Asking Friendly Strangers: Non-Semantic Attribute Transfer

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ICML

Latinx in AI

Introduction

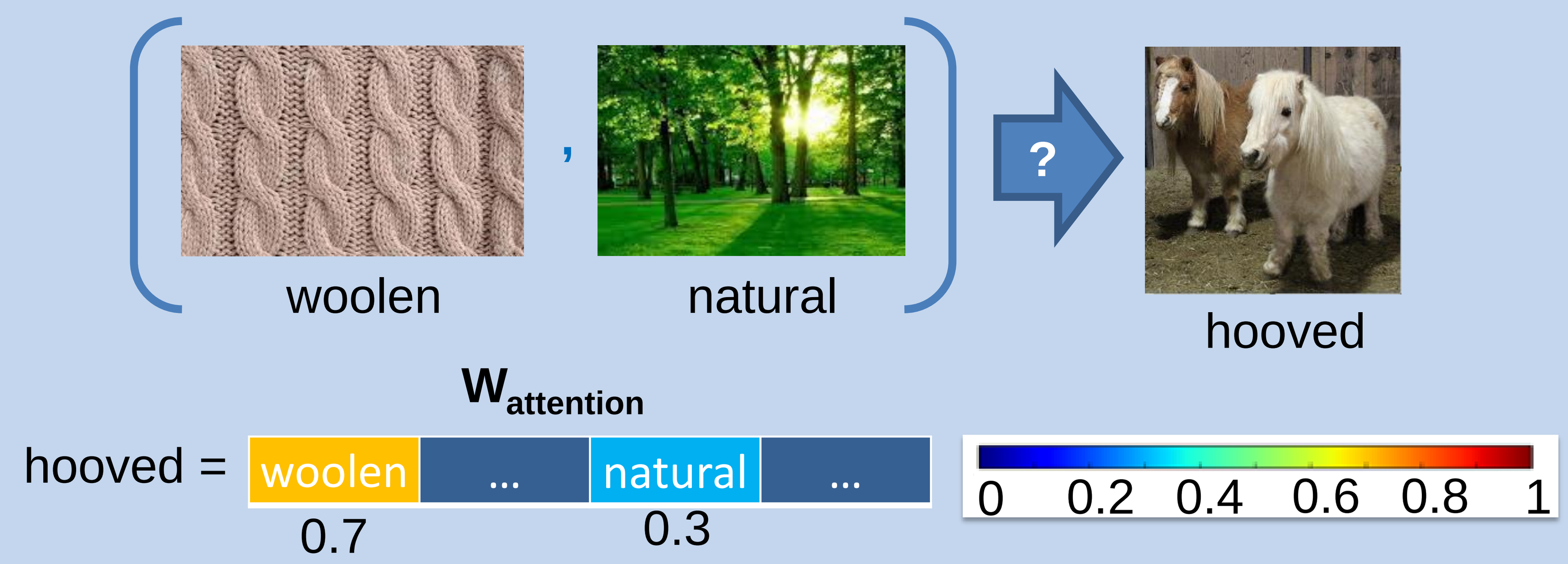
- We examine how to transfer knowledge from attribute classifiers on **unrelated domains**.
- We intelligently select how to weigh the contribution of the semantically unrelated source models using an attention-guided network.
- Employing this attention network, we outperform five different baselines.

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**.

