Domain Adaptation for Text Recognition

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Overview



Datasets

STL-10



CIFAR-10







Fashion MNIST



xView-10



MNIST



Domains

• Train and Test in same domain

CIFAR-10



Train

Test

Domain Shift

• Source and Target domain are different



Train

Test

Domain Shift





Why We Care?

- Historical documents usually come from different domains:
 - Documents are different time, authors, etc
- Documents in Different Languages could cause also a domain shift

DA for Character Recog.



Source

Target

Domain Adversarial Training (DANN) - Classifier



Ganin, Yaroslav, et al. "Domain-adversarial training of neural networks." The Journal of Machine Learning Research 17.1 (2016)

Domain Adversarial Training (DANN) - Discriminator



Ganin, Yaroslav, et al. "Domain-adversarial training of neural networks." The Journal of Machine Learning Research 17.1 (2016)

Domain Adversarial Training (DANN) – Reversal Layer



Ganin, Yaroslav, et al. "Domain-adversarial training of neural networks." The Journal of Machine Learning Research 17.1 (2016)

VADA

- Virtual Adversarial Domain Adaptation (Shu 2018)
- Unsupervised Domain Adaptation
- Conditional Entropy Minimization
- https://github.com/ozanciga/dirt-t



Source Target	MNIST SVHN
Source Only	40.9
VADA	74.0



Source Classification Loss





Discriminator Loss



Target Classification Accuracy

Conclusion and Future Work

- DA techniques can alleviate domain shift problem
- DA significantly improve over simple transfer leaning
- DA can be applied to other datasets relevant to text and handwriting recognition

References

- Ganin, Yaroslav, et al. "Domain-adversarial training of neural networks." The Journal of Machine Learning Research 17.1 (2016)
- Shu, Rui, et al. "A dirt-t approach to unsupervised domain adaptation." arXiv preprint arXiv:1802.08735 (2018).

Questions