- On the other hand, objects, scenes, animals do benefit from semantically related attributes, but **the overall within-domain model similarity is lower than 50%**, again reaffirming our choice to allow non-semantic transfer.
- We illustrate what visual information is being transferred across domains, for particular attribute examples. Some of them have an intuitive explanation.

Domain	Target attribute	Relevant source attributes from [domain]
textures	Aluminum	muscular [animal], made of glass [object]
shoes	long-on-the-leg	has leg [object]
object	has stem	dirty soil [scene], feed from fields [animal]
animal	tough-skinned	stressful [scene]
scene	shrubby	tough-skinned [animal]

## Contributions

- We find that attributes from a **different domain** than the target attributes are quite beneficial for transfer learning via our **attention-guided transfer network**.
- We develop a **study of transferability** of attributes across semantic boundaries.