

Adapted Deep Embeddings: A Synthesis of Methods for k -Shot Inductive Transfer Learning

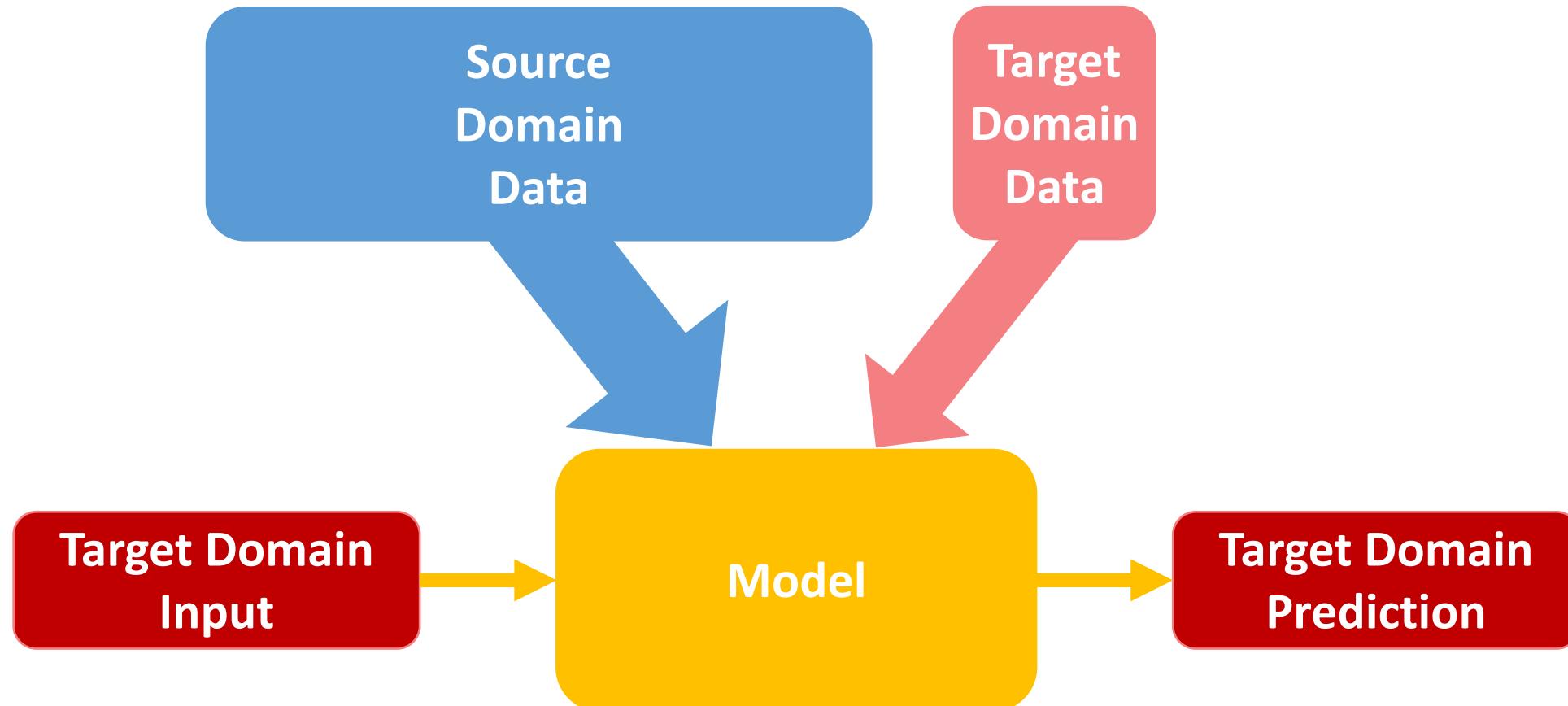
Tyler R. Scott^{1,2}, Karl Ridgeway^{1,2}, Michael C. Mozer^{1,3}

