

UNIVERSITY OF REGINA

DEEP CONVOLUTIONAL SUM-PRODUCT NETWORKS

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OUTLINE



GENERATIVE MODELS

IN DEEP LEARNING



SUM-PRODUCT NETWORKS (SPNs)



CONVOLUTIONAL
NEURAL NETWORKS
AS SPNs



CONVOLUTIONAL SPNs (CSPNs)

OUTLINE









DEEP CONVOLUTIONAL SPNs (DCSPNs)

STATE-OF-THE-ART RESULTS

AND A FEW NICE SURPRISES

CONCLUSIONS



GENERATIVE MODELS IN DEEP LEARNING

GENERATIVE MODELS ARE OF CURRENT INTEREST



NADE

Larochelle and Murray 2011



VARIATIONAL AUTOENCODERS

Kingma and Welling 2014



GANs

Goodfellow et al. 2014



PIXEL RNN

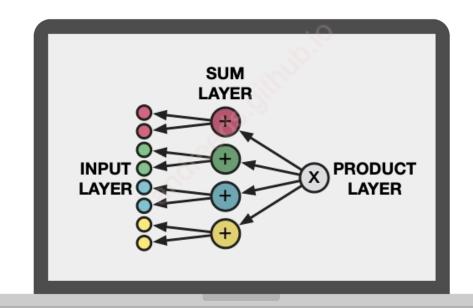
Oord, Kalchbrenner, and Kavukcuoglu 2016

SUM-PRODUCT NETWORKS

GENERATIVE DEEP LEARNING MODEL



WHEN COMPLETE AND DECOMPOSABLE



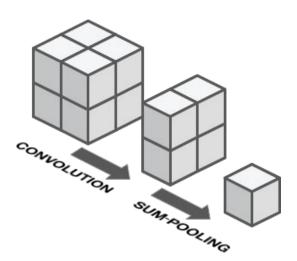


LIMITED ATTENTION

RECEIVED FROM THE DEEP LEARNING COMMUNITY

Peharz et al.

