Transfer Adversarial Training:
A General Approach to Adapting Deep Classifiers

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Outline

1 Domain Adaptation

2 Hidden Limitations of Adversarial Feature Adaptation
   - The adaptability

3 Transferable Adversarial Training
   - Generating Transferable Examples
   - Training with Transferable Examples

4 Experiments
Transfer Learning

- In real-world applications, the IID assumption is frequently violated.
- How to generalize a learner across Non-IID distributions $P \neq Q$. 

$P(x,y) \neq Q(x,y)$

Source Domain

Target Domain

Model $f: x \rightarrow y$

Representation

Model $f: x \rightarrow y$
Domain Adaptation

Transfer knowledge across different domains:

- The learner is provided with $n_s$ i.i.d. observations $\{x^{(i)}_s, y^{(i)}_s\}_{i=1}^{n_s}$ from a source domain of distribution $P(x_s, y_s)$, and $n_t$ i.i.d. observations $\{x^{(i)}_t\}_{i=1}^{n_t}$ from a target domain of distribution $Q(x_t, y_t)$.
- Learn an accurate model for the target domain
- Formally bound the target risk with the source risk
The $\mathcal{H} \Delta \mathcal{H}$-divergence

For any hypothesis $h \in \mathcal{H}$, with probability no less than $1 - \delta$,

$$\epsilon_Q(h, f_Q) \leq \epsilon_P(h, f_P) + D_{\mathcal{H} \Delta \mathcal{H}}(\hat{P}, \hat{Q}) + \lambda$$

$$+ 10\hat{R}_P(h) + 8\hat{R}_Q(h) + 6\sqrt{\frac{\log \frac{6}{\delta}}{m}} + 3\sqrt{\frac{\log \frac{6}{\delta}}{n}},$$

where $D_{\mathcal{H} \Delta \mathcal{H}}(P, Q) = \sup_{h, h' \in \mathcal{H}} |\epsilon_Q(h, h') - \epsilon_P(h, h')|$, 

$$\lambda = \epsilon_P(h^*, f_P) + \epsilon_Q(h^*, f_Q),$$

$$h^* = \arg \min_{h \in \mathcal{H}} \epsilon_P(h, f_P) + \epsilon_Q(h, f_Q).$$

Intuitively, the target risk can be bounded with the source risk + discrepancy between the source and the target + the best hypothesis risk we can expect.

Adversarial Feature Adaptation

Minimize the source risk
- Train the model with supervision from the source domain

Minimize the discrepancy term
- Learn a new feature representation where the discrepancy is minimized.

The two-player game
- A domain discriminator tries to discriminate the source and target domains, while the feature extractor tries to confuse it.
- Two classifier try to maximize their disagreement while the feature extractor tries to minimize it.


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Hidden Limitations of Adversarial Feature Adaptation

Adaptability quantified by $\lambda$, is an essential prerequisite of domain adaptation.

- If $\lambda$ is large, we can never expect to adapt a learner trained on the source domain to the target domain.
- Simply learning a new feature representation cannot guarantee that the ideal joint risk won’t explode!

Diminishing domain-specific variations inevitably breaks the discriminative structures of the original representations.
Possible Solutions

Since we have no access to target labels, we cannot expect to minimize $\lambda$ directly. Can we at least prevent the adaptability from going worse?

- **FIX** the feature representations and adapt classifiers instead.

With feature representations fixed, how can we adapt to the target domain?

- Adapt deep classifiers instead.
- Extend adversarial training paradigm to domain adaptation.
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Transferable Adversarial Training

Instead of feature adaptation, associate the source and target domain with transferable examples.