¹ *University of Colorado, Boulder*

² *Sensory Inc.*

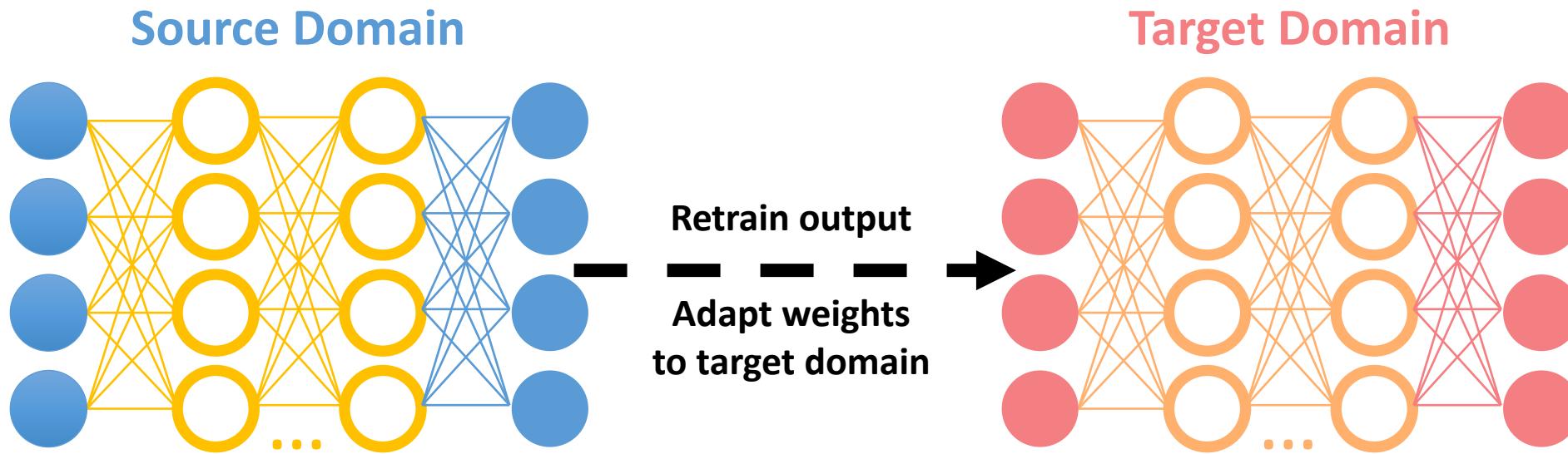
³ *Presently at Google Brain*

Inductive Transfer Learning



Inductive Transfer Learning

Weight Transfer

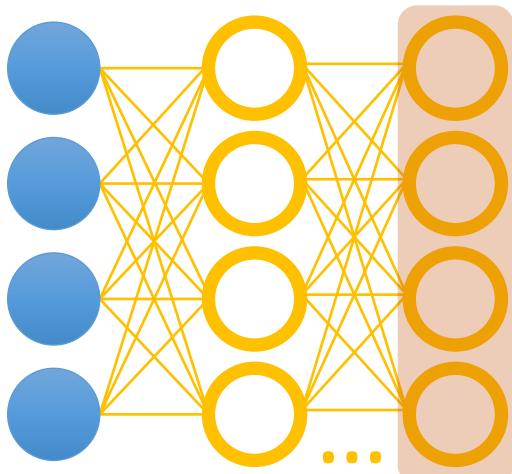


Inductive Transfer Learning

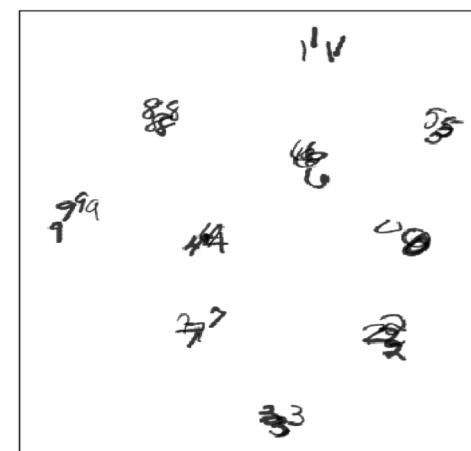
Weight Transfer

Deep Metric Learning

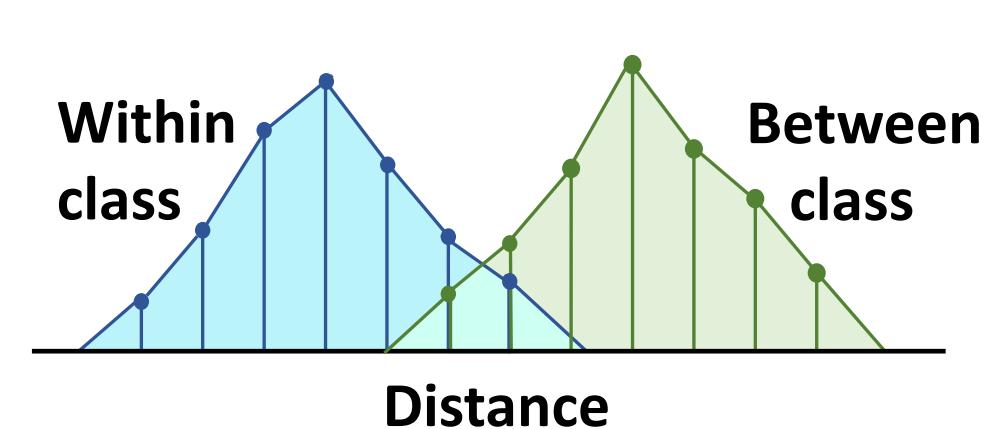
Source Domain



Source & Target
Domain Embedding



Histogram loss
(Ustinova & Lempitsky, 2016)