CONVOLUTIONAL NEURAL NETWORKS

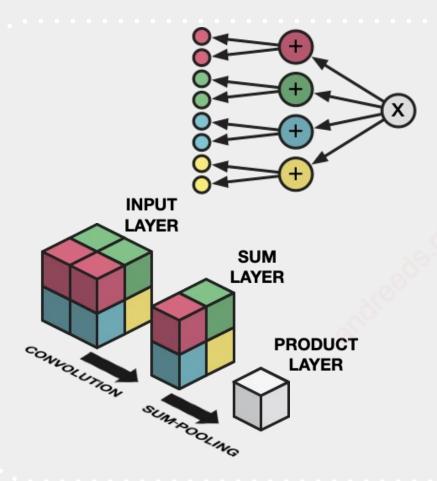


CONVOLUTIONAL LAYERS

NETWORK PARAMETERS ARE FILTERS

POOLING LAYERS

USES SLIDING WINDOWS



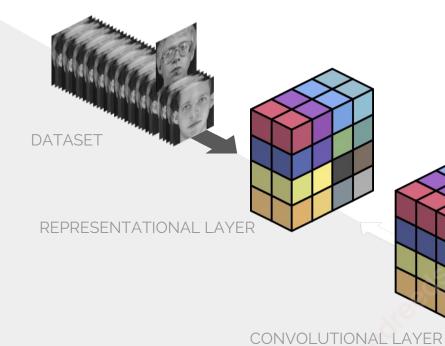
CNNs AS SPNs

CONVOLUTIONAL LAYERS

- FILTERS OF CERTAIN SIZES
- MAINTAINS COMPLETENESS

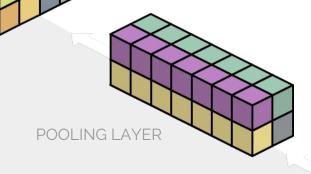
POOLING LAYERS

- NON-OVERLAPPING WINDOWS
- MAINTAINS **DECOMPOSABILITY**

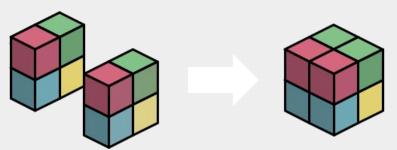


C*NVOLUTIONAL SPNs

A CHAIN STRUCTURE



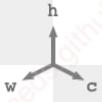
CONVOLUTIONAL LAYER



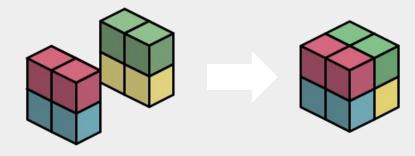
LAYERS (TENSORS) CAN BE AUGMENTED

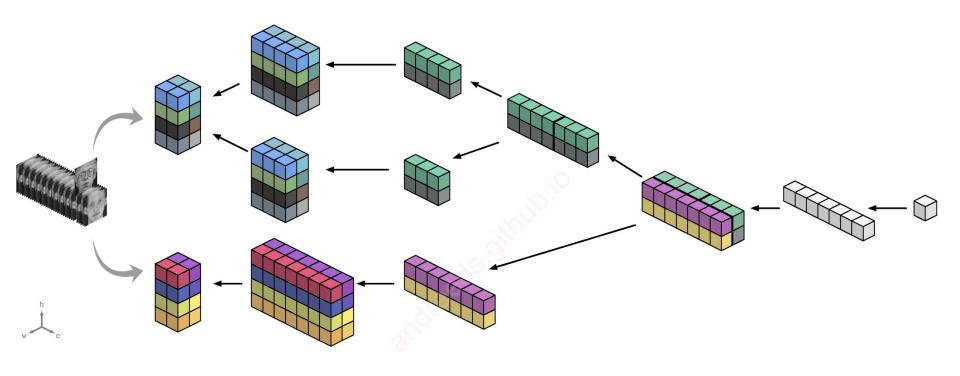
WHILE MAINTAINING

COMPLETENESS AND DECOMPOSABILITY



