Semi-Supervised Labeling of Data with Varying Distributions

PreciBake GmbH

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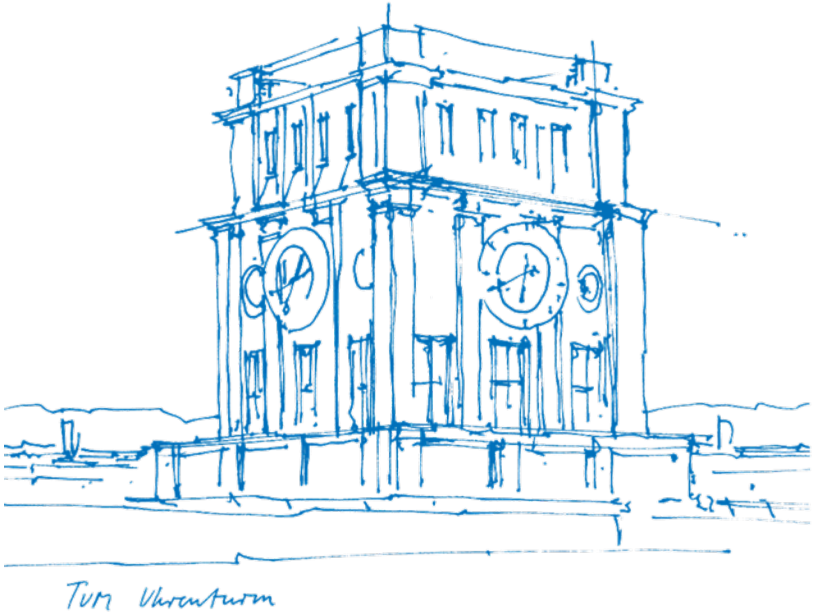
Final Presentation



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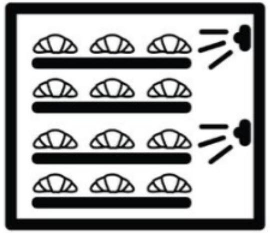
Introduction

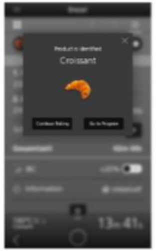
PreciBake®



Sensors analyze the baking chamber

Quelle: shutterstock

Artificial intelligence processes the data and identifies what is in the oven



The AI-CPU transfers its decision to the control and chooses the right baking program

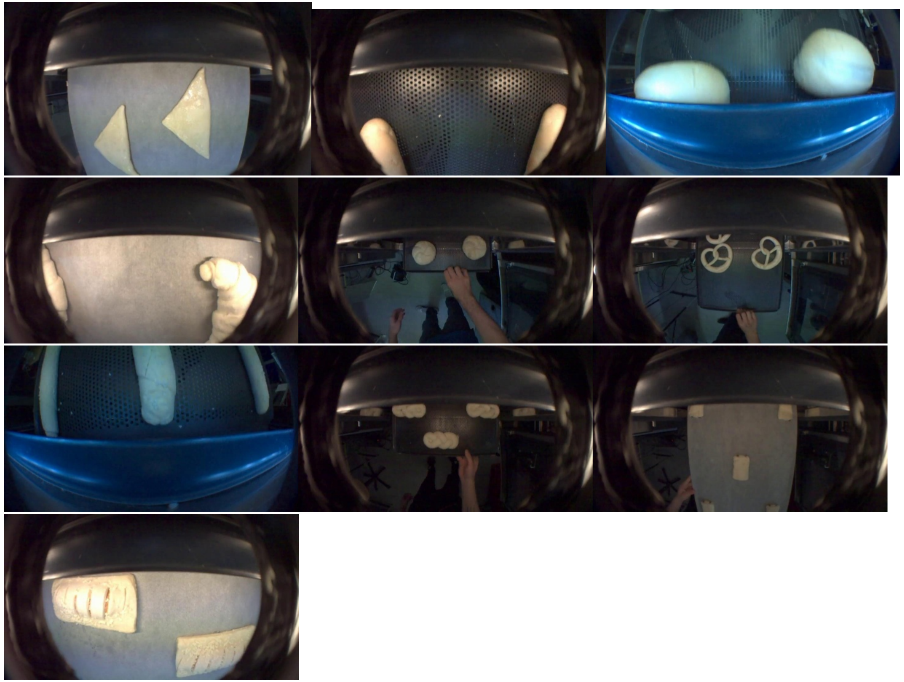
Photos and videos can be used for documentary purposes and quality assurance