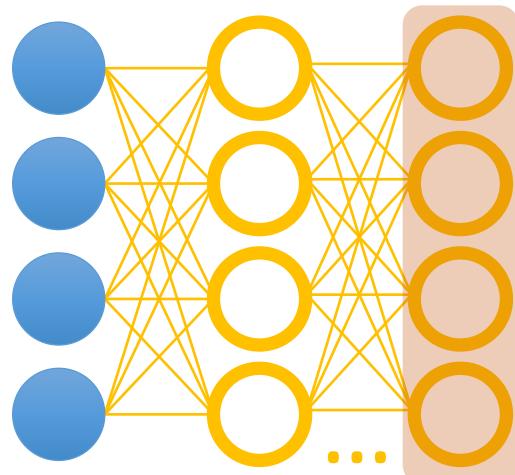
Inductive Transfer Learning

Weight Transfer

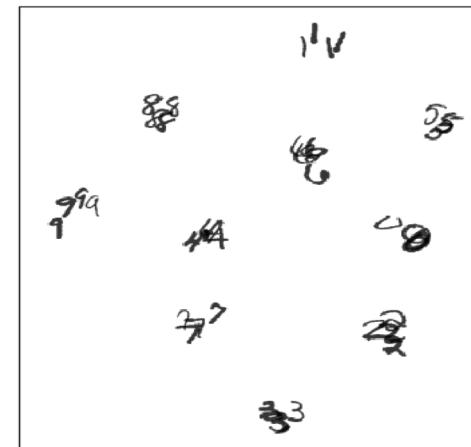
Deep Metric Learning

Few-Shot Learning

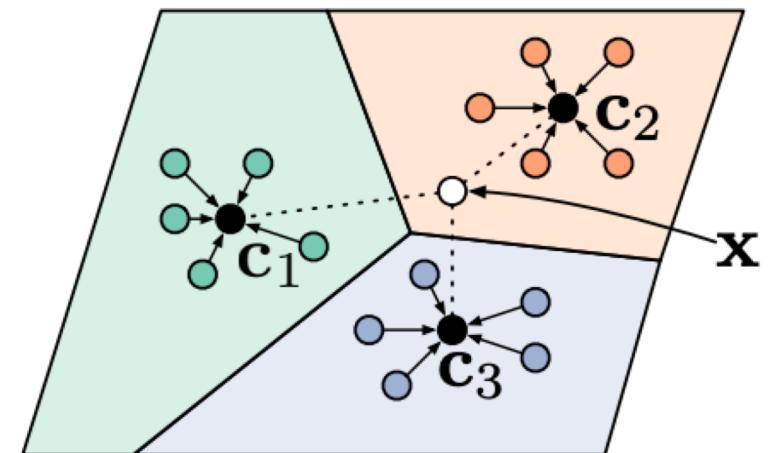
Source Domain



Source & Target
Domain Embedding



Prototypical nets
(Snell et al., 2017)

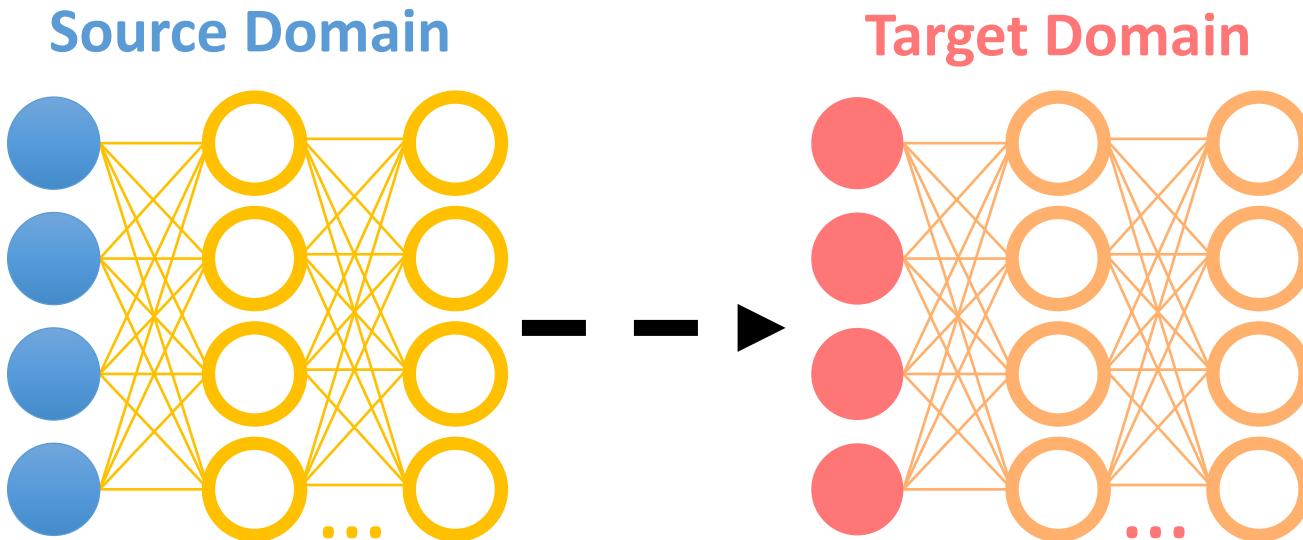
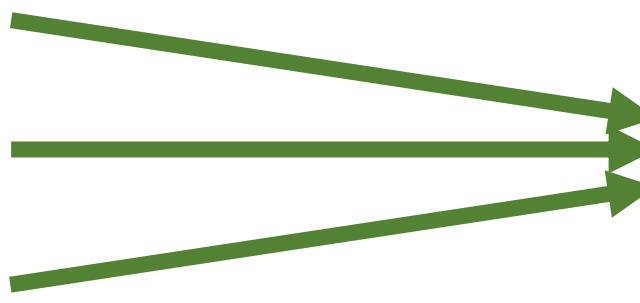


Inductive Transfer Learning

Weight Transfer

Deep Metric Learning

Few-Shot Learning



Adapted Deep
Embeddings

1. Train network using embedding loss
 - Histogram loss,
Prototypical nets
2. Adapt weights using limited target-domain data