- Generate **transferable examples** at feature level.
- Adapt the classifier to the target domain by training on transferable examples.
Generating Transferable Examples

Generate Transferable Examples to bridge domain gap.
- Train a classifier and a domain discriminator.
- Transferable examples should confuse both the classifier and the domain discriminator.

\[
\ell_d(\theta_D, f) = -\frac{1}{n_s} \sum_{i=1}^{n_s} \log[D(f_s^{(i)})] - \frac{1}{n_t} \sum_{i=1}^{n_t} \log[1 - D(f_t^{(i)})].
\] (4)

\[
\ell_c(\theta_C, f) = \frac{1}{n_s} \sum_{i=1}^{n_s} \ell_{ce}(C(f_s^{(i)}), y_s^{(i)}).
\] (5)

Concretely, we generate transferable examples from both domains in an iterative manner,

\[
f_{t^{k+1}} \leftarrow f_{t^k} + \beta \nabla_{f_{t^k}} \ell_d(\theta_D, f_{t^k}) - \gamma \nabla_{f_{t^k}} \ell_2(f_{t^k}, f_{t^0}),
\] (6)

\[
f_{s^{k+1}} \leftarrow f_{s^k} + \beta \nabla_{f_{s^k}} \ell_d(\theta_D, f_{s^k}) - \gamma \nabla_{f_{s^k}} \ell_2(f_{s^k}, f_{s^0}) + \beta \nabla_{f_{s^k}} \ell_c(\theta_C, f_{s^k}).
\] (7)
Training with Transferable Examples

Training the classifier and the domain discriminator on transferable examples.

- We require the classifier to make consistent predictions for the transferable examples and their original counterparts.
- Train the domain discriminator to further distinguish transferable examples generated from the source and target.

\[
\ell_{c, \text{adv}}(\theta_C, f_*) = \frac{1}{n_s} \sum_{i=1}^{n_s} \ell_{ce}(C(f^{(i)}_{s*}), y^{(i)}_{s*}) + \frac{1}{n_t} \sum_{i=1}^{n_t} \left| C((f^{(i)}_{t*})) - C((f^{(i)}_t)) \right|, \tag{8}
\]

\[
\ell_{d, \text{adv}}(\theta_D, f_*) = -\frac{1}{n_s} \sum_{i=1}^{n_s} \log[D(f^{(i)}_{s*})] - \frac{1}{n_t} \sum_{i=1}^{n_t} \log[1 - D(f^{(i)}_{t*})]. \tag{9}
\]
The Overall Optimization Problem

\[
\min_{\theta_D, \theta_C} \ell_d(\theta_D, f) + \ell_c(\theta_C, f) + \ell_{d,adv}(\theta_D, f^*) + \ell_{c,adv}(\theta_C, f^*).
\] (10)

- **Fixed** feature representations – guaranteed adaptability
- No need of feature adaptation – light weight computation
- An order of magnitude faster than adversarial feature adaptation
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Analysis

The rotating two moon problem: The target domain is rotated $30^\circ$ from the source domain.

Behaviors on the *two moon* problem. Purple and yellow ”+”s indicate source samples, blue ”+”s are target samples, while dots are transferable examples. (a) The source only model. (b) The decision boundary of TAT. (c) The distribution of the transferable examples.

- As expected, transferable examples bridge domain gap effectively.
Experimental Setups

Datasets
- Office-31: Standard benchmark
- Image-CLEF: Balanced domains
- Office-home: Large domain gap
- VisDA: Large-scale synthetic-to-real
- Multi-domain sentiment: Sentiment polarity classification
# Results

Table: Classification accuracies (%) on Office-31 with ResNet-50.