Photos and videos can be used for quality assurance or documentary purposes

Data is available from everywhere on many devices

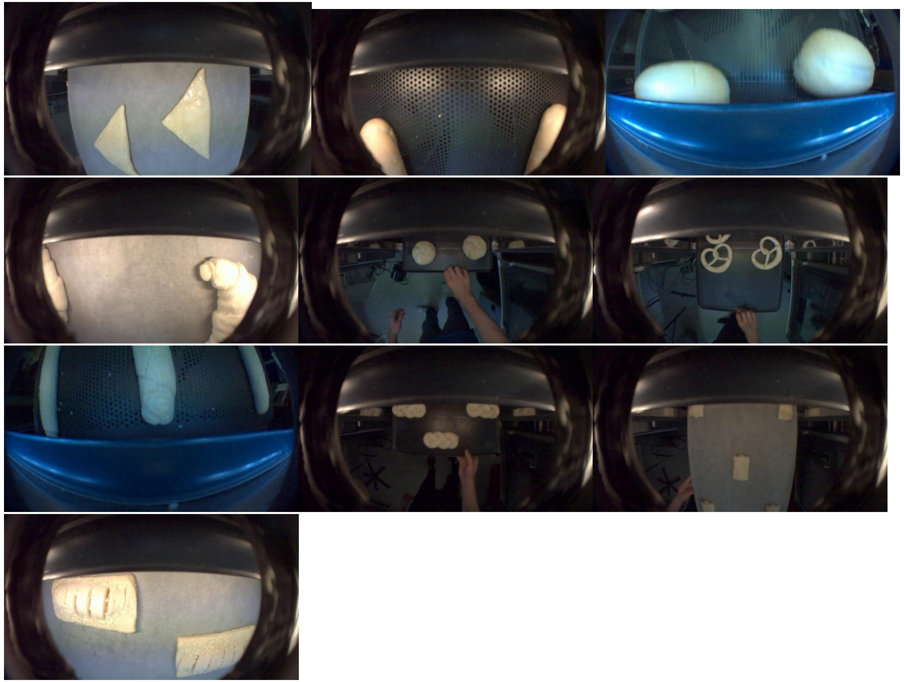
Data Sets

Data PreciBake

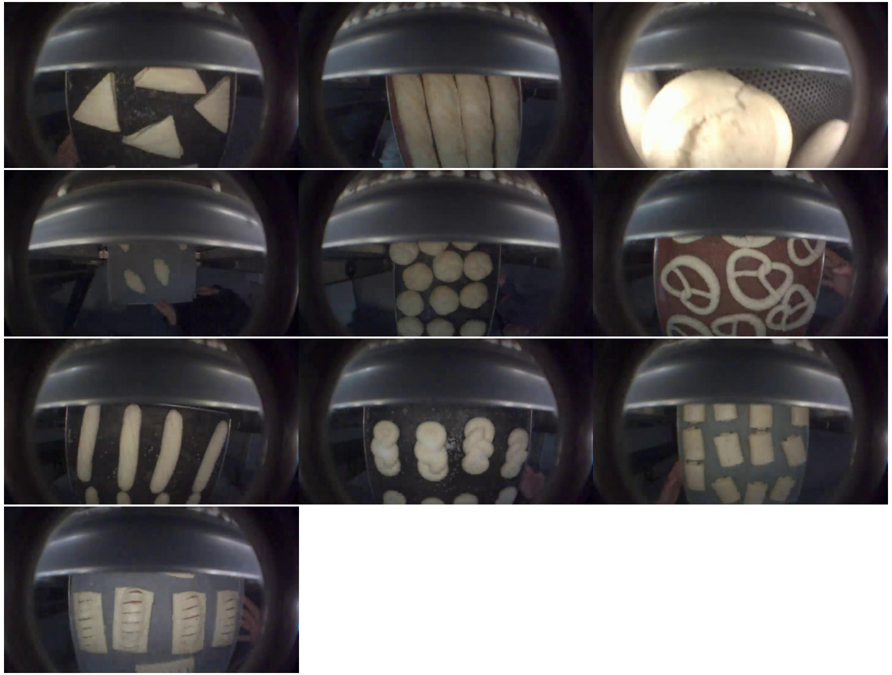


Data Sets

Data PreciBake



Data Fieldtest



Problem

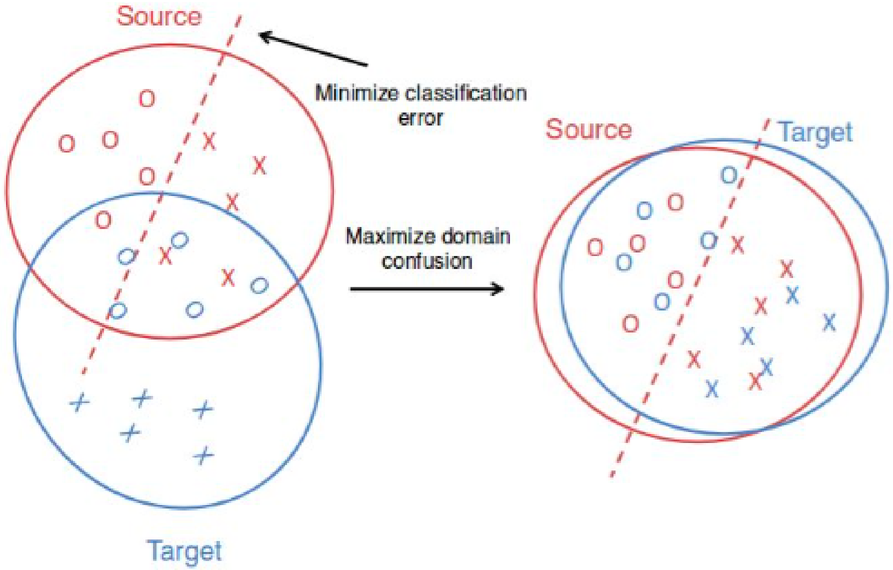
PreciBake Data

- Images made in the PreciBake Lab
- Has labeled images
- Model is trained on this domain

Fieldtest Data

- Images made in the of the customer’s site
- Has only unlabeled images
- We need to classify the images of this domain

Problem



1

[1] E. Tzeng et al. (2014). “Deep domain confusion: Maximizing for domain invariance”. In: *arXiv preprint arXiv:1412.3474*.

Solution Approaches: Transfer Learning

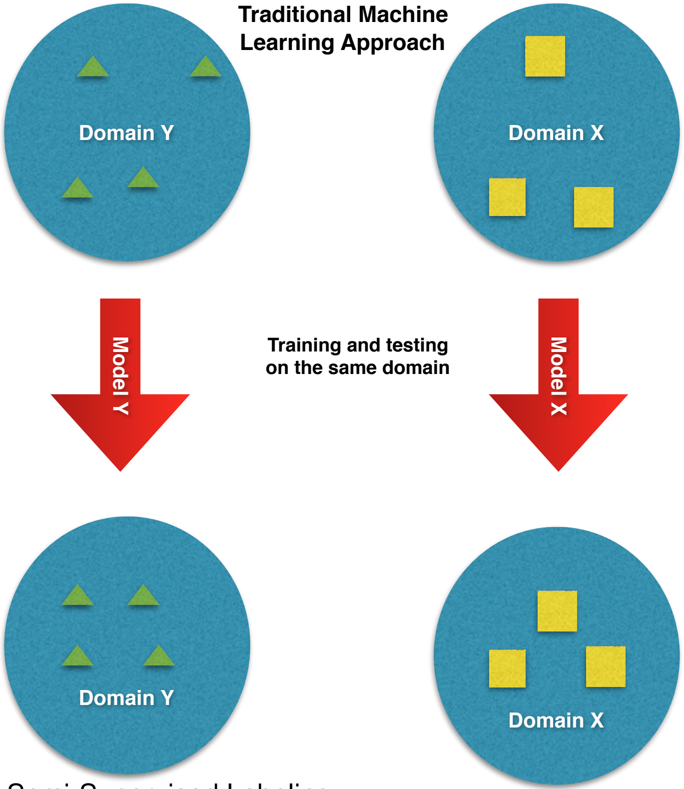
Solution Ideas

- Online learning: treat test domain data as incoming data to complete the training data set.
- Or tune the model to be insensitive to environmental variables.
- ...

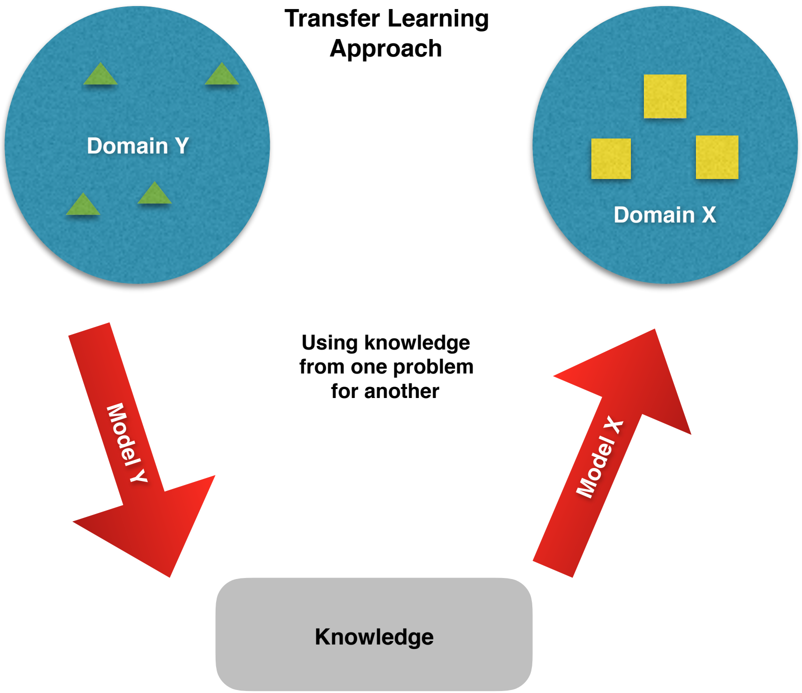
Image to Image Translation

- No need to update the model trained on PreciBake.
- For any new customer data, only need to learn a new image to image mapping

Traditional Machine Learning Approach



Transfer Learning Approach



Background

Classification Method (Resnet 18 model)

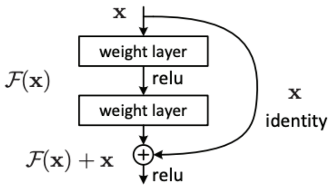


Figure: Residual learning: a building block.

2

- Observation: deep neural network may have degrading performances.
- Explanations: networks try to skip layers by setting input equal to outputs.
- Solutions: change the structure of the intermediate layers

[2] K. He et al. (2016). “Deep Residual Learning for Image Recognition”. In: *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*.

