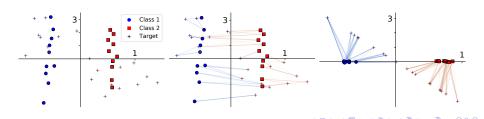
Metric Learning in Optimal Transport for Domain Adaptation

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Domain Adaptation (DA) : Intuition



HOW TO TRANSFER?











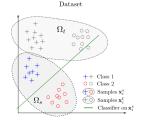
tumor or not tumor

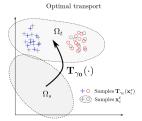
Discrete Optimal Transport (OT)

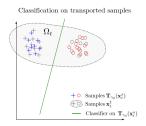
Discrete Optimal Transport

$$W^{2}(\hat{\mu}_{s}, \hat{\mu}_{t}) = \min_{T \in \hat{\Pi}(\hat{\mu}_{s}, \hat{\mu}_{t})} \sum_{i=1}^{m_{s}} \sum_{j=1}^{m_{t}} \|x_{i}^{s} - x_{j}^{t}\|_{2}^{2} T_{ij} = \min_{T \in \hat{\Pi}(\hat{\mu}_{s}, \hat{\mu}_{t})} \langle T, C^{2} \rangle.$$

With
$$\hat{\Pi}(\hat{\mu}_s, \hat{\mu}_t) = \{ T \in \mathbb{R}_+^{m_s \times m_t} | T \mathbf{1}_{m_t} = \hat{\mu}_s, T^T \mathbf{1}_{m_s} = \hat{\mu}_t \}$$

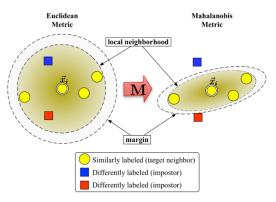






Optimal Transport for DA [Courty et al., 2017]

Metric learning



LMNN [Weinberger et al., 2006]

Mahalanobis metric

• $C_M^2(x,x') = (x-x')M(x-x')^T = ||Lx-Lx'||_2^2$ with $L^TL = M$

Table of Contents

- Main contributions
 - Bound on the Target Risk
 - PCA and Wasserstein Distance
 - Algorithm : Metric Learning for Optimal Transport

Bound on the Target Risk

Classical form of Target Risk Bound [Ben-David et al., 2007]

target risk
$$\leq$$
 source risk
$$+ \operatorname{distance}(\mu_s, \mu_t)$$
 (1)
$$+ \lambda \text{ (error of the best classifier)}$$

Bound on the Target Risk

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Our Target Risk Bound

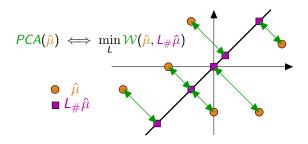
target risk
$$\leq$$
 source risk $+ \mathcal{W}(L_{s\#}\hat{\mu}_s, L_{t\#}\hat{\mu}_t)$
 $+ \mathcal{W}(\hat{\mu}_s, L_{s\#}\hat{\mu}_s) + \mathcal{W}(L_{t\#}\hat{\mu}_t, \hat{\mu}_t)$ (2)
 $+ \mathcal{W}(\mu_s, \hat{\mu}_s) + \mathcal{W}(\hat{\mu}_t, \mu_t) + \lambda$



PCA and Wasserstein Distance

Our Target Risk Bound

target risk
$$\leq$$
 source risk $+ \mathcal{W}(L_{s\#}\hat{\mu}_{s}, L_{t\#}\hat{\mu}_{t})$
 $+ \mathcal{W}(\hat{\mu}_{s}, L_{s\#}\hat{\mu}_{s}) + \mathcal{W}(\hat{\mu}_{t}, L_{t\#}\hat{\mu}_{t})$ (3)
 $+ \mathcal{W}(\mu_{s}, \hat{\mu}_{s}) + \mathcal{W}(\hat{\mu}_{t}, \mu_{t}) + \lambda$



Metric Learning for Optimal Transport (MLOT)

```
Input: \eta (gradient step) X_s X_t Y_s

1: V_s = PCA(X_s), V_t = PCA(X_t)

2: L_s = V_s^T V_s, L_t = V_t^T V_t

3: for i = 1 to N do

4: \gamma = \text{Solve } OT(C(L_s, L_t))

5: L_s = L_s - \eta \nabla_{L_s}(\langle \gamma, C^2(L_s, L_t) \rangle + \lambda_I \Omega_I(L_s))

6: end for

7: \tilde{X}_s = \gamma L_t X_t

8: return classifier((\tilde{X}_s, Y_s), X_t)
```

Metric Learning for Optimal Transport (MLOT)

Input : η (gradient step) $X_s X_t Y_s$

1:
$$V_s = PCA(X_s)$$
, $V_t = PCA(X_t)$

2:
$$L_s = V_s^T V_s$$
, $L_t = V_t^T V_t$

3: for
$$i = 1$$
 to N do

4:
$$\gamma = \text{Solve } OT(C(L_s, L_t))$$

5:
$$L_s = L_s - \eta \nabla_{L_s} (\langle \gamma, C^2(L_s, L_t) \rangle + \lambda_I \Omega_I(L_s))$$

- 6: end for
- 7: $\tilde{X}_s = \gamma L_t X_t$
- 8: **return** classifier($(\tilde{X}_s, Y_s), X_t$)

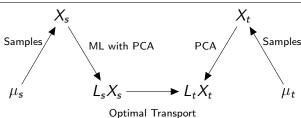


Illustration of the usefulness of Metric Learning

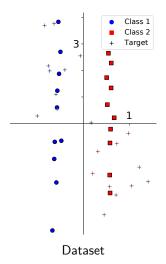


Illustration of the usefulness of Metric Learning

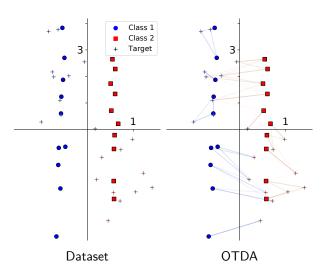
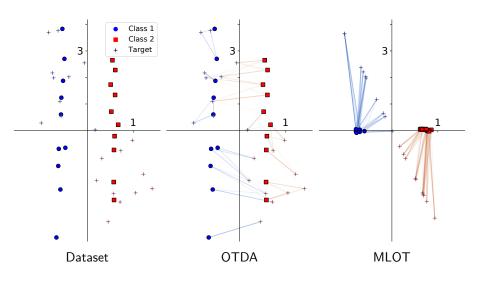


Illustration of the usefulness of Metric Learning



References



Ben-David, S., Blitzer, J., Crammer, K., and Pereira, F. (2007).

Analysis of representations for domain adaptation. In NIPS.



Courty, N., Flamary, R., Tuia, D., and Rakotomamonjy, A. (2017).

Optimal transport for domain adaptation.

PAMI.



Weinberger, K. Q., Blitzer, J., and Saul, L. K. (2006).

Distance metric learning for large margin nearest neighbor classification.

In Advances in neural information processing systems.

Optimal Transition between slide

 To use the Optimal Transition of the presented work see my github: https://github.com/HvOnnus/TransitionPDF