CREATING DEEPER STRUCTURES

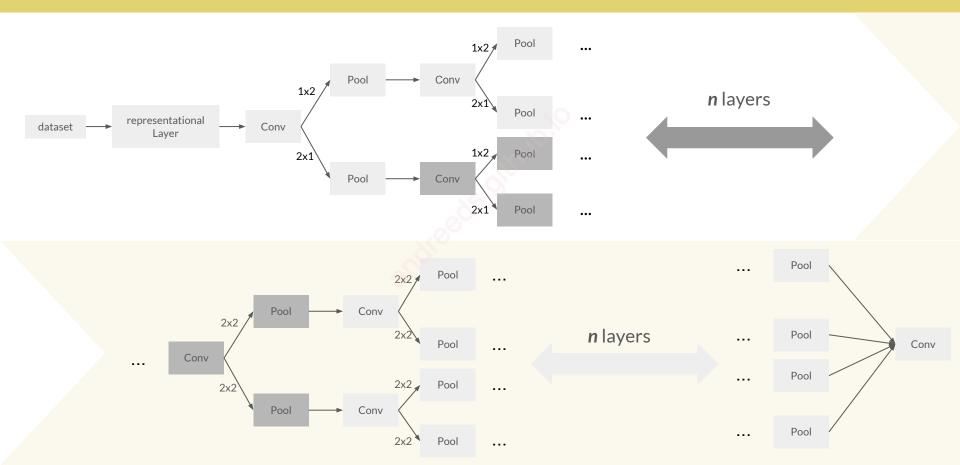




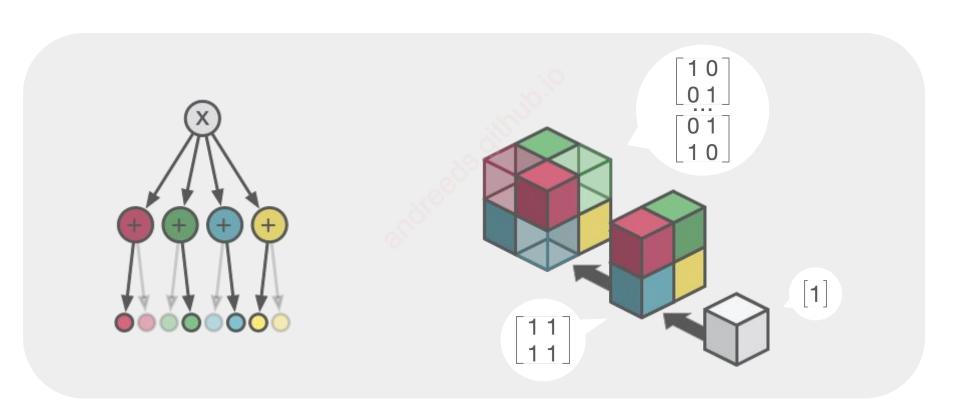
DEEP CONVOLUTIONAL SPNs

A RICH DAG OF CONVOLUTIONAL AND SUM-POOLING LAYERS

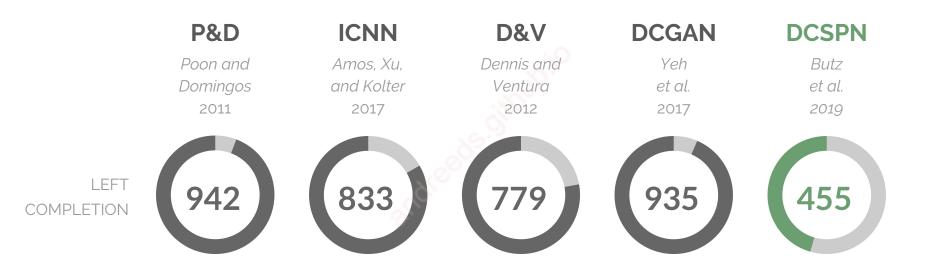
A WINNING STRUCTURE



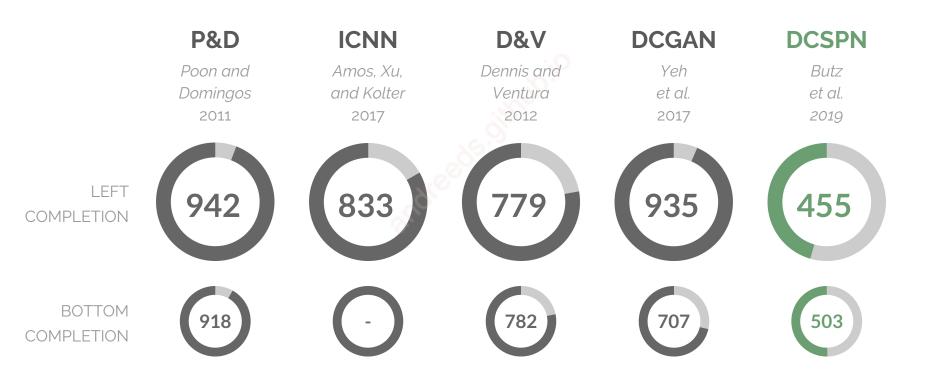
VECTORIZED MPE



STATE-OF-THE-ART RESULTS IN OLIVETTI FACE



STATE-OF-THE-ART RESULTS IN OLIVETTI FACE



STATE-OF-THE-ART RESULTS IN CALTECH

LEFT COMPLETION	FACE	1815	1657	1334	1178	
	DOLPHIN	3096		4096	2002	
COMPLETION	HELICOPTER	2749	- ON-	3925	1702	
воттом	FACE	1924	1517	1046	1149	
	DOLPHIN	2767	-	4016	2102	
COMPLETION	HELICOPTER	3064	-	3811	2103	
		P&D	D&V	DCGAN	DCSPN	

Dennis and

Ventura

2012

Yeh

et al.

2017

Butz

et al.