Problem with Classification

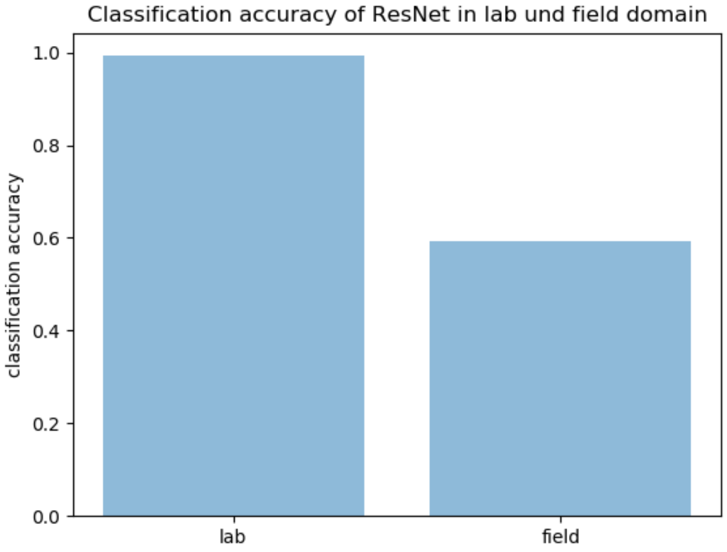
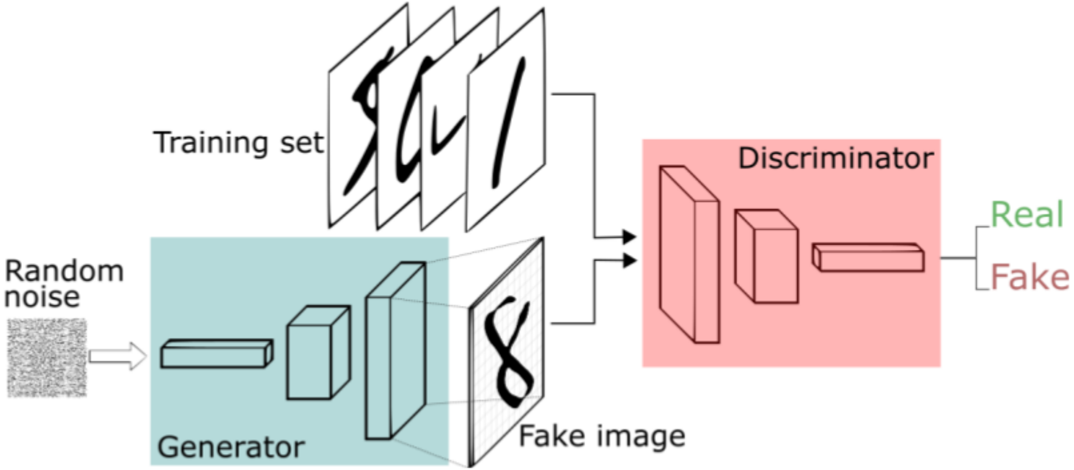


Figure: Classification accuracy of a ResNet18 on the lab and field test data.

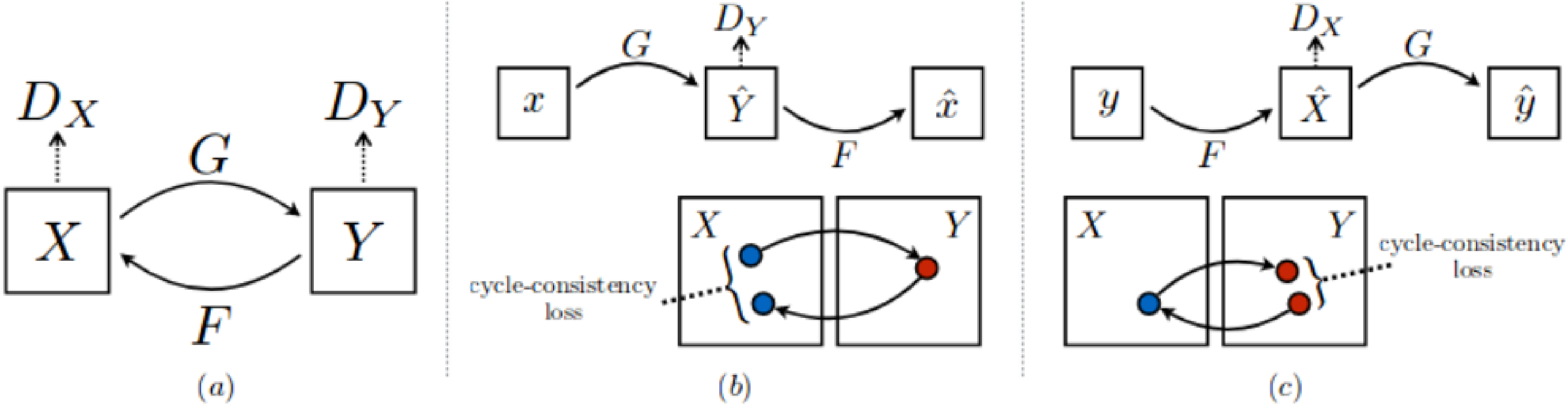
Generative Adversarial Networks (GAN)



3

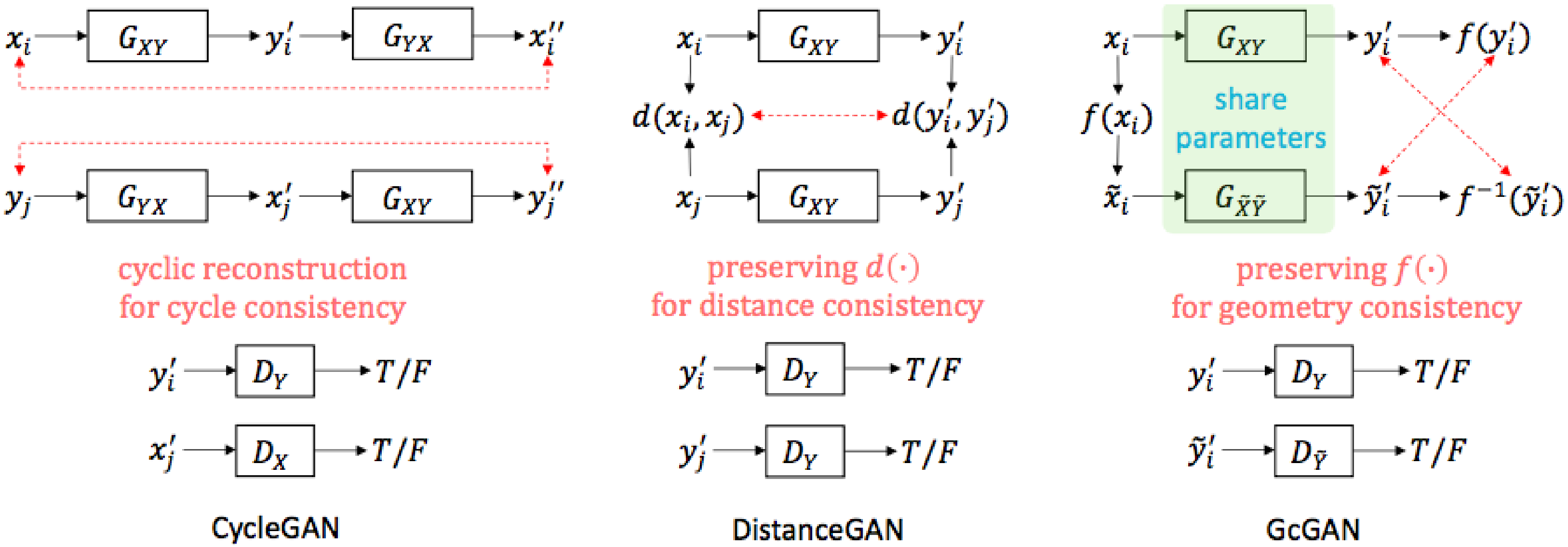
[3] https://medium.freecodecamp.org/an-intuitive-introduction-to-generative-adversarial-networks-gans-7a2264a81394.

Unsupervised Image to Image Translation - cycleGAN



[4] J.-Y. Zhu et al. (2017). "Unpaired Image-to-Image Translation Using Cycle-Consistent Adversarial Networks". In: *2017 IEEE International Conference on Computer Vision (ICCV)*.