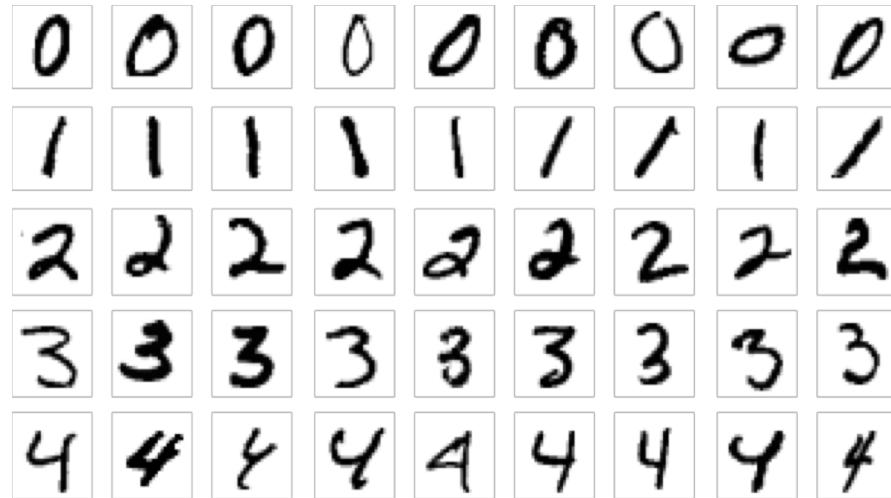
Inductive Transfer Learning

Why hasn't a comparison been explored?