2019

Poon and

Domingos

2011

LEFT COMPLETION BOTTOM COMPLETION

ORIGINAL

DCSPN

P&D

GAN



DCSPNs with differentiable MPE

with GANs

with variability

performance on a dataset with 65 images

LEARNING DCSPN WITH DIFFERENTIABLE MPE

MOTIVATED BY FUTURE WORK SUGGESTED IN

(Vergari et al., AAAI 2018)

LEARN DCSPNs USING DIFFERENTIABLE MPE

$$\min_{G} \max_{D} \mathbb{E}[\log D(\mathbf{x})] + \mathbb{E}[\log(1 - D(G(\mathbf{z})))]$$



DCSPNs yields an MSE score of 651



More promising than simply a low MSE score

RELATIONSHIP WITH GANS

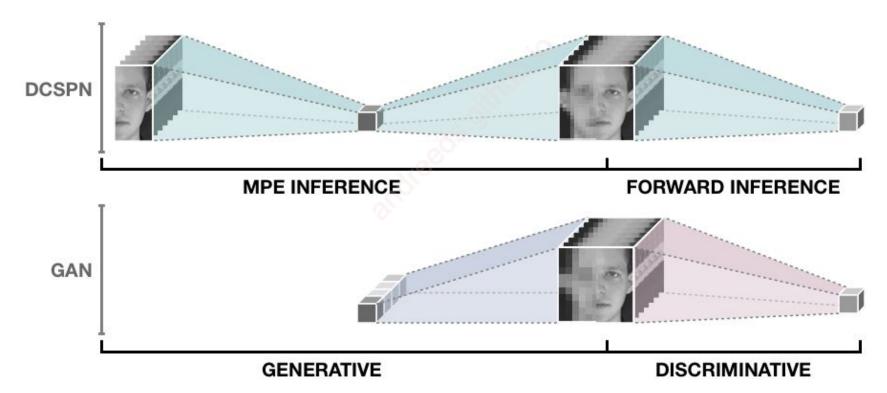


IMAGE SAMPLING



Simple modification in MPE Algorithm



DCSPN sampled images exhibit variability



GOOD PERFORMANCE ON A SMALL DATASET



ORIGINAL

DCSPN

P&D

GAN



DCSPNs left-complete well on a small dataset



Caltech Dolphin contain 65 images

ANALYSIS



SMALL HORIZONTAL AND VERTICAL SUM-POOLING WINDOW SIZES CAN

- yield **deeper** structures
- leverage **local structure** in the image data



ALTERNATING SUM-POOLING WINDOW SIZES CAN

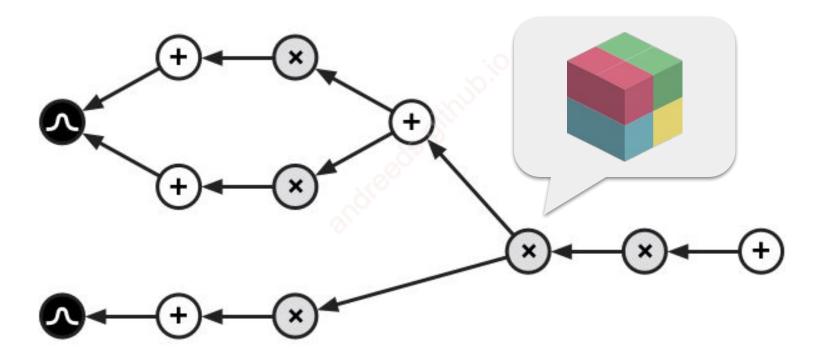
- serve as a **regularization** technique
- alleviate vanishing gradient



TWO FILTER SIZE OPTIONS ALLOWS FOR

controlling trade-off between quality and size

FUTURE WORK



CONCLUSION

WE ESTABLISH WHEN
SUBCLASSES OF CNNs
DEFINE SPNs





DCSPNs ARE CNNs WHICH ALSO
CAN TAKE ADVANTAGE OF KNOWN
TECHNIQUES IN PROBABILISTIC
GRAPHICAL MODELS

SEVERAL STATE-OF-THE-ART MSE SCORES IN IMAGE COMPLETION





AND NICE SURPRISES INCLUDING
VARIABILITY IN IMAGE SAMPLING
AND AN INTRIGUING
RELATIONSHIP WITH GAN



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