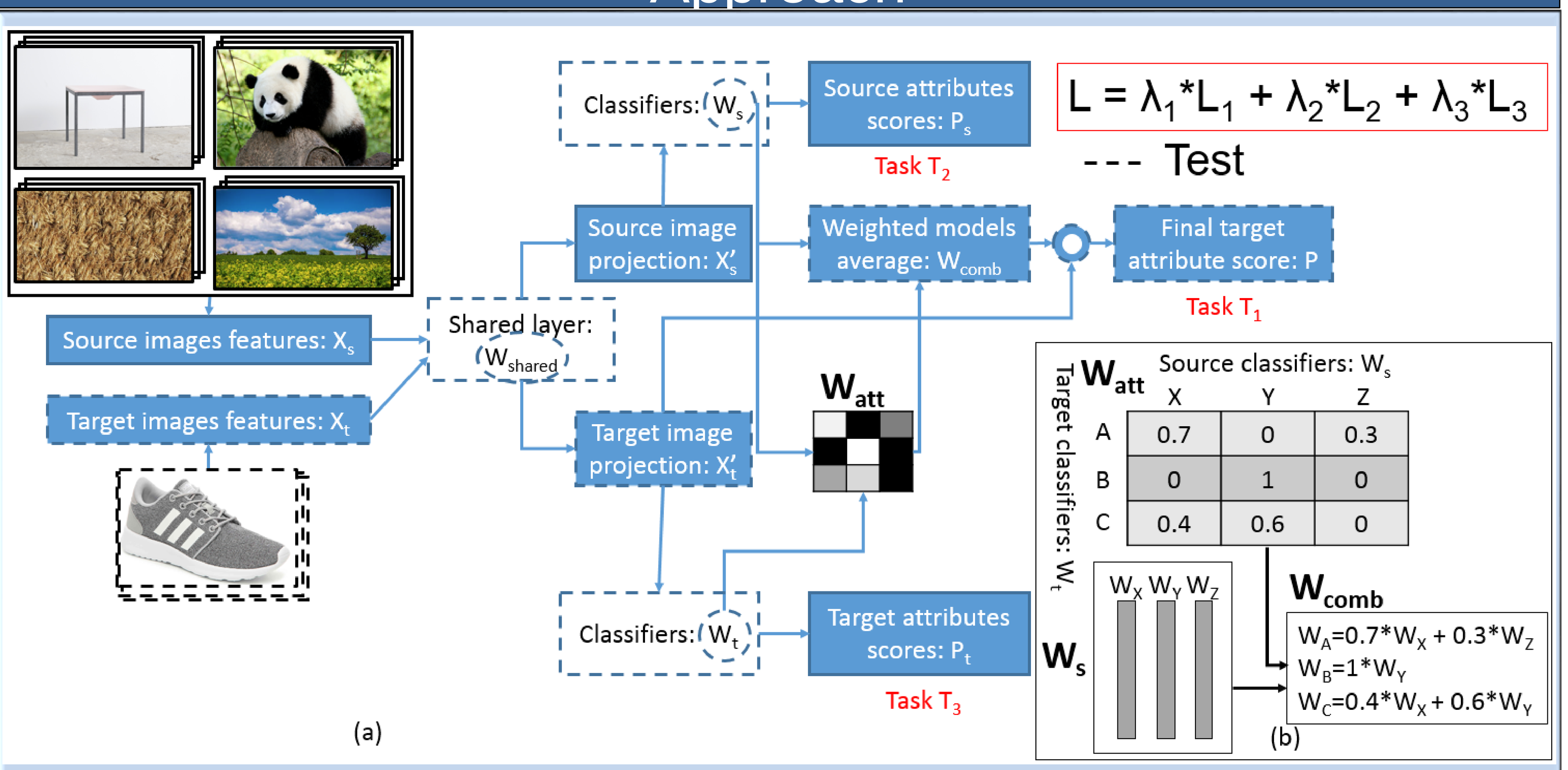


Take away message: Unrelated domains have valuable knowledge for learning attributes.

Related work

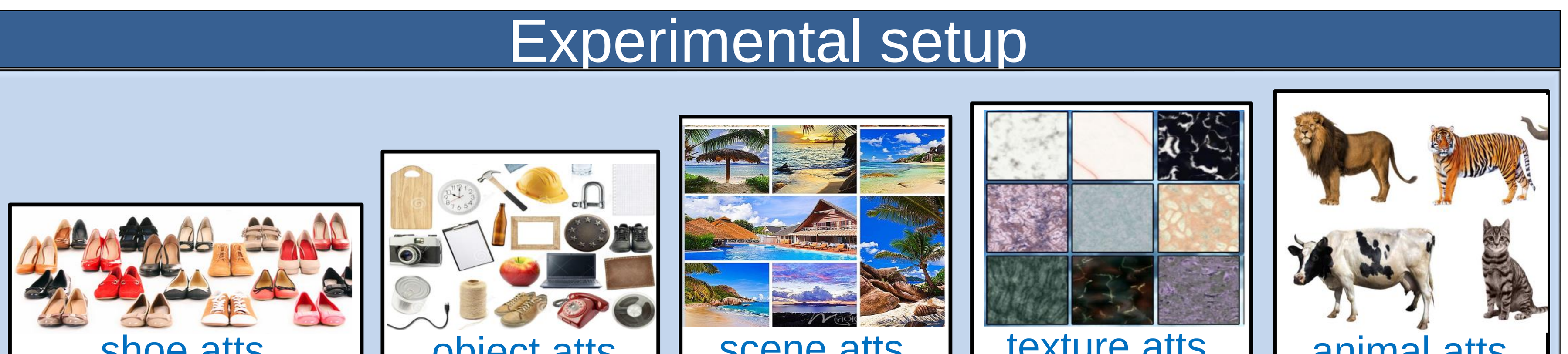
- We use **multi-task neural networks** for attribute transfer learning.
- Prior work only considers objects and attributes from the **same domain** (Chen and Grauman, CVPR 2014; Liu and Kovashka, WACV 2016). Our study differs in that we study if transferability of **unrelated attributes** (from **different 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