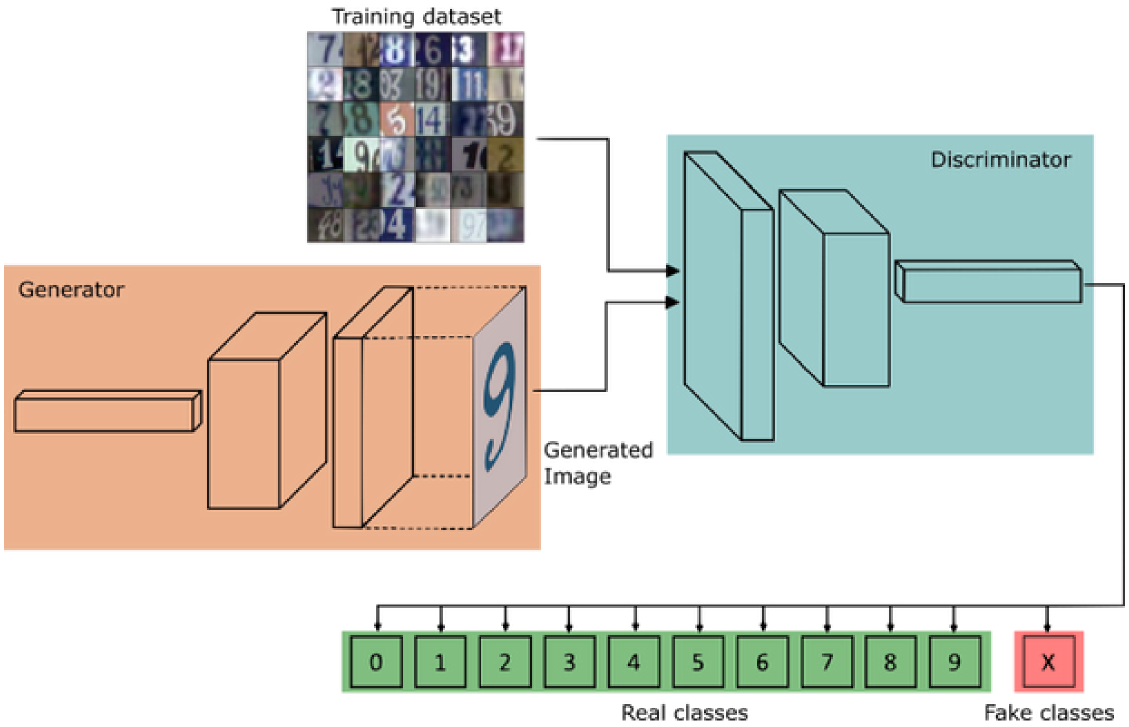
Versions of cycleGAN



[5]

[5]H. Fu et al. (2018). "Geometry-Consistent Adversarial Networks for One-Sided Unsupervised Domain Mapping". In: *arXiv preprint arXiv:1809.05852*.

Discriminator for classification



[6]

[6] **https://towardsdatascience.com/semi-supervised-learning-with-gans-9f3cb128c5e**.

Unsupervised Image-to-Image Translation Network (UNIT)

- Image translation is achieved by the latent space assumption.
- Latent space as the extracted essence of the object that stays invariant in either domain.
- Latent space is generated by variational auto-encoder.
- Cycle consistency is implied by such a construction.
- Performance depending on the combined interactions of Generators and Discriminators.

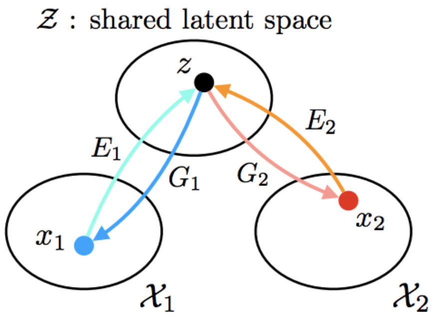


Figure: Illustration of UNIT model under the latent space constraint.

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[7] J.-Y. Zhu et al. (2017). "Unpaired Image-to-Image Translation Using Cycle-Consistent Adversarial Networks". In: *2017 IEEE International Conference on Computer Vision (ICCV)*.

Unsupervised Image-to-Image Translation Network (UNIT)

Figure: Attribute-based face translation results.

[8]

[8] K. He et al. (2016). "Deep Residual Learning for Image Recognition". In: *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*.

Unsupervised Image-to-Image Translation Network (UNIT)

Cons

- UNIT model is intrinsically a variation of the cycle GAN, so it also satisfies the cycle consistency constraint.
- Restrict the capacity of our network if we specify the transform from domain X to Y is though the auto-encoders.

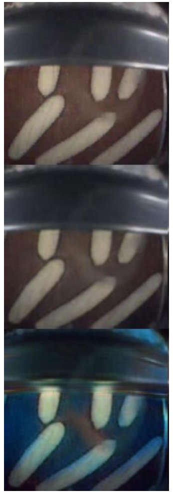
Pros

- Generate the hidden latent space which is not explored in other GAN models.
- The hidden latent space can be used as ground for classification.

Experiments and Results: Different stages for training the UNIT model (under-fitting)

X2Y

Y2X



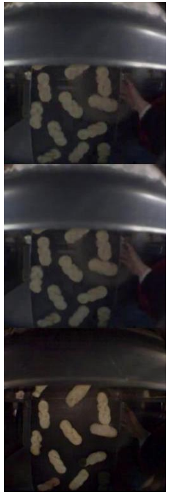
Explanations

When the training has just started and the weight has just been initialized, it can be observed that our model is trying to mimic the blue lighting in the training set.

Experiments and Results:Different stages for training the UNIT model (Over-fitting)

X2Y

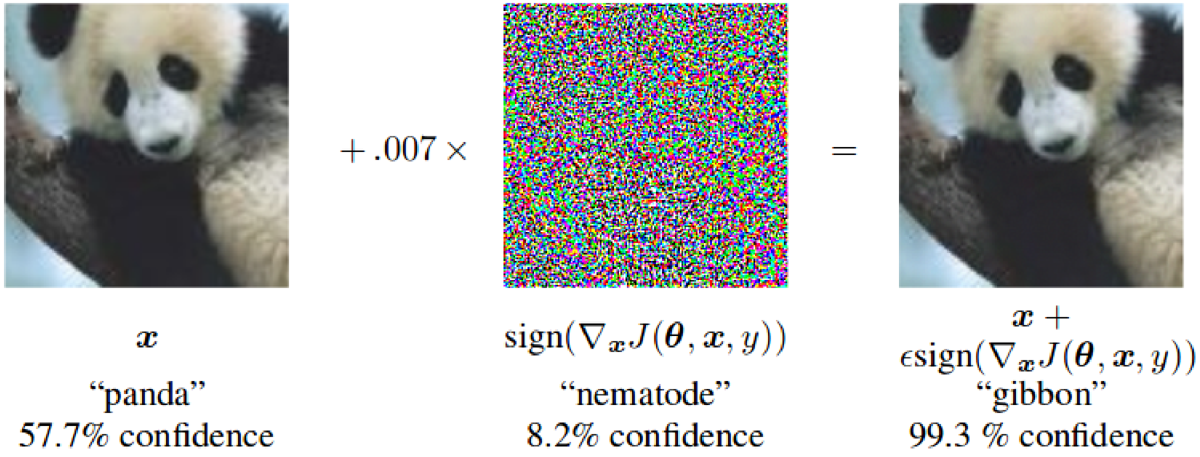
Y2X



Explanations

A typical observation when over-fitting occurs is the network tries to remember not only the environmental parameters, but also tries to manipulate the object distribution.