# labeled examples per target class (k)	
Weight Transfer	> 100
Deep Metric Learning	agnostic
Few-Shot Learning	< 20

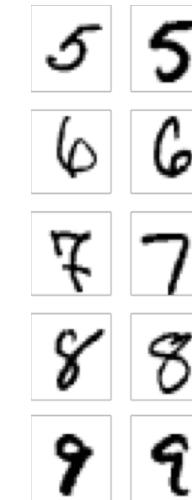
MNIST

Source Domain



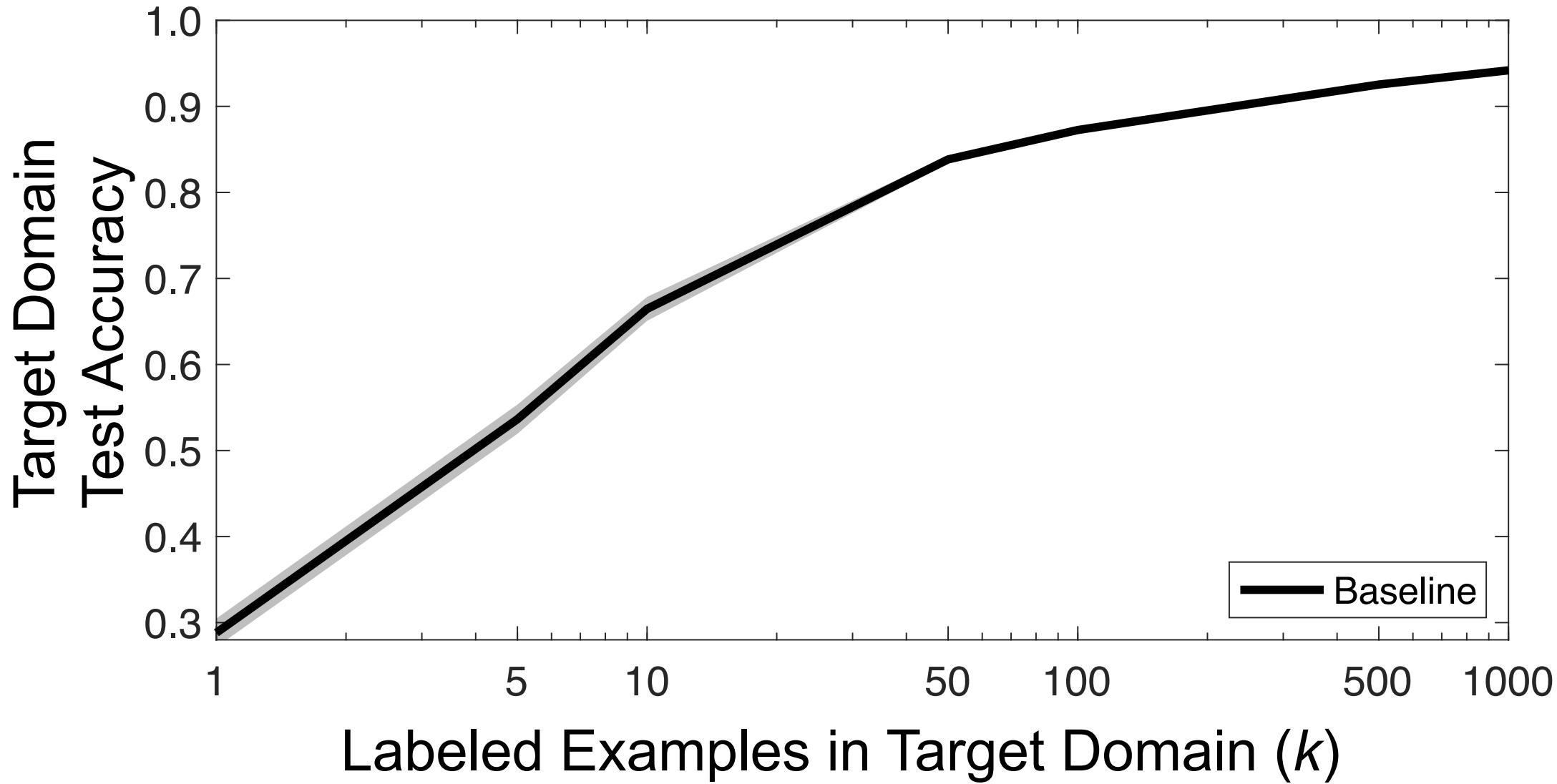
