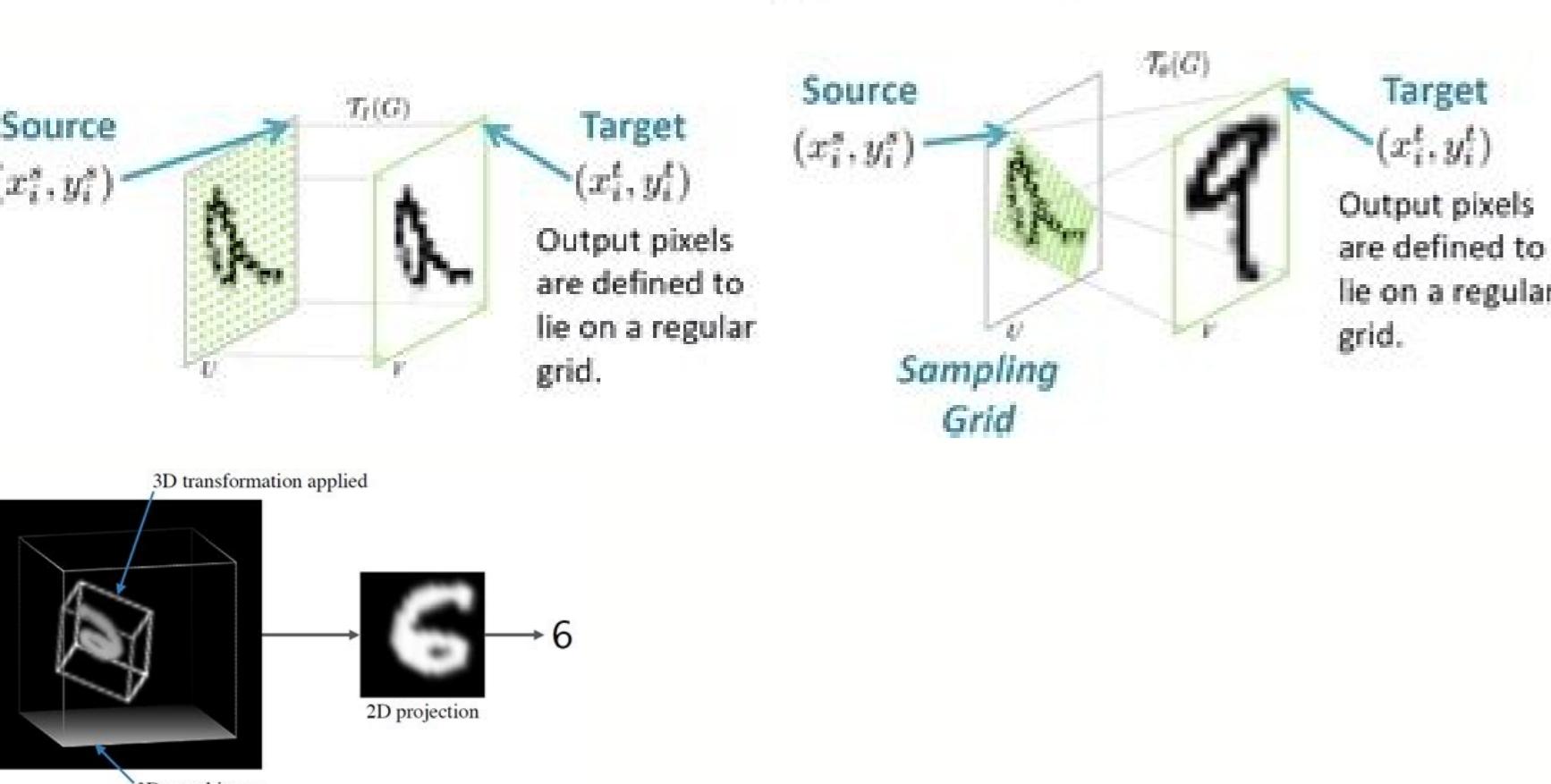
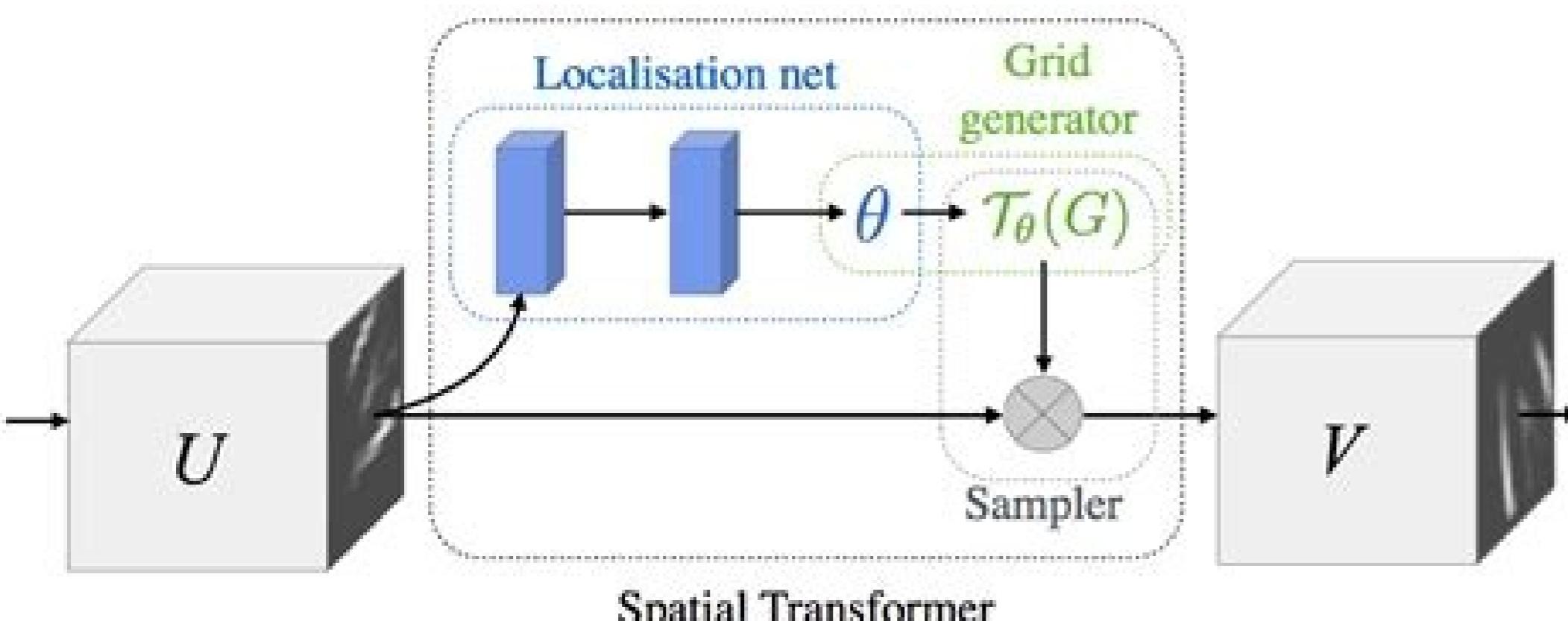
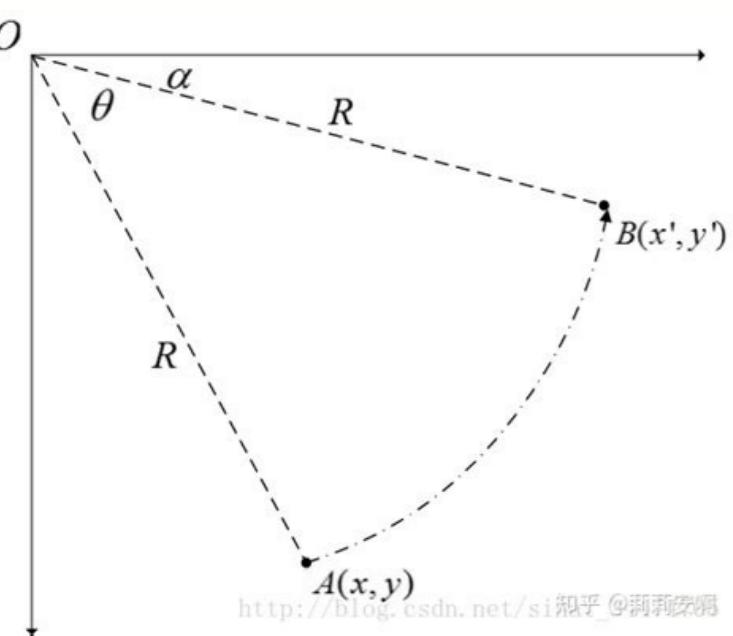
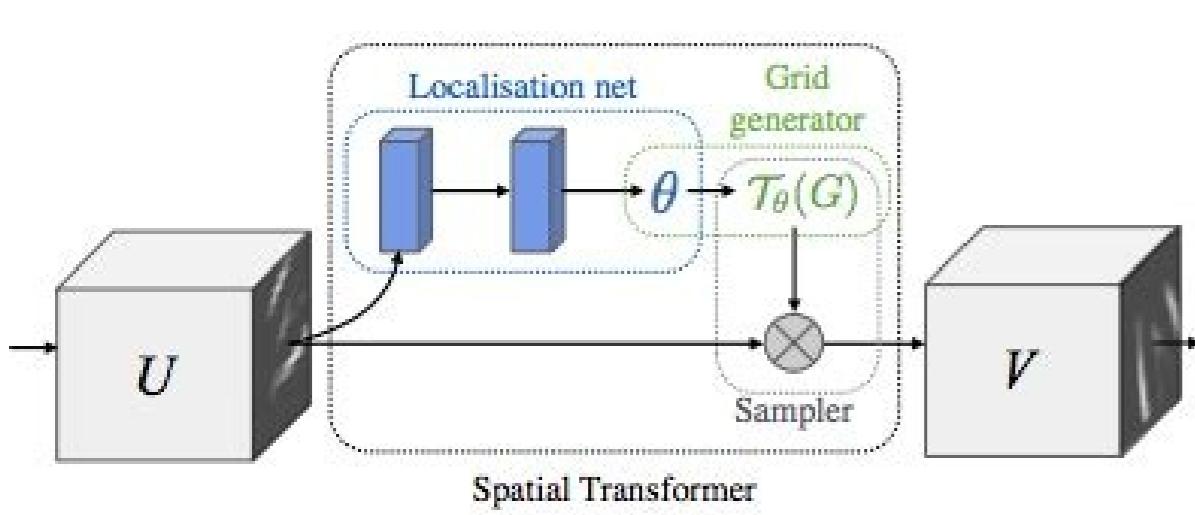


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Check if you have access through your login credentials or your institution to get full access on this article. Sign in View this article in digital edition. View Digital Edition 08thMARCH2018 Max Jaderberg, Karen Simonyan, Andrew Zisserman, Koray Kavukcuoglu. Spatial Transformer Networks. NIPS, 2015. Part of Advances in Neural Information Processing Systems 28 (NIPS 2015) Bibtex Metadata Paper Reviews Supplemental Authors Max Jaderberg, Karen Simonyan, Andrew Zisserman, koray kavukcuoglu Abstract Convolutional Neural Networks define an exceptionally powerful class of model, but are still limited by the lack of ability to be spatially invariant to the input data in a computationally and parameter efficient manner. In this work we introduce a new learnable module, the Spatial Transformer, which explicitly allows the spatial manipulation of data within the network. This differentiable module can be inserted into existing convolutional architectures, giving neural networks the ability to actively spatially transform feature maps, conditional on the feature map itself, without any extra training supervision or modification to the optimisation process. We show that the use of spatial transformers results in models which learn invariance to translation, scale, rotation and more generic warping, resulting in state-of-the-art performance on several benchmarks, and for a number of classes of transformations. Convolutional Neural Networks define an exceptionally powerful class of models, but are still limited by the lack of ability to be spatially invariant to the input data in a computationally and parameter efficient manner. In