

## 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**

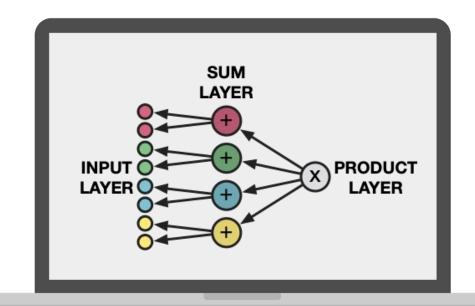
Oord, Kalchbrenner, and Kavukcuoglu 2016

#### **SUM-PRODUCT NETWORKS**

GENERATIVE DEEP LEARNING MODEL



WHEN COMPLETE AND DECOMPOSABLE



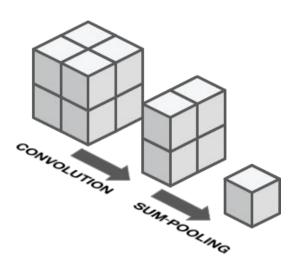


#### LIMITED ATTENTION

RECEIVED FROM THE DEEP LEARNING COMMUNITY

Peharz et al.

#### **CONVOLUTIONAL NEURAL NETWORKS**

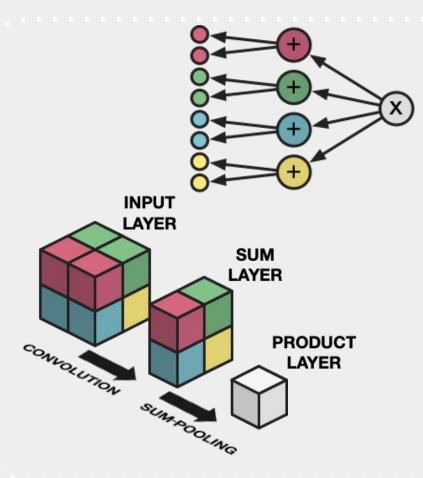


#### **CONVOLUTIONAL LAYERS**

NETWORK PARAMETERS ARE FILTERS

#### **POOLING LAYERS**

USES SLIDING WINDOWS



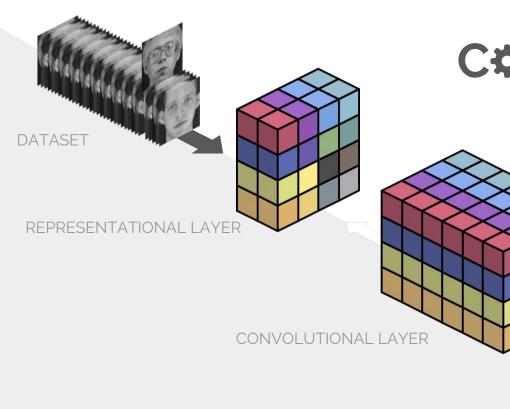
#### **CNNs AS SPNs**

#### **CONVOLUTIONAL LAYERS**

- FILTERS OF CERTAIN SIZES
- MAINTAINS COMPLETENESS

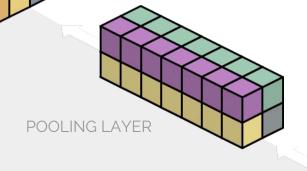
#### **POOLING LAYERS**

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

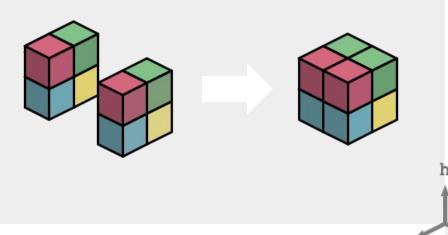


# C\*NVOLUTIONAL SPNs

A CHAIN STRUCTURE



