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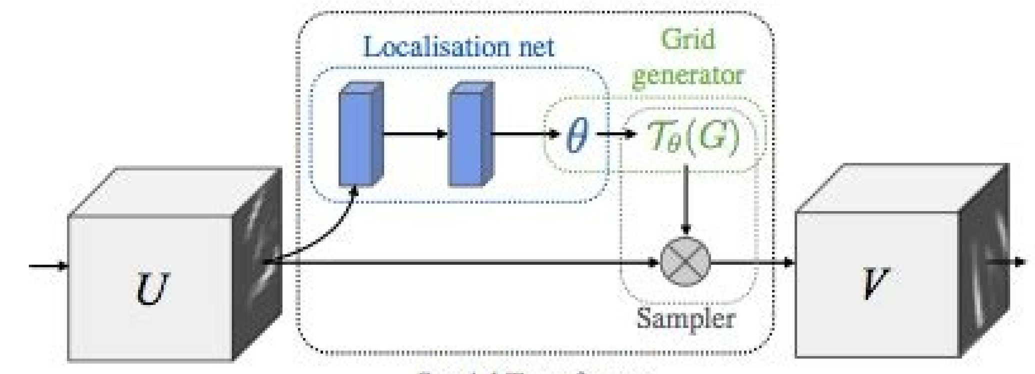

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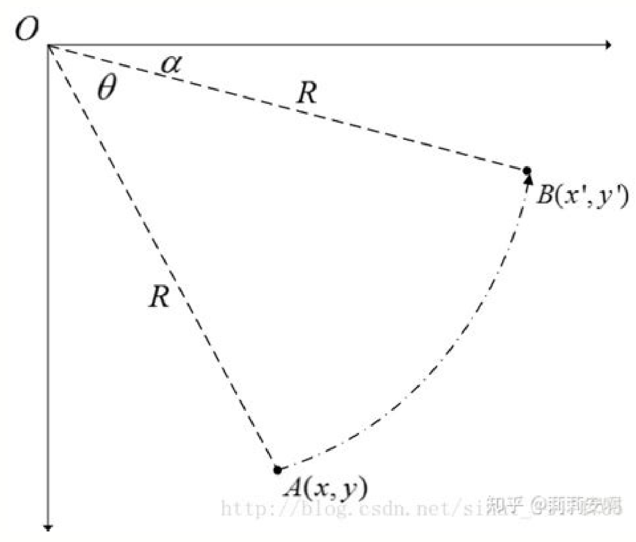