this work we introduce a new learnable module, the Spatial Transformer, which explicitly allows the spatial manipulation of data within the network. This differentiable module can be inserted into existing convolutional architectures, giving neural networks the ability to actively spatially transform feature maps, conditional on the feature map itself, without any extra training supervision or modification to the optimisation process. We show that the use of spatial transformers results in models which learn invariance to translation, scale, rotation and more generic warping, resulting in state-of-the-art performance on several benchmarks, and for a number of classes of transformations. Spatial Transformations in Deep Neural Networks Michal Bednarek, K. Walas Computer Science 2018 Signal Processing: Algorithms, Architectures, Arrangements, and Applications (SPA) 2018 This paper introduces the end-to-end system that is able to learn spatial invariance including in-plane and out-of-plane rotations and shows that it can successfully improve the classification score by implementing so-called Spatial Transformer module. 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Vedaldi Computer Science 2017 This work presents a construction that is simple and exact, yet has the same computational complexity that standard convolutions enjoy, consisting of a constant image warp followed by a simple convolution, which are standard blocks in deep learning toolboxes. View 8 excerpts, cites methods and background Transform-Invariant Convolutional Neural Networks for Image Classification and Search This paper proposes randomly transforming feature maps of CNNs during the training stage to prevent complex dependencies of specific rotation, scale, and translation levels of training images in CNN models and shows that random transformation provides significant