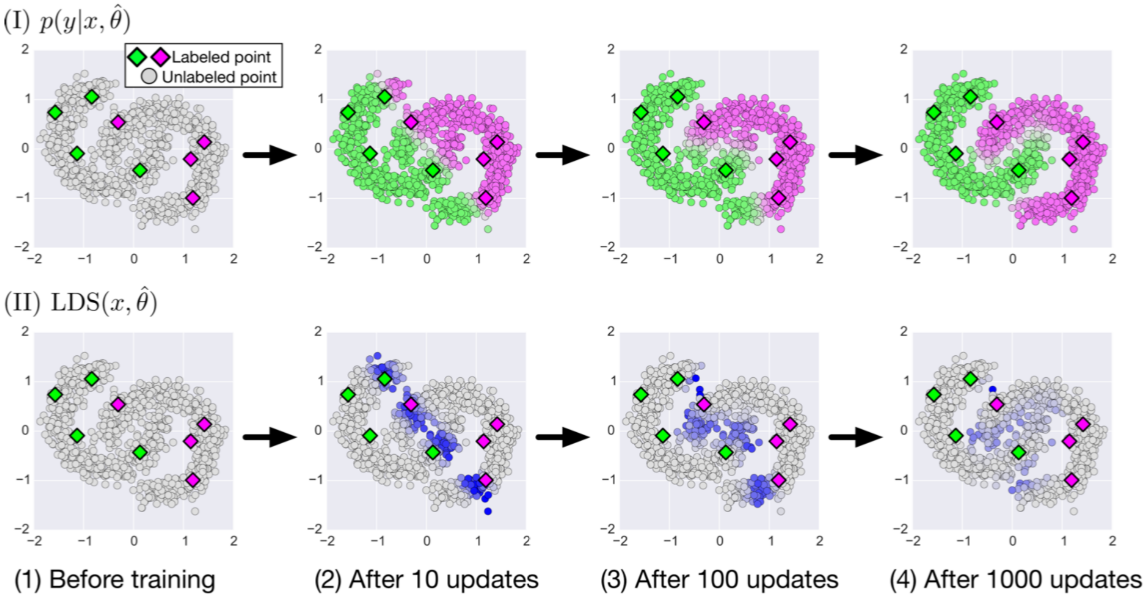
Adversarial Training



[9]

[9] I. J. Goodfellow, J. Shlens, and C. Szegedy (n.d.). *Explaining and harnessing adversarial examples. CoRR (2015)*.

Virtual Adversarial Training



[10]

[10] T. Miyato et al. (2018). "Virtual adversarial training: a regularization method for supervised and semi-supervised learning". In: *IEEE transactions on pattern analysis and machine intelligence*.

Our Approach

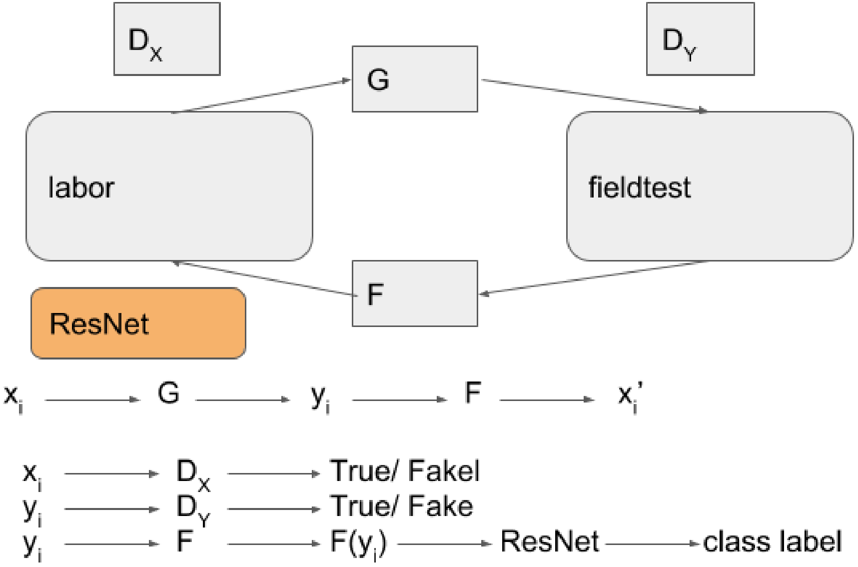
Evaluation Metrics

[11]

- classification accuracy of unlabeled field test data
- benchmark: in lab trained ResNet

[11] **https://www.manufactum.de/messbecher-borosilikatglas-p1467369/**.

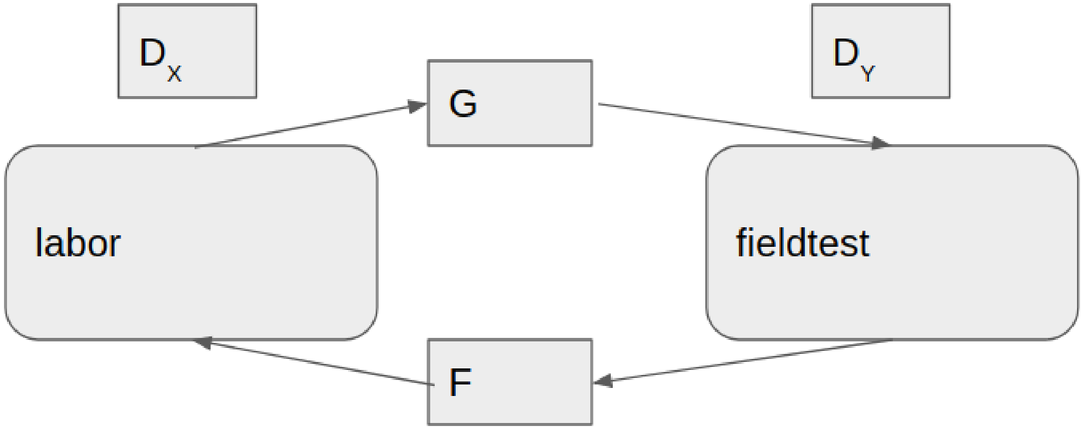
Circular mapping with pretrained ResNet



[12]

[12] **have fun drawing a nice sketch with the resnet ;)** .

Circular mapping with discriminator as classifier



$x_i \longrightarrow G \longrightarrow y_i \longrightarrow F \longrightarrow x_i'$

$x_i \longrightarrow D_X \longrightarrow$ True/ Fake
$x_i \longrightarrow D_X \longrightarrow$ class label
$y_i \longrightarrow D_Y \longrightarrow$ True/ Fake

Augmentation

Figure

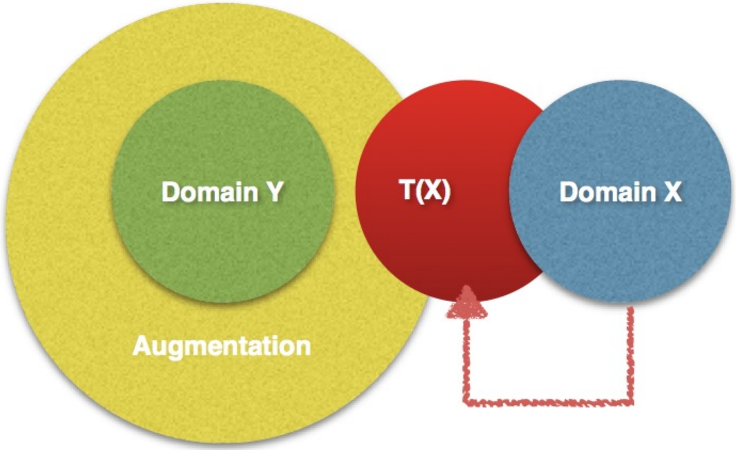


Figure: Effect of Augmentation; Domain Y - PreciBake Data; T(X) - Transfer Model on Domain X; Domain X - Fieldtest Data

Augmentation

Figure

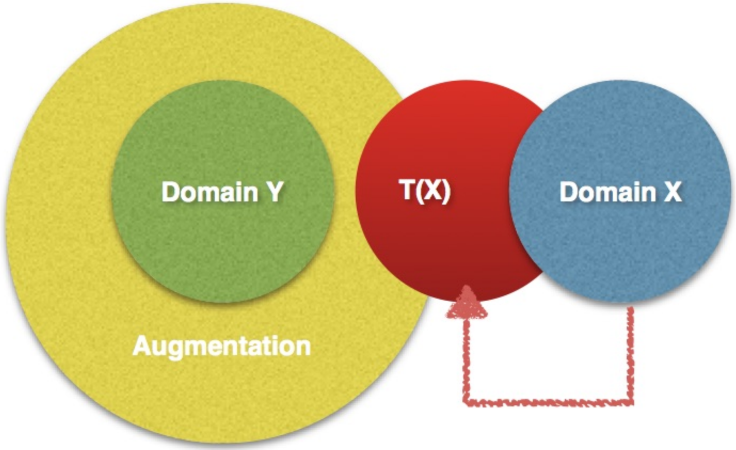


Figure: Effect of Augmentation; Domain Y - PreciBake Data; T(X) - Transfer Model on Domain X; Domain X - Fieldtest Data

Explanation

- May add more variance to data
- May shift data to the other domain
- Equalize distribution of classes
- Higher amount of training images