2200 labeled
examples per
class

Target Domain

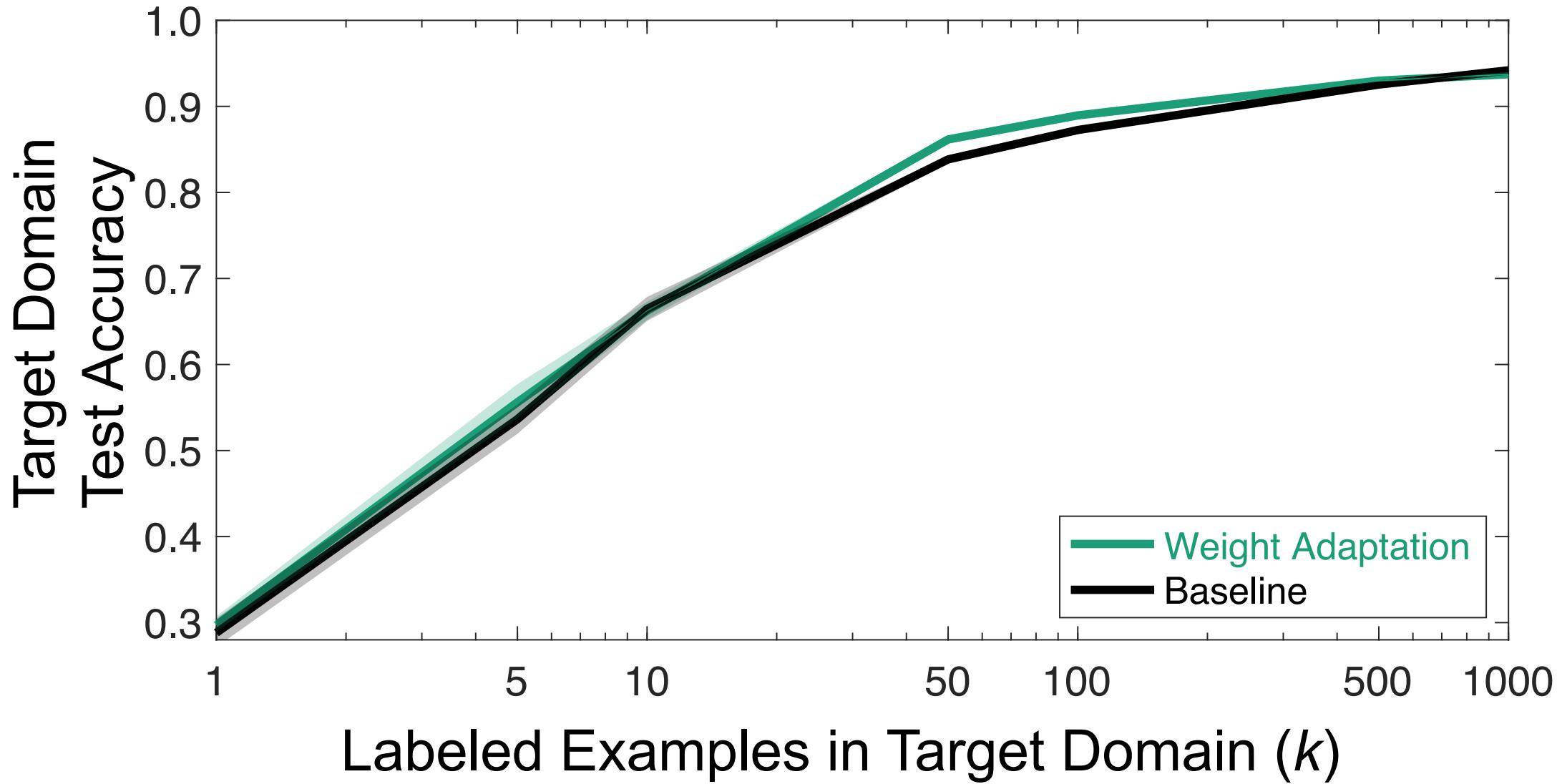


k labeled
examples per
class

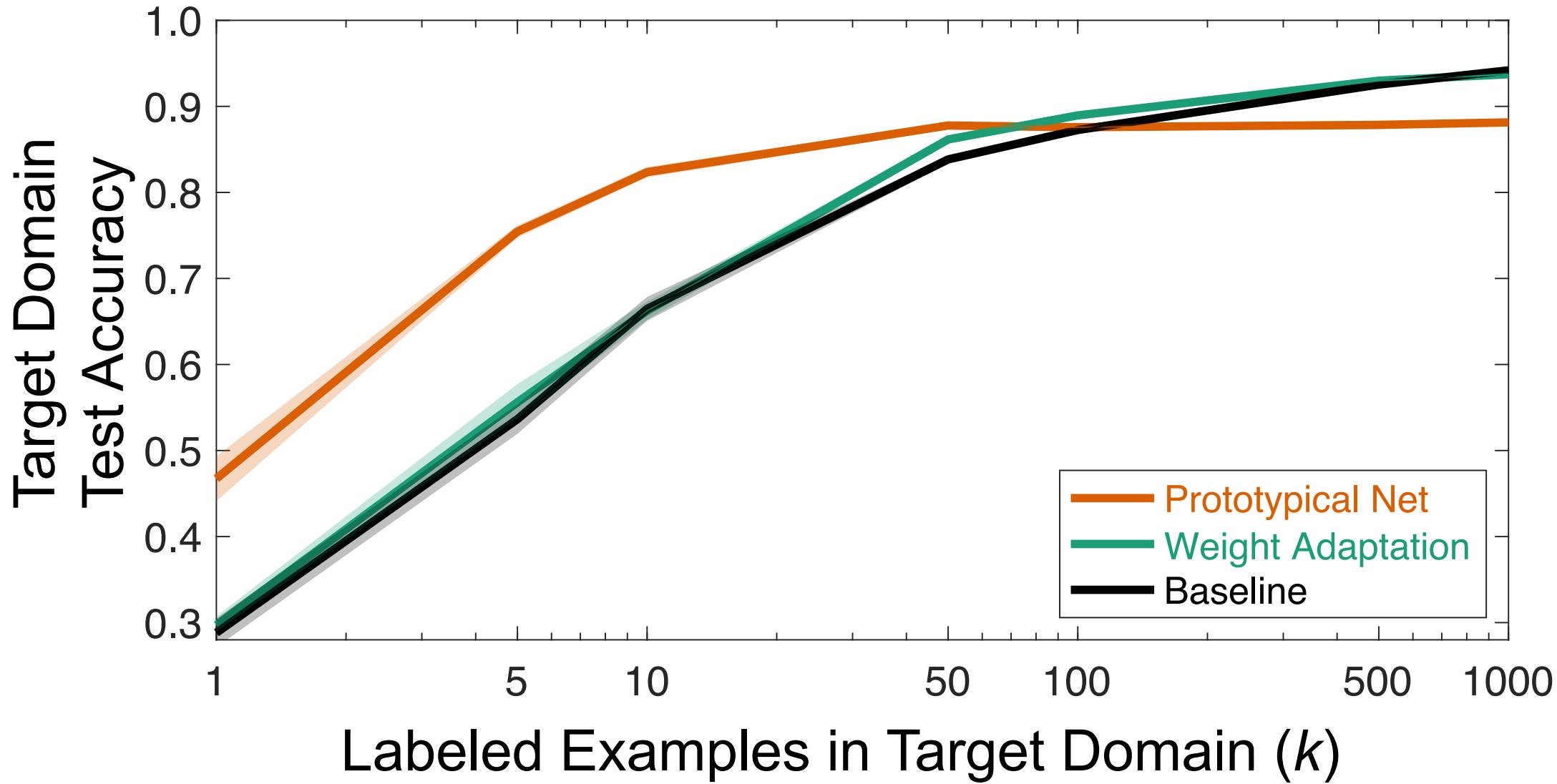
MNIST



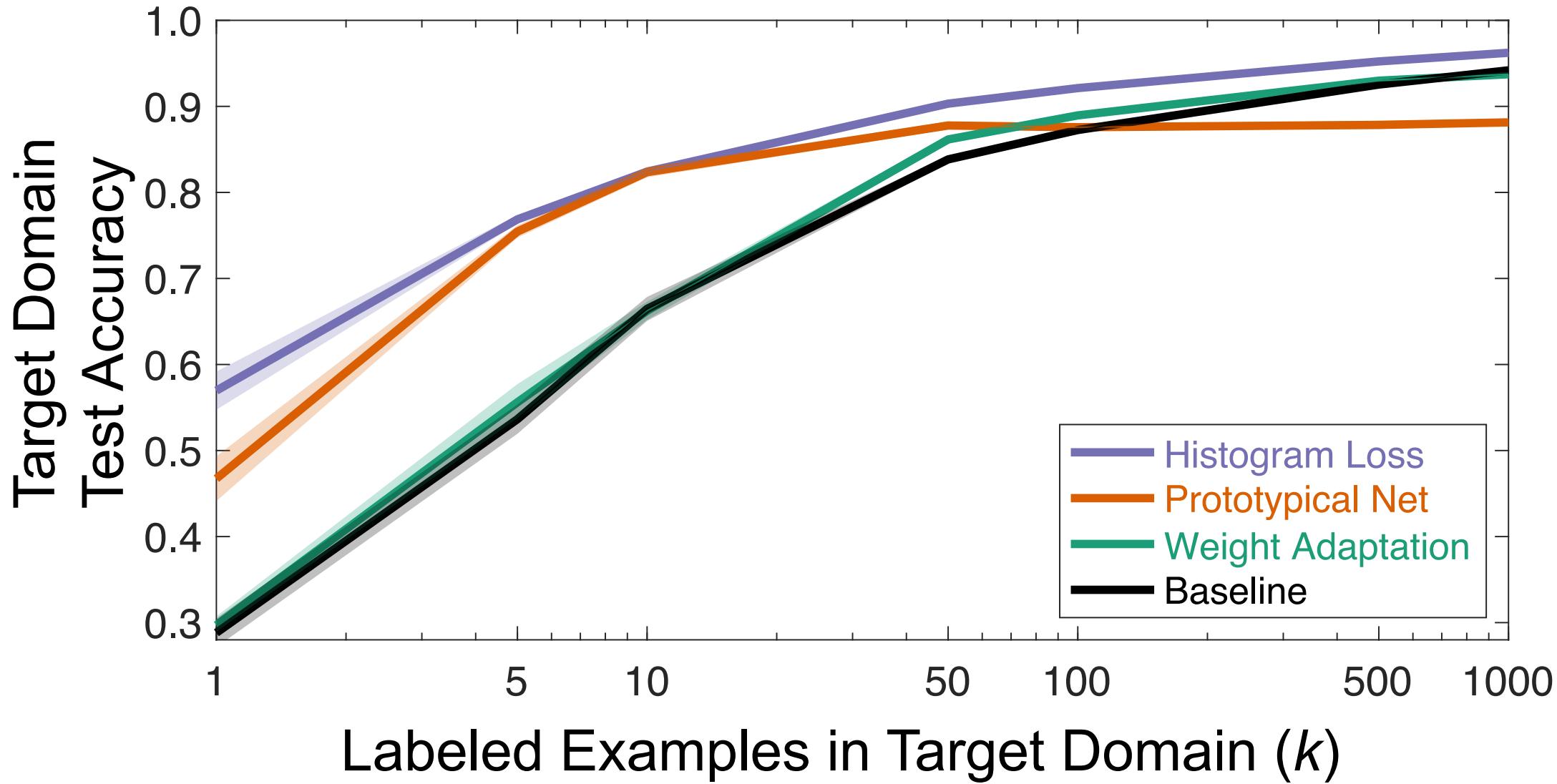
