Exploring uncertainty in pseudo-label Guided Domain Adaptation

23.04.03

이정민

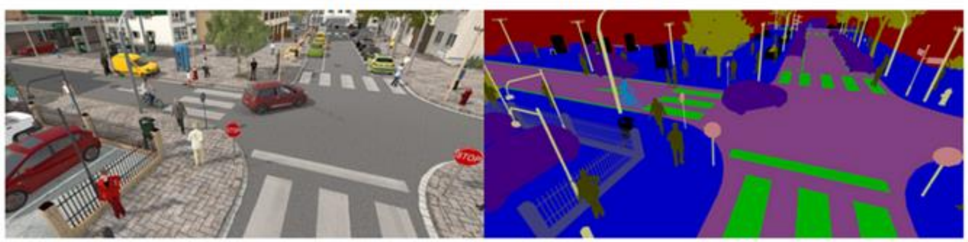
연구 배경

❖ Unsupervised Domain Adaptation(UDA)

- Target domain dataset에 labeled data가 없을 때

Domain Adaptation

Synthetic (source domain)



< Labeled dataset >

Real (target domain)

< Unlabeled dataset >

연구 배경

❖ Unsupervised Domain Adaptation(UDA)

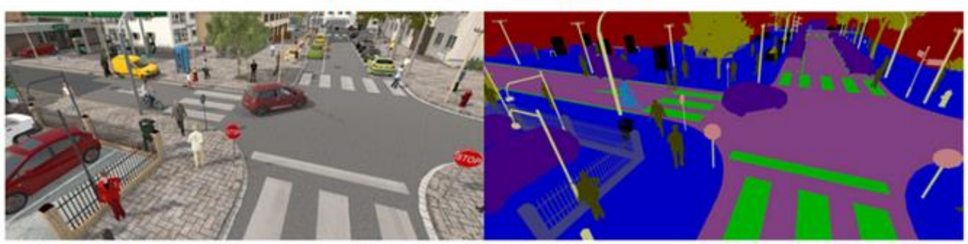
- Target domain dataset에 labeled data가 없을 때
- Target domain dataset에 pseudo-labeling을 진행하는 연구들 다수 존재
    - ➢ But, pseudo-label에 대한 신뢰도 부족

0
1
0
⋮
1

Pseudo label

Domain Adaptation

Synthetic (source domain)



Real (target domain)

< Labeled dataset >

< Unlabeled dataset >

https://lhw0772.medium.com/study-da-domain-adaptation-%EC%95%8C%EC%95%84%EB%B3%B4%EA%B8%B0-%EA%B8%B0%EB%B3%B8%ED%8E%B8-4af4ab63f871

기여점

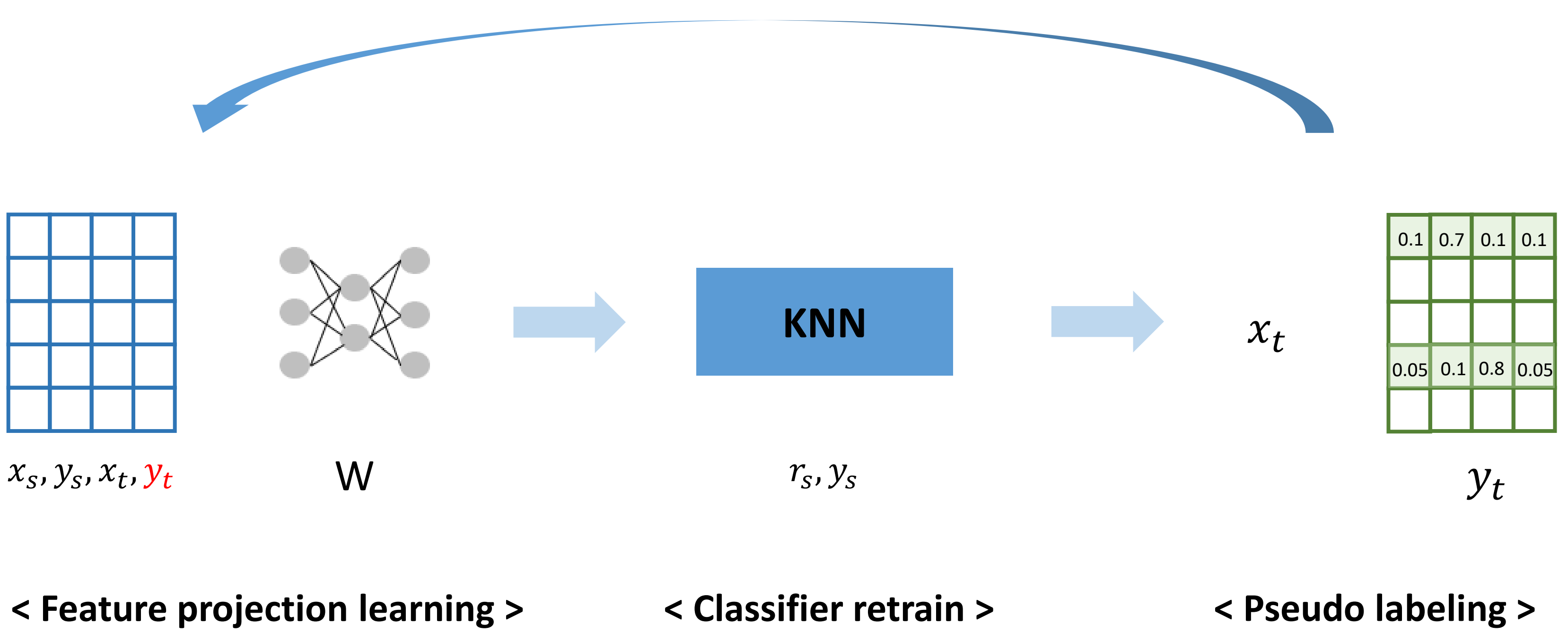
❖ **PACET(Progressive leArning with Confidence-wEighted Targets)**