improvements of CNNs on many benchmark tasks, including small-scale image recognition, large-scale image recognition, and image retrieval. SHOWING 1-10 OF 47 REFERENCES SORT BY Relevance Most Influenced Papers Recency Transform Auto-Encoders Geoffrey E. Hinton, A. Krizhevsky, Sida I. Wang Computer Science ICANN 2011 It is argued that neural networks can be used to learn features that output a whole vector of instantiation parameters and this is a much more promising way of dealing with variations in position, orientation, scale and lighting than the methods currently employed in the neural networks community. View 2 excerpts, references background Deep Symmetry Networks Robert Gens, Pedro M. Domingos Computer Science NIPS 2014 Deep symmetry networks (symnets), a generalization of convnets that forms feature maps over arbitrary symmetry groups that uses kernel-based interpolation to tractably tie parameters and pool over symmetry spaces of any dimension are introduced. View 3 excerpts, references background Locally Scale-Invariant Convolutional Neural Networks Angjoo Kanazawa, Abhishek Sharma, D. Jacobs Computer Science ArXiv 2014 A simple model is presented that allows ConvNets to learn features in a locally scale-invariant manner without increasing the number of model parameters, and is shown on a modified MNIST dataset that when faced with scale variation, building in scale-invariance allows Conv net to learn more discriminative features with reduced chances of over-fitting. View 1 excerpt, references background Going deeper with convolutions We propose a deep convolutional neural network architecture, codenamed Inception, that achieves the new state of the art for classification and detection in the ImageNet Large-Scale Visual Recognition. View 1 excerpt, references background

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