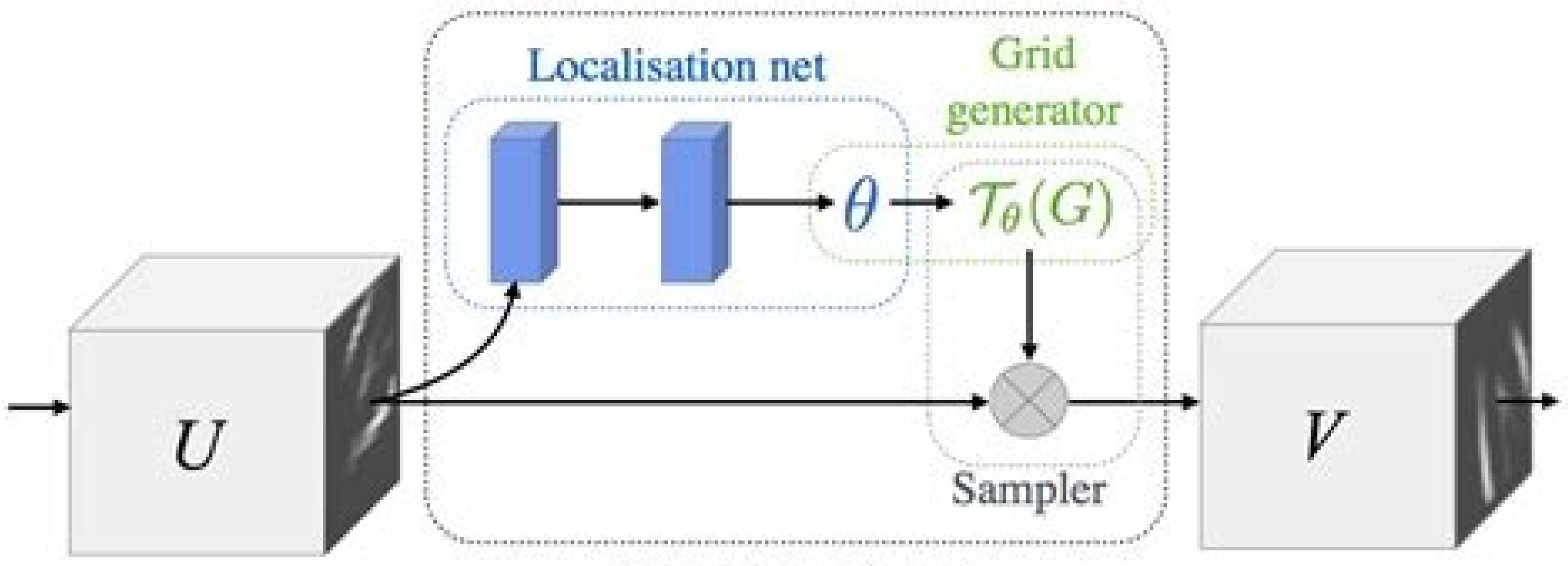

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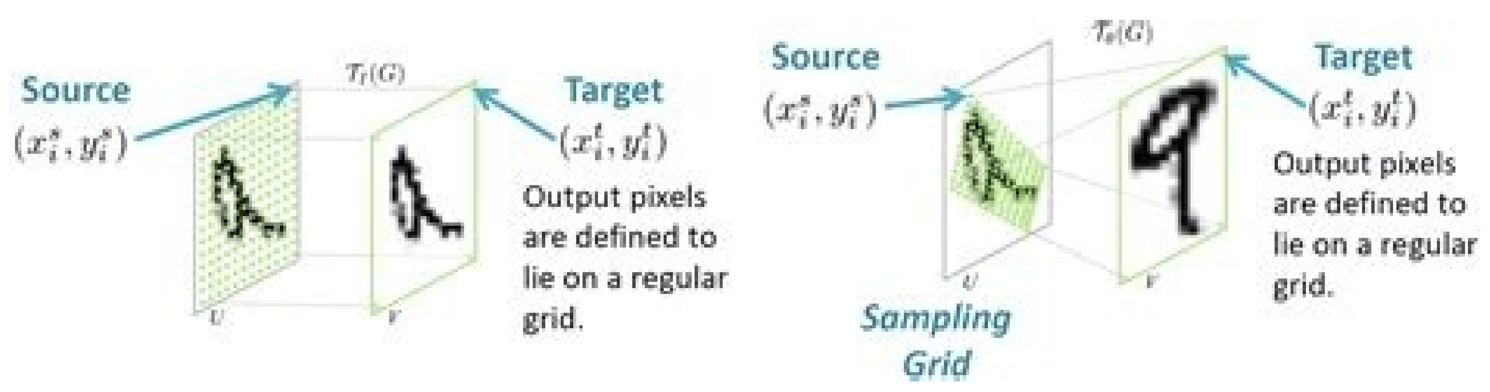

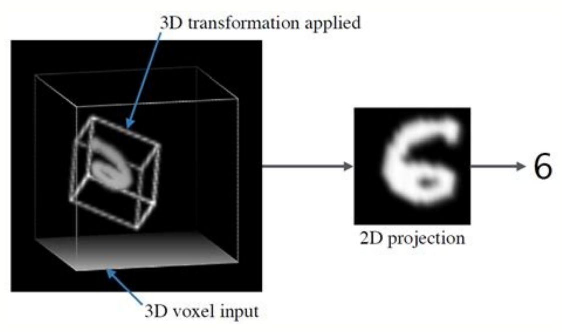

Spatial transformer networks PreviousChapterNextChapter Convolutional Neural Networks define an exceptionally powerful class of models, but are still limited by the lack of ability to be spatially invariant to the input data in a computationally and parameter efficient manner. In this work we introduce 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. J. Ba, V. Mnih, and K. 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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 exceptionallypowerful class of model, but are still limited by the lack of abilityto be spatially invariant to the input data in a computationally and parameterefficient manner. In this work we introduce a new learnable module, theSpatial Transformer, which explicitly allows the spatial manipulation ofdata within the network. This differentiable module can be insertedinto existing convolutional architectures, giving neural networks the ability toactively 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 useof spatial transformers results in models which learn invariance to translation,scale, rotation and more generic warping, resulting in state-of-the-artperformance on several benchmarks, and for a numberof 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 NetworksMichal Bednarek, K. WalasComputer Science2018 Signal Processing: Algorithms, Architectures, Arrangements, and Applications (SPA)2018This 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.View 7 excerpts, cites methods and backgroundA Refined Spatial Transformer NetworkChang Shu, Xi Chen, Chong Yu, Hua HanComputer ScienceICONIP2018Experimental results reveal that the design of a module to estimate the difference between the ground truth and STN output outperforms the state-of-the-art methods in the cluttered MNIST handwritten digits classification task and planar image alignment task.Volumetric Transformer NetworksSeungryong Kim, S. Süsstrunk, M. SalzmannComputer ScienceECCV2020This work proposes a loss function defined between the warped features of pairs of instances, which improves the localization ability of VTN and consistently boosts the features' representation power and consequently the networks' accuracy on fine-grained image recognition and instance-level image retrieval.View 5 excerpts, cites background and methodsSPATIAL TRANSFORMATIONSJoão F. Henriques, A. VedaldiComputer Science2017This 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 backgroundTransform-Invariant Convolutional Neural Networks for Image Classification and SearchThis 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 ofCNNs on many benchmark tasks, including small-scaleimage recognition, large-scale image recognition, and image retrieval.SHOWING 1-10 OF 47 REFERENCESSORT BYRelevanceMost Influenced PapersRecencyTransforming Auto-EncodersGeoffrey E. Hinton, A. Krizhevsky, Sida I. WangComputer ScienceICANN2011It 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 backgroundDeep Symmetry NetworksRobert Gens, Pedro M. DomingosComputer ScienceNIPS2014Deep 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 and methodsLocally Scale-Invariant Convolutional Neural NetworksAngjoo Kanazawa, Abhishek Sharma, D. JacobsComputer ScienceArXiv2014A 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 2 excerpts, references backgroundGoing deeper with convolutionsWe 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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