<table>
<thead>
<tr>
<th>Method</th>
<th>A→W</th>
<th>D→W</th>
<th>W→D</th>
<th>A→D</th>
<th>D→A</th>
<th>W→A</th>
<th>Avg.</th>
</tr>
</thead>
<tbody>
<tr>
<td>ResNet-50</td>
<td>68.4±0.2</td>
<td>96.7±0.1</td>
<td>99.3±0.1</td>
<td>68.9±0.2</td>
<td>62.5±0.3</td>
<td>60.7±0.3</td>
<td>76.1</td>
</tr>
<tr>
<td>DAN</td>
<td>80.5±0.4</td>
<td>97.1±0.2</td>
<td>99.6±0.1</td>
<td>78.6±0.2</td>
<td>63.6±0.3</td>
<td>62.8±0.2</td>
<td>80.4</td>
</tr>
<tr>
<td>DANN</td>
<td>82.6±0.4</td>
<td>96.9±0.2</td>
<td>99.3±0.2</td>
<td>81.5±0.4</td>
<td>68.4±0.5</td>
<td>67.5±0.5</td>
<td>82.7</td>
</tr>
<tr>
<td>ADDA</td>
<td>86.2±0.5</td>
<td>96.2±0.3</td>
<td>98.4±0.3</td>
<td>77.8±0.3</td>
<td>69.5±0.4</td>
<td>68.9±0.5</td>
<td>82.9</td>
</tr>
<tr>
<td>VADA</td>
<td>86.5±0.5</td>
<td>98.2±0.4</td>
<td>99.7±0.2</td>
<td>86.7±0.4</td>
<td>70.1±0.4</td>
<td>70.5±0.4</td>
<td>85.4</td>
</tr>
<tr>
<td>GTA</td>
<td>89.5±0.5</td>
<td>97.9±0.3</td>
<td>99.7±0.2</td>
<td>87.7±0.5</td>
<td>72.8±0.3</td>
<td>71.4±0.4</td>
<td>86.5</td>
</tr>
<tr>
<td>MCD</td>
<td>88.6±0.2</td>
<td>98.5±0.1</td>
<td>100.0±0.0</td>
<td>92.2±0.2</td>
<td>69.5±0.1</td>
<td>69.7±0.3</td>
<td>86.5</td>
</tr>
<tr>
<td>CDAN</td>
<td>93.1±0.1</td>
<td>98.6±0.1</td>
<td>100.0±0.0</td>
<td>92.9±0.2</td>
<td>71.0±0.3</td>
<td>69.3±0.3</td>
<td>87.5</td>
</tr>
<tr>
<td>TAT</td>
<td>92.5±0.3</td>
<td>99.3±0.1</td>
<td>100.0±0.0</td>
<td>93.2±0.2</td>
<td>73.1±0.3</td>
<td>72.1±0.3</td>
<td>88.4</td>
</tr>
</tbody>
</table>

Table: Classification accuracies (%) on Office-Home with ResNet-50.

| Method  | AR→Cl | AR→Pr | AR→Rw | Cl→AR | Cl→Pr | Cl→Rw | Pr→AR | Pr→Cl | Pr→Rw | Rw→AR | Rw→Cl | Rw→Pr | Avg.  |
|---------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| ResNet-50 | 34.9  | 50.0  | 58.0  | 37.4  | 41.9  | 46.2  | 38.5  | 31.2  | 60.4  | 53.9  | 41.2  | 59.9  | 46.1  |
| DAN     | 43.6  | 57.0  | 67.9  | 45.8  | 56.5  | 60.4  | 44.0  | 43.6  | 67.7  | 63.1  | 51.5  | 74.3  | 56.3  |
| DANN    | 45.6  | 59.3  | 70.1  | 47.0  | 58.5  | 60.9  | 46.1  | 43.7  | 68.5  | 63.2  | 51.8  | 76.8  | 57.6  |
| CDAN    | 49.0  | 69.3  | 74.5  | 54.4  | 66.0  | 68.4  | 55.6  | 48.3  | 75.9  | 68.4  | 55.4  | 80.5  | 63.8  |
| TAT     | 51.6  | 69.5  | 75.4  | 59.4  | 69.5  | 68.6  | 59.5  | 50.5  | 76.8  | 70.9  | 56.6  | 81.6  | 65.8  |
Summary

- Adaptability quantified by $\lambda$ is not guaranteed by feature adaptation and may be worsened.
- A new perspective: Adapt deep classifiers instead of feature representations.
- Associate the source and target domains with transferable examples: Extending adversarial training paradigm to transfer learning.
- Free from adversarial feature learning: Lighter computation, faster speed, and even better performance.
Thanks!

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Poster: Pacific Ballroom #255, Wed, June 12
Code: github.com/thuml/Transferable-Adversarial-Training