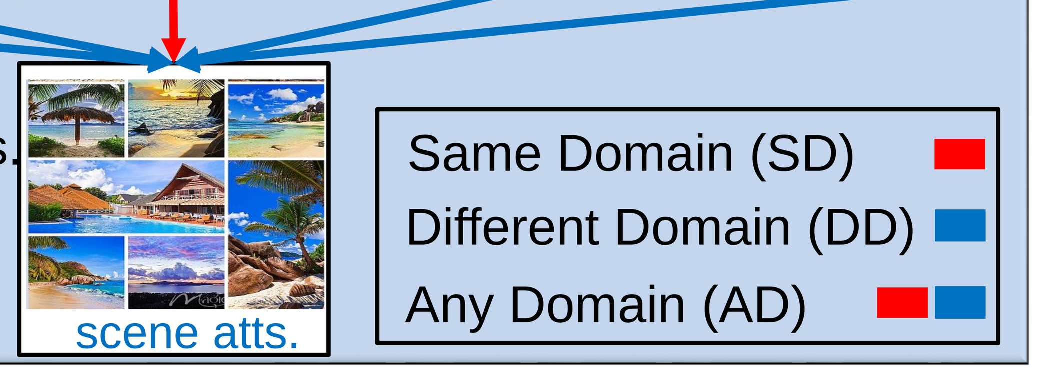
- We use an attention network to select relevant source models for our target attributes.
- We find a common feature space for source and target images via W_{shared}.
- In order to transfer knowledge between the source and target classifiers, we calculate normalized similarities W_{att} (attention weights).
  - W_{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



We split our data in:

- 40% for training source models.
- 10% for training target models.
- 10% for selecting optimal pars.
- 40% for testing.



Evaluation

We compare our methods:

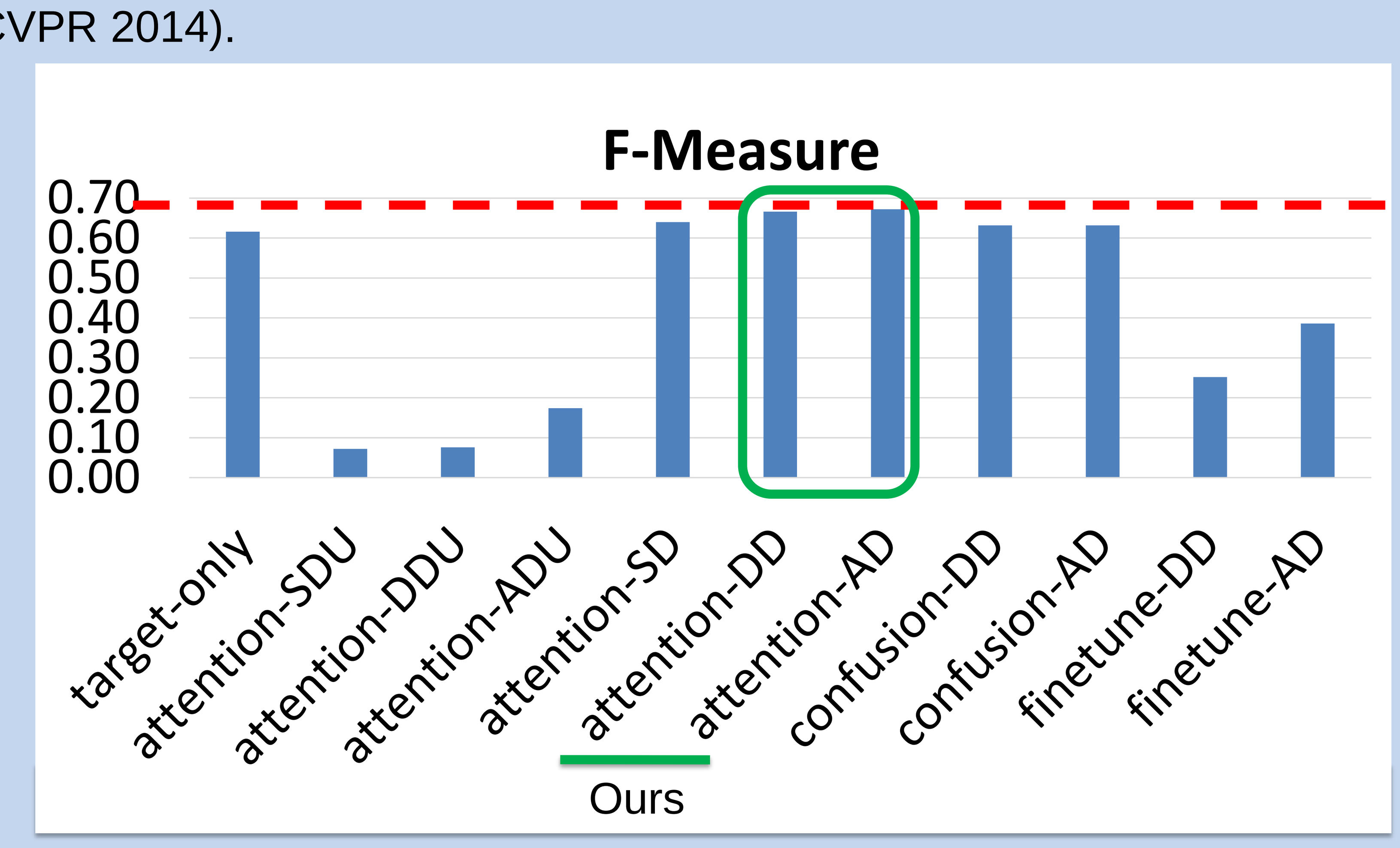
- *Attention – **D**ifferent **D**omain* **(ours)**, which uses D_i as target domain and D/D_i as source domains.
- *Attention – **A**ny **D**omain* **(ours)**, which uses D_i as target domain and D as source domains.