MNIST



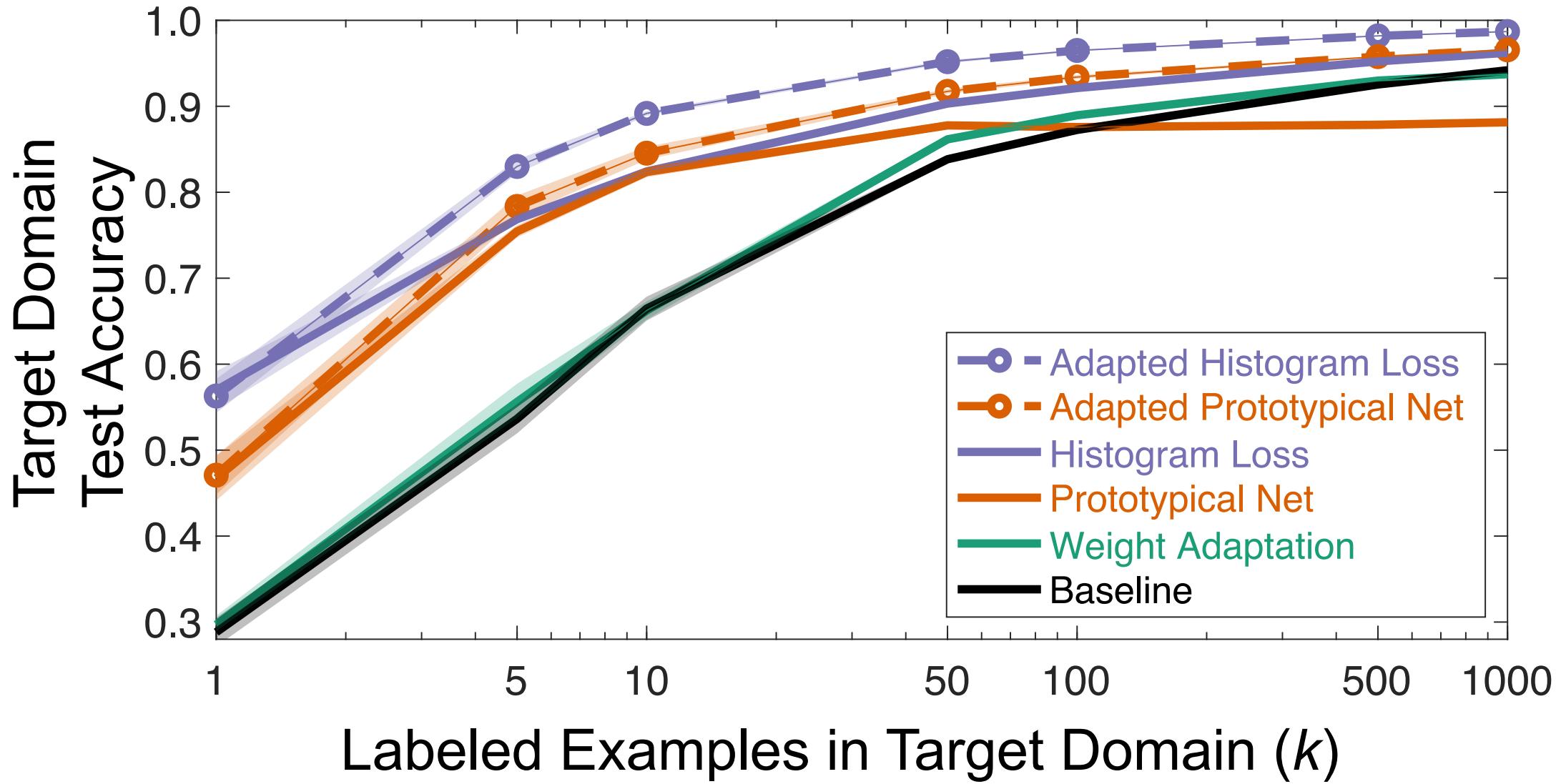
MNIST

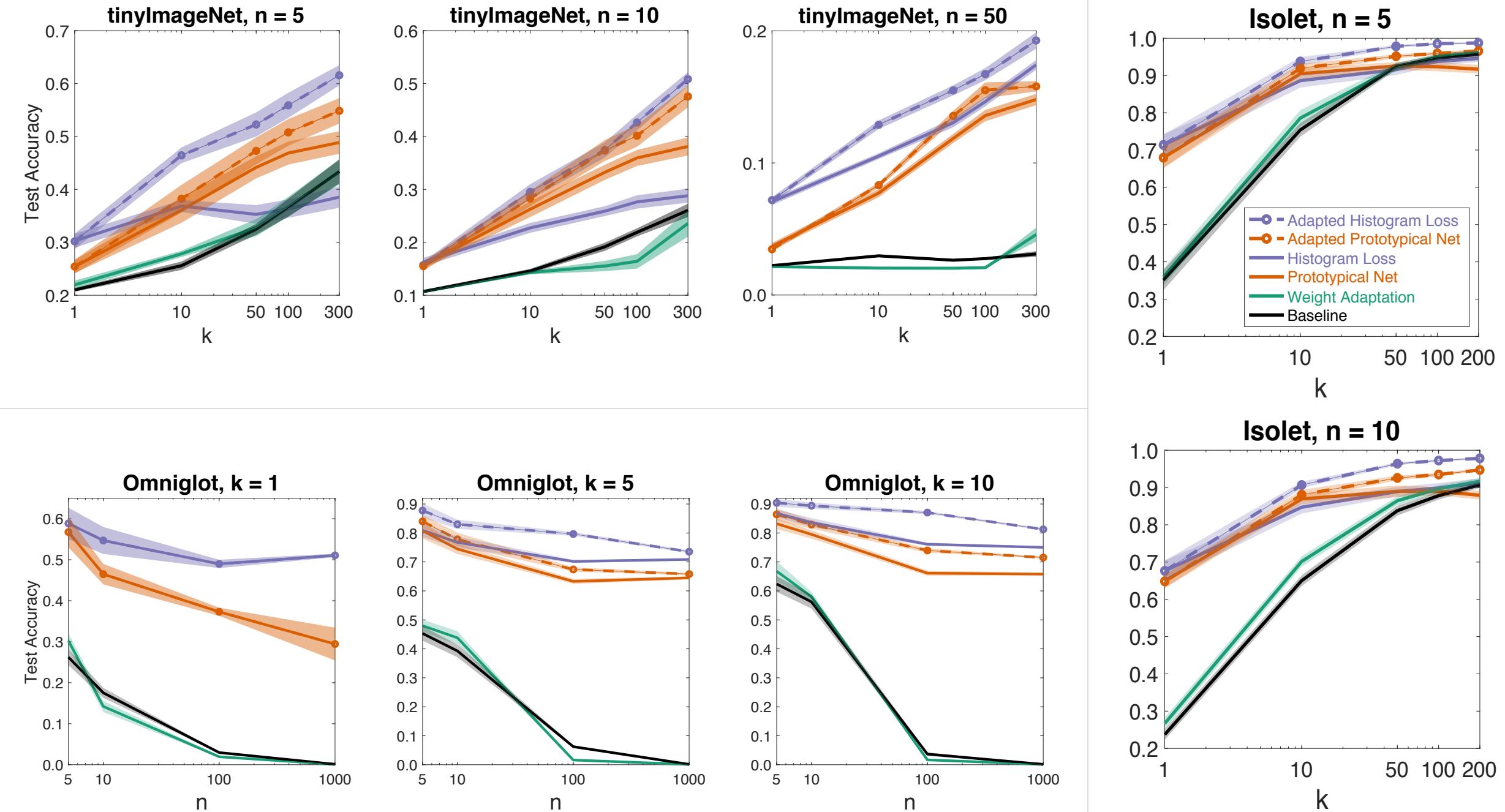


MNIST



MNIST





Conclusion

- Weight transfer is the least effective method for inductive transfer learning
- Histogram loss is robust regardless of the amount of labeled data in the target domain
- Adapted embeddings outperform *every* static embedding method previously proposed

Poster #167

Room 210 & 230 AB

Today, 5:00 - 7:00 PM