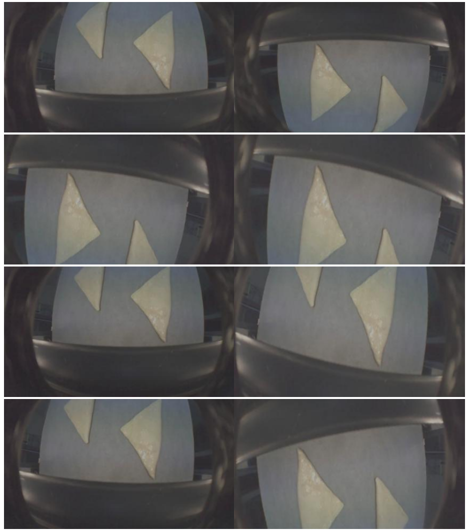
Augmentation

Augmentation Name	Augmentations used[13]	Lab Accuracy
Augment5	p.rotate(probability=0.7, max-l-rot=10, max-r-rot=10) p.crop-rnd(probability = 1, percentage-area = .9) p.flip-rnd(probability = 1) p.rnd-contrast(probability = 1, min-f = 0.5, max-f = 0.5)	0.8026
Augment7	p.rotate(probability=0.7, max-l-rot=10, max-r-rot=10) p.crop-rnd(probability = 1, percentage-area = .9) p.flip-rnd(probability = 1) p.rnd-color(probability = 1, min-f = 0.5, max-f = 0.5)	0.905579
Augment13	p.skew(probability = 0.5) p.rotate(probability=0.7, max-l-rot=10, max-r-rot=10) p.crop-rnd(probability = 1, percentage-area = .9) p.flip-rnd(probability = 1) p.rnd-contrast(probability = 1, min-f = 0.5, max-f = 0.5) p.rnd-brness(probability = 1, min-f = 0.95, max-f = 0.95) p.rnd-color(probability = 1, min-f = 0.5, max-f = 0.5)	0.832618

[13] M. D. Bloice, C. Stocker, and A. Holzinger (2017). "Augmentor: an image augmentation library for machine learning". In: *arXiv preprint arXiv:1708.04680*.

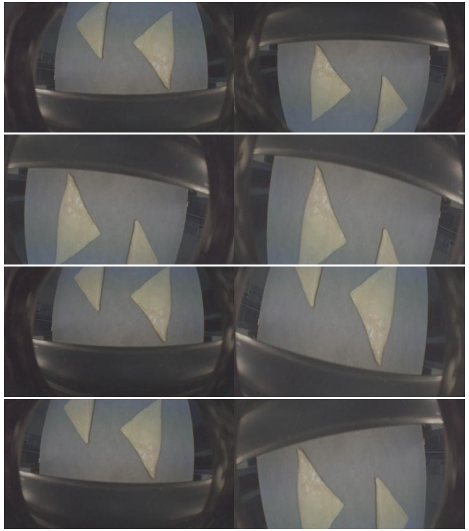
Augmentation

Augment5



Augmentation

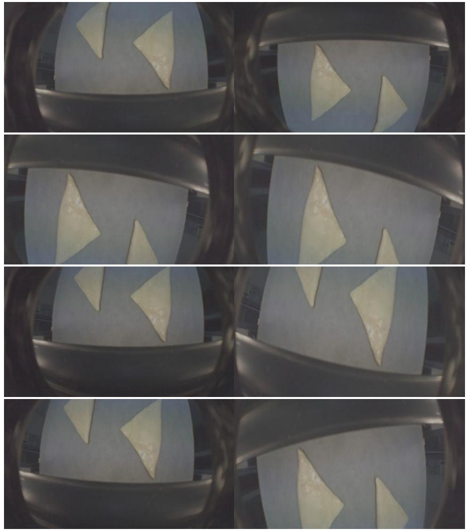
Augment5



Augment7

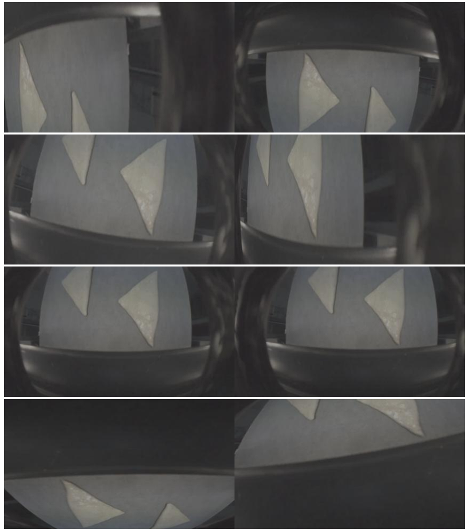
Augmentation

Augment5



Augment7

Augment13



Examples of Transferred Image on CycleGAN

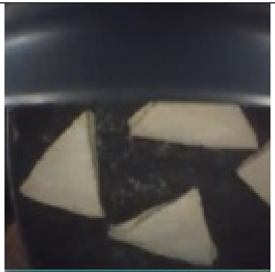
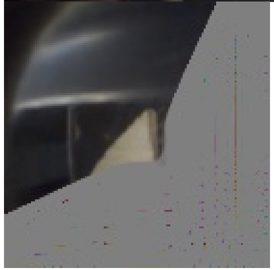
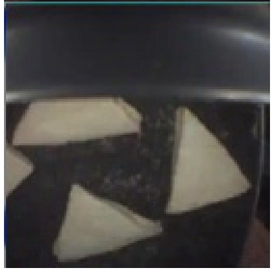
Table: Hyperparameters GcGAN

Name	Geometric Transformation	λ_{geo}	Details
rot_90_l10	Rotation	10	90 degrees
rot_180_l20	Rotation	20	180 degrees
per_l20	Perspective	20	Points (0,0),(0,28),(28,0),(28,28) to Points (0,0),(0,26),(26,0),(50,28)
rot_90_l20	Rotation	20	90 degrees
rot_180_l10	Rotation	10	180 degrees
per_l10	Perspective	10	Points (0,0),(0,28),(28,0),(28,28) to Points (0,0),(0,23),(23,0),(28,28)

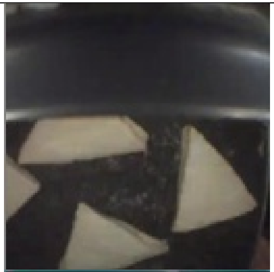
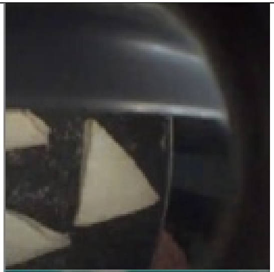
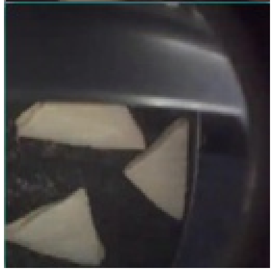
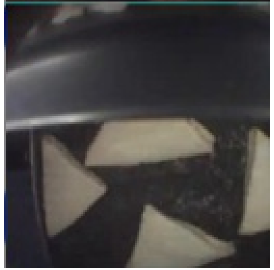
Table: Hyperparameters DistanceGAN

Name	Details
dis	self distance

Examples of Transferred Image on CycleGAN

Model Name	Picture	Model Name	Picture
fieldtest		dis	
per_l10		per_l20	

Examples of Transferred Image on CycleGAN

Model Name	Picture	Model Name	Picture
rot_90_l10		rot_90_l20	
rot_180_l10		rot_180_l20	