- Target pseudo labeling에 불확실성을 반영
- within- / cross- domain relation 반영한 progressive learning 방법론 제안
- Joint distribution adaptation을 통해 discriminative cross-domain structure 구축

방법론

❖ Framework

- 처음에는 source dataset을 통해 학습된 classifier로 target dataset pseudo labeling
- Target y에 대한 확률 값들 중 상위 값(Easy)에 대한 것만 pseudo labeling -> **불확실성 반영**



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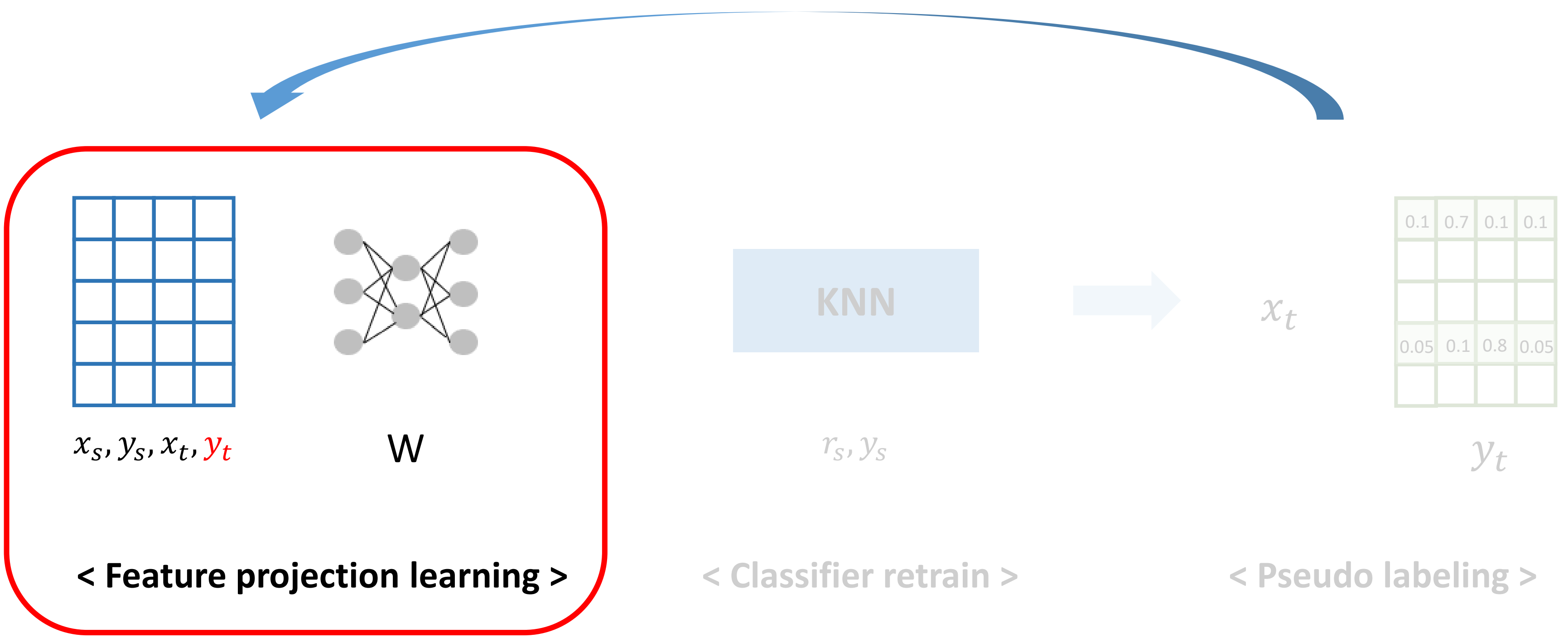