D_i : domain (instances + attributes)

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

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

- *Attention – **S**ame **D**omain*, 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_{att}) with uniform weights.
- *Confusion – **D**ifferent **D**omain* and *Confusion – **A**ny **D**omain,* which use a transfer learning approach with invariant feature representation (Tzeng et al., ICCV 2015).
- *Finetune – **D**ifferent **D**omain* and *Finetune – **A**ny **D**omain*, which finetune an AlexNet with source data, and then with target data (Oquab et al., CVPR 2014).

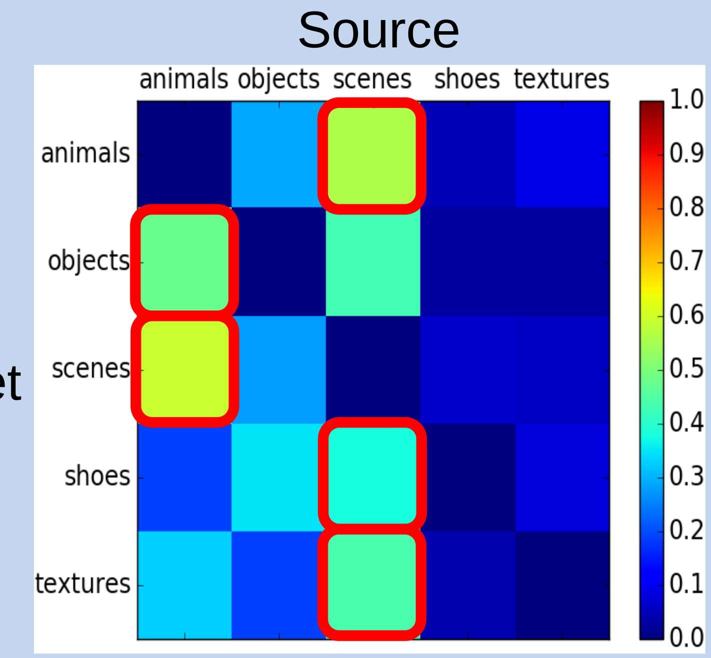


- We believe the success of our method is due to a common feature representation (**shared layer:** W_{shared}) and parameter transfer (**attention weights:** W_{att}).

Qualitative results

Source

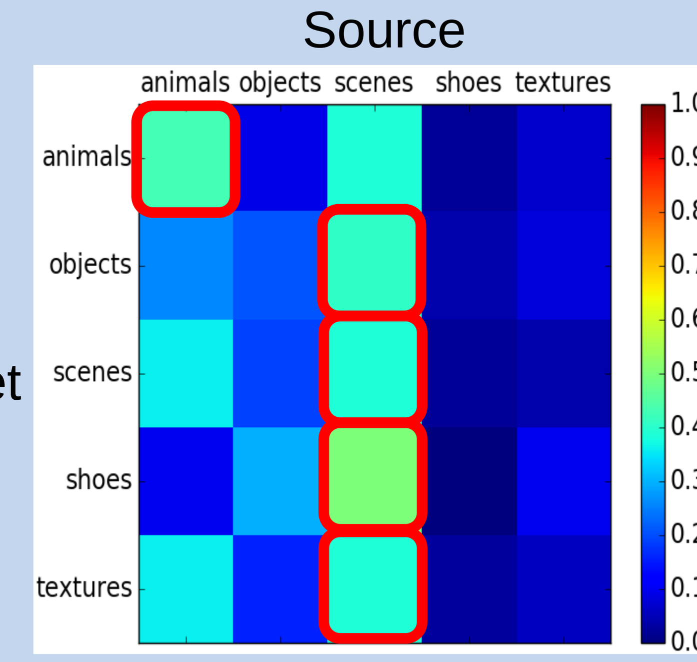
Target



Different Domain (DD)

Source

Target



Any Domain (AD)

- 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	shrubbery	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.