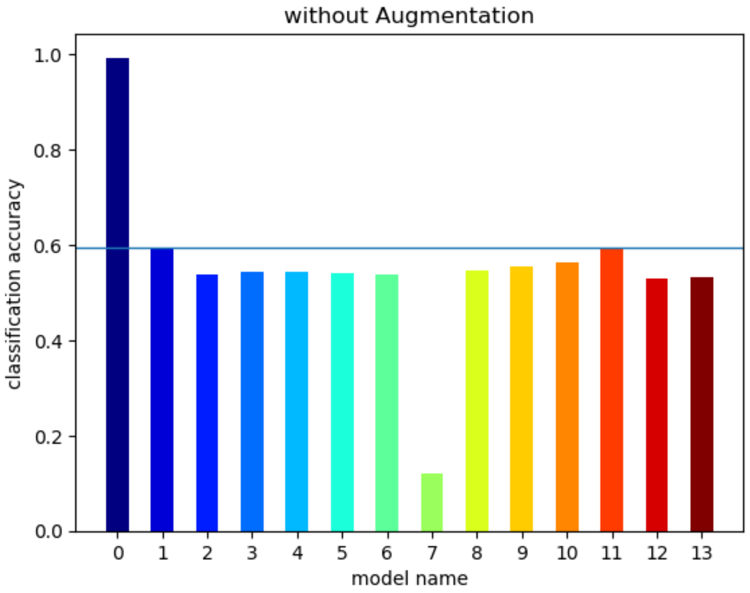
Results

Results - Models used

- 0 - domain Y, 1 - domain X
- CycleGAN: 2 - rot_90_l10, 3 - rot_180_l20, 4 - per_l20, 5 - rot_90_l20, 6 - rot_180_l10, 7 - per_l10, 8 - dis
- UNIT: 9 - iter_10000, 10 - iter_20000, 11 - iter_30000, 12 - iter_40000

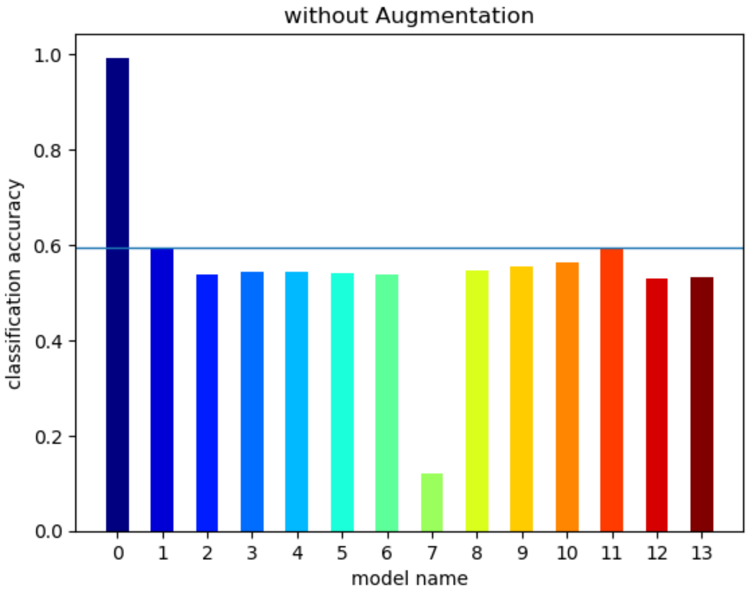
Results

Histogram



Results

Histogram

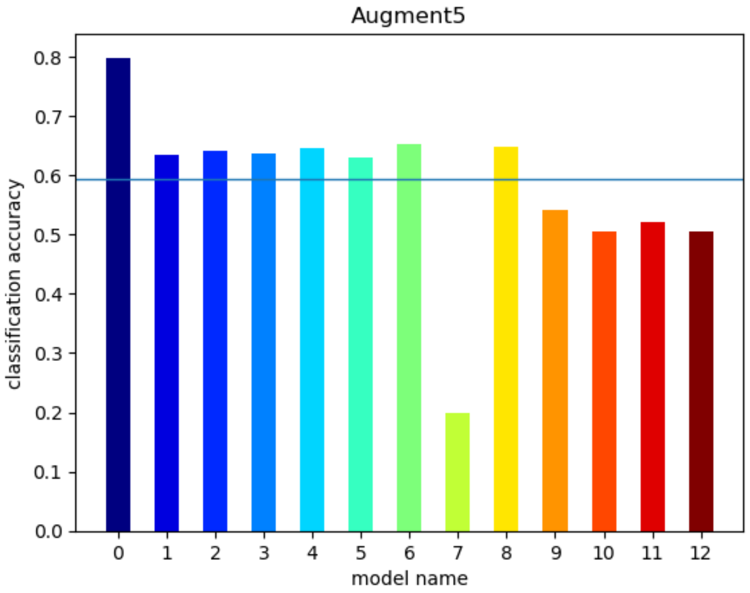


Description

- No transfer model achieves a higher accuracy than it is achieved without using one
- UNIT model (11) achieves highest accuracy of all transfer models
- Accuracy of ResNet at domain Y close to 100%

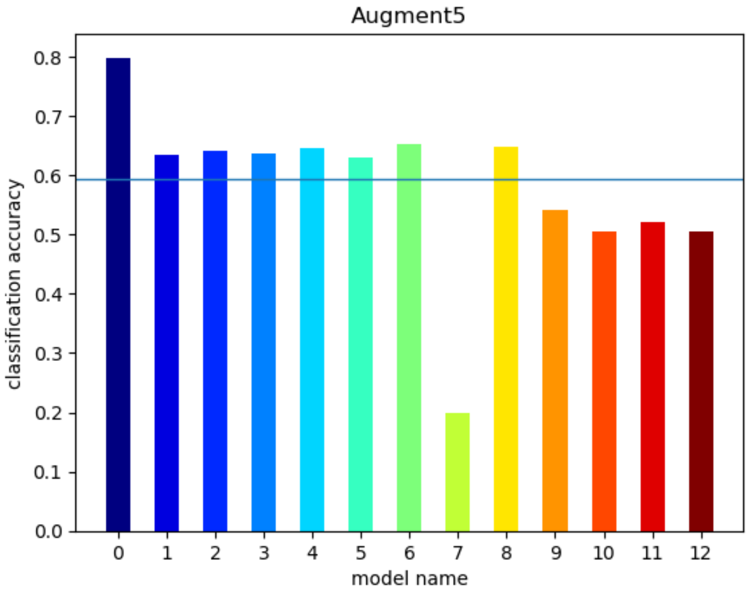
Results

Histogram



Results

Histogram

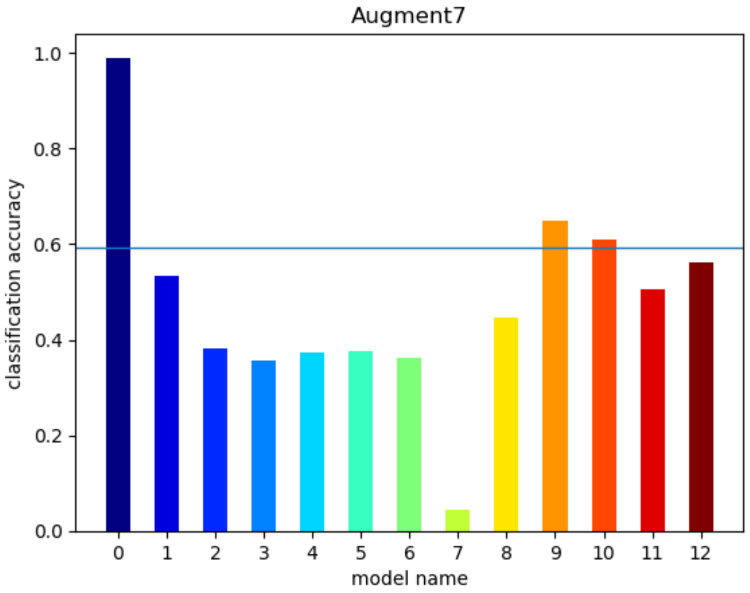


Description

- ResNet achieves higher accuracy on domain X without any transfer model
- ResNet achieves higher accuracy on domain X using CycleGAN transfer models
- ResNet achieves lower accuracy on domain X using UNIT transfer models
- ResNet achieves lower accuracy on domain Y