방법론

$$d: feature\ length$$
$$W \in R^{d*k} (feature\ mapping\ matrix)$$

❖ PACET(Progressive leArning with Confidence-wEighted Targets)

- Joint Distribution Discrepancy
- Cross-Domain Local Structure
- Intra-class variance and total variance

$$\left\| \frac{1}{n_s} \sum_{i=1}^{n_s} W^T x_i - \frac{1}{n_t} \sum_{j=n_s+1}^{n} W^T x_j \right\|_2^2 + \frac{1}{C} \sum_{c=1}^{C} \left\| W^T e_c^s - W^T e_c^t \right\|_2^2,$$

Source, target 간
전체적인 차이

Source, target 간
class별 차이

$$e_c^s = \sum_{i=1}^{n_s} x_i I(y_i, c) / n_s^c$$

$$e_c^t = \sum_{j=n_s+1}^{n} x_j I(y_j, c) / n_t^c$$

방법론

$$d: feature\ length$$
$$W \in R^{d*k} (feature\ mapping\ matrix)$$
$$z_j: closest\ negative\ class\ of\ x_j$$

❖ PACET(Progressive leArning with Confidence-wEighted Targets)

- Joint Distribution Discrepancy
- Cross-Domain Local Structure
- Intra-class variance and total variance

Target data와 그 class와 다른 class 중 가장 가까운 class에 해당하는 source data의 중심과의 거리

$$\sum_{j=n_s+1}^{n} \|W^T x_j - W^T e^s_{y_j}\|_2^2 - \|W^T x_j - W^T e^s_{z_j}\|_2^2,$$

Target data와 그 class에 해당하는 source data의 중심과의 거리

방법론

$d: feature\ length$
$W \in R^{d*k}(feature\ mapping\ matrix)$

❖ **PACET(Progressive leArning with Confidence-wEighted Targets)**

- Joint Distribution Discrepancy
- Cross-Domain Local Structure
- Intra-class variance and total variance

Source data와 그 class의 중심과의 거리 / Target data와 그 class의 중심과의 거리

$$\sum_{i=1}^{n_s} \left\| W^T x_i - W^T e^s_{y_i} \right\|_2^2 + \sum_{j=n_s+1}^{n} \left\| W^T x_j - W^T e^t_{y_i} \right\|_2^2,$$

Intra-class variance

and

$$\sum_{i=1}^{n} \left\| W^T x_i - \frac{1}{n} W^T \sum_{q=1}^{n} x_q \right\|_2^2.$$

Total variance

d: feature length
$W \in R^{d*k}$(feature mapping matrix)
z_j: closest negative class of x_j

❖ PACET(Progressive leArning with Confidence-wEighted Targets)

- Joint Distributior
- Cross-Domain L
- Intra-class variance ar

$$\left\| \frac{1}{n_s}\sum_{i=1}^{n_s} W^T x_i - \frac{1}{n_t}\sum_{j=n_s+1}^{n} W^T x_j \right\|_2^2 + \frac{1}{C}\sum_{c=1}^{C} \| W^T e_c^s - W^T e_c^t \|_2^2, \quad (1)$$

$$\sum_{j=n_s+1}^{n} \| W^T x_j - W^T e_{y_j}^s \|_2^2 - \| W^T x_j - W^T e_{z_j}^s \|_2^2, \quad (2)$$

$$\sum_{i=1}^{n_s} \| W^T x_i - W^T e_{y_i}^s \|_2^2 + \sum_{j=n_s+1}^{n} \| W^T x_j - W^T e_{y_i}^t \|_2^2,$$

(3) Intra-class variance

$$\text{and} \quad \sum_{i=1}^{n} \left\| W^T x_i - \frac{1}{n} W^T \sum_{q=1}^{n} x_q \right\|_2^2 .$$

Total variance

최종 Optimization

$$(X\tilde{M}X^T + \lambda I_k)W = \Psi \cdot XHX^T W.$$