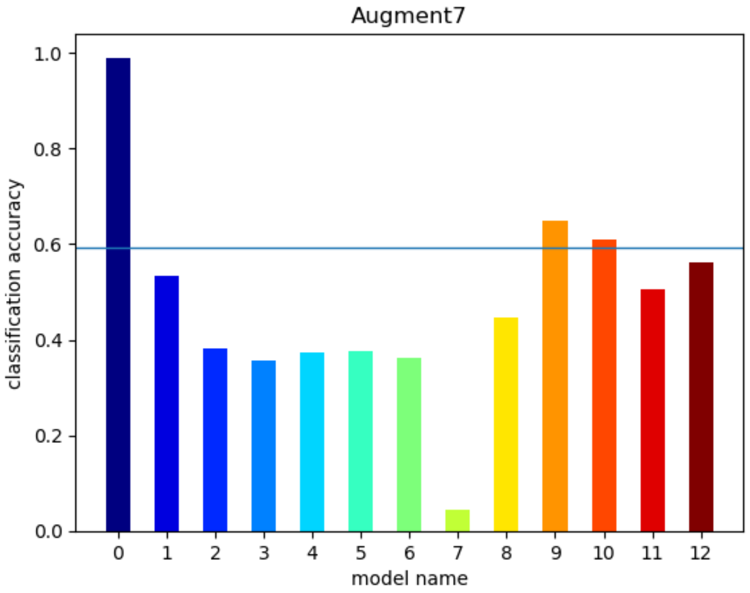
Results

Histogram



Results

Histogram

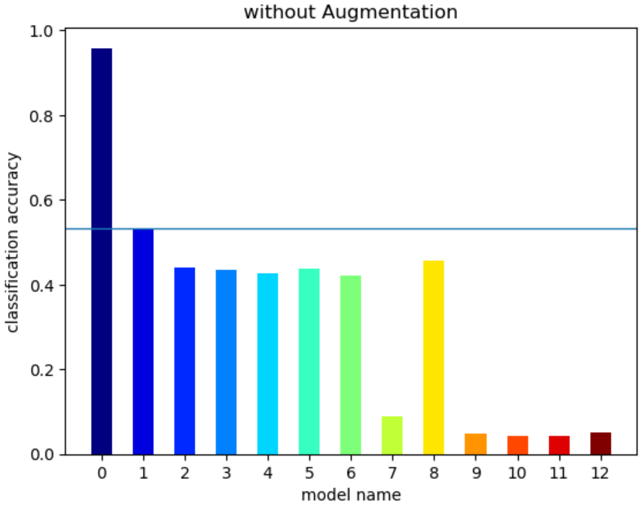


Description

- ResNet achieves lower accuracy on domain X without any transfer model
- ResNet achieves lower accuracy on domain X using cycleGAN transfer models
- ResNet achieves higher accuracy on domain X using UNIT transfer models
- ResNet achieves higher accuracy on domain Y compared to Augment5

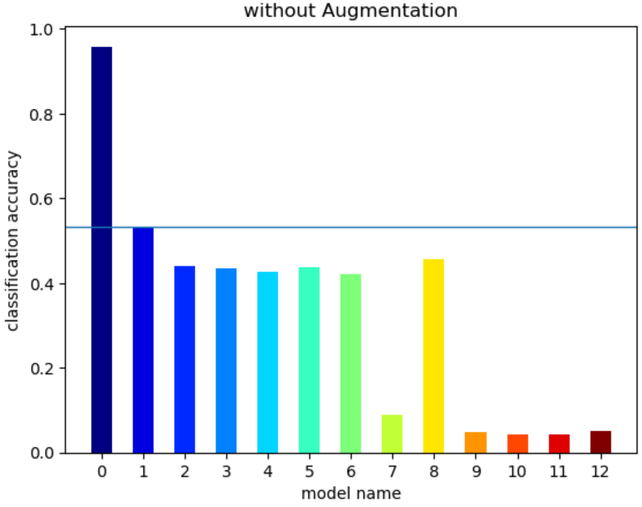
Results using VAT

Histogram



Results using VAT

Histogram



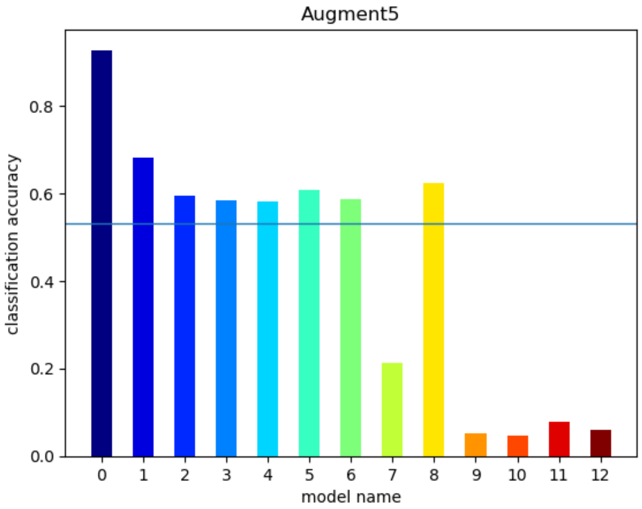
Description

- ResNet achieves higher accuracy on domain X without any transfer model
- ResNet achieves lower accuracy on domain X using cycleGAN transfer models [14]
- ResNet achieves low accuracy on domain X using UNIT transfer models
- ResNet achieves high accuracy on domain Y [12]

[/] lower than without using VAT

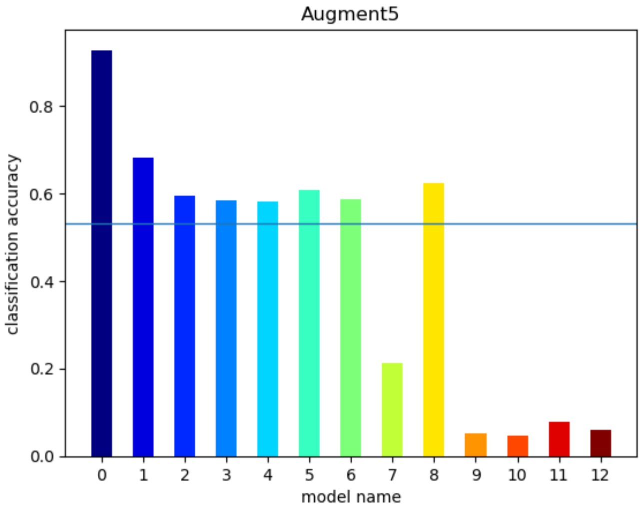
Results using VAT

Histogram



Results using VAT

Histogram



Description

- ResNet achieves highest accuracy on domain X without any transfer model
- ResNet achieves highest accuracy on domain X using cycleGAN transfer models [1]
- ResNet achieves low accuracy on domain X using UNIT transfer models
- ResNet achieves high accuracy on domain Y [1]

[1] lower than without using VAT

Conclusion and Outlook

Conclusion and Outlook

- augmentation matters
- circular mapping help to improve accuracy
- combining methods with individually trained hyper parameters is non trivial
- the generator architecture has a huge impact upon the training time

Conclusion and Outlook

- augmentation matters
- circular mapping help to improve accuracy
- combining methods with individually trained hyper parameters is non trivial
- the generator architecture has a huge impact upon the training time

- learn optimal augmentation
- use reinforcement learning to tune the hyper parameters
- perform classification in the latent space
- learn uncertainty about the classification of a specific sample

References

- Bloice, M. D., C. Stocker, and A. Holzinger (2017). "Augmentor: an image augmentation library for machine learning". In: *arXiv preprint arXiv:1708.04680*.
- Fu, H. et al. (2018). "Geometry-Consistent Adversarial Networks for One-Sided Unsupervised Domain Mapping". In: *arXiv preprint arXiv:1809.05852*.
- Goodfellow, I. J., J. Shlens, and C. Szegedy (n.d.). *Explaining and harnessing adversarial examples. CoRR (2015)*.
- He, K. et al. (2016). "Deep Residual Learning for Image Recognition". In: *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*.
- Miyato, T. et al. (2018). "Virtual adversarial training: a regularization method for supervised and semi-supervised learning". In: *IEEE transactions on pattern analysis and machine intelligence*.
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- Zhu, J.-Y. et al. (2017). "Unpaired Image-to-Image Translation Using Cycle-Consistent Adversarial Networks". In: *2017 IEEE International Conference on Computer Vision (ICCV)*.