CONVOLUTIONAL LAYER

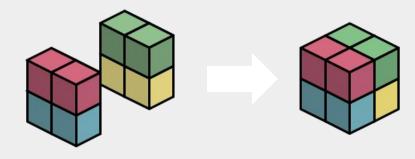


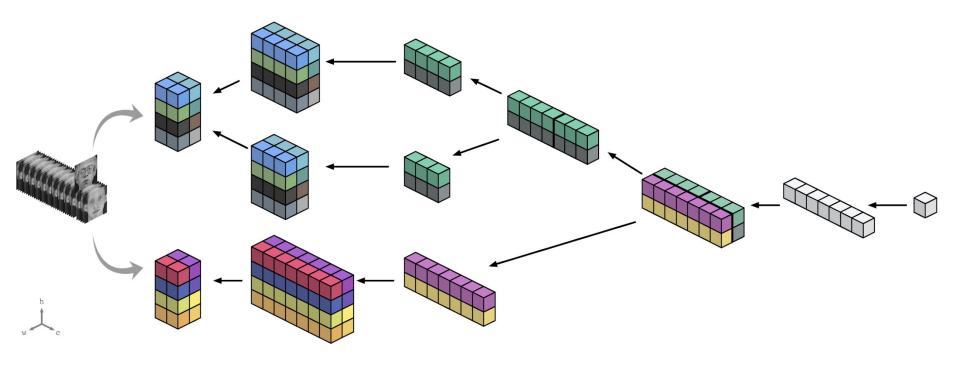
# LAYERS (TENSORS) CAN BE AUGMENTED

WHILE MAINTAINING

COMPLETENESS AND DECOMPOSABILITY

# CREATING DEEPER STRUCTURES

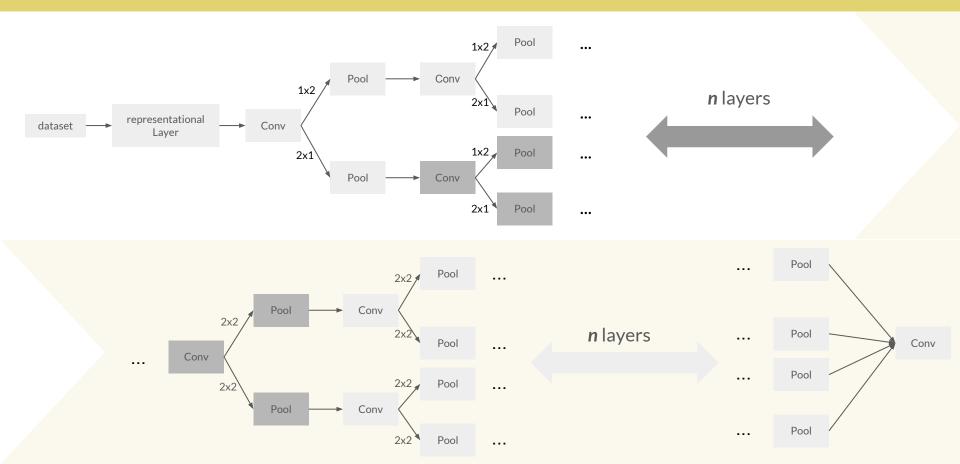




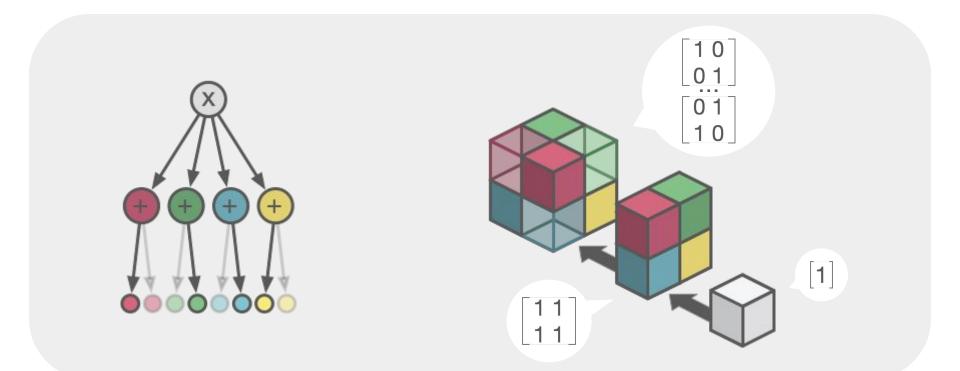
#### **DEEP CONVOLUTIONAL SPNs**

A RICH DAG OF CONVOLUTIONAL AND SUM-POOLING LAYERS

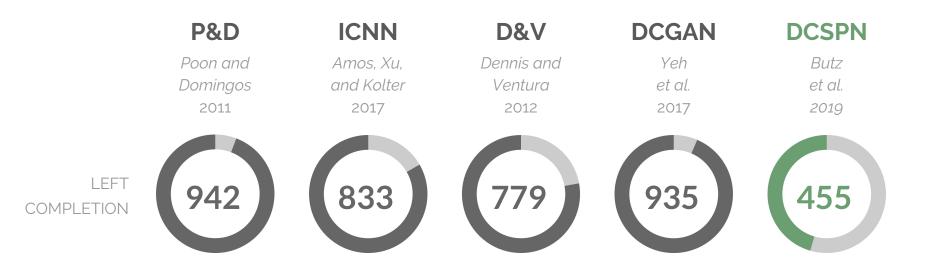
#### A WINNING STRUCTURE



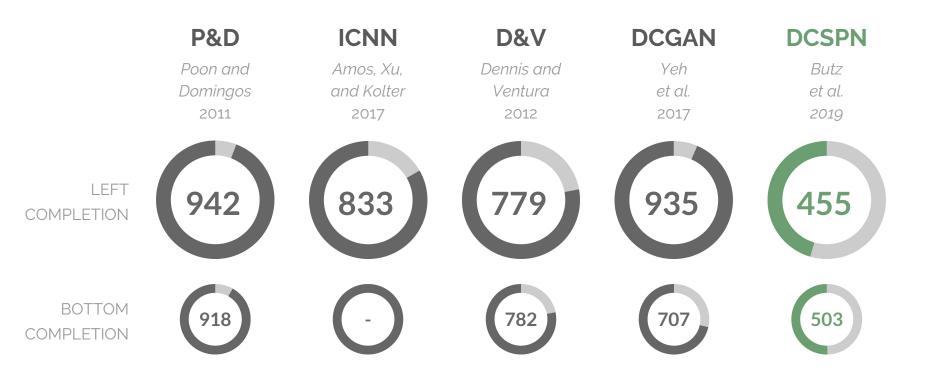
### **VECTORIZED MPE**



#### 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	
	HELICOPTER	2749	-	3925	1702	
	FACE	1924	1517	1046	1149	
BOTTOM	DOLPHIN	2767	-	4016	2102	
	HELICOPTER	3064	-	3811	2103	
		P&D	D&V	DCGAN	DCSPN	
		Poon and	Dennis and	Yeh	Butz	
		Domingos	Ventura	et al.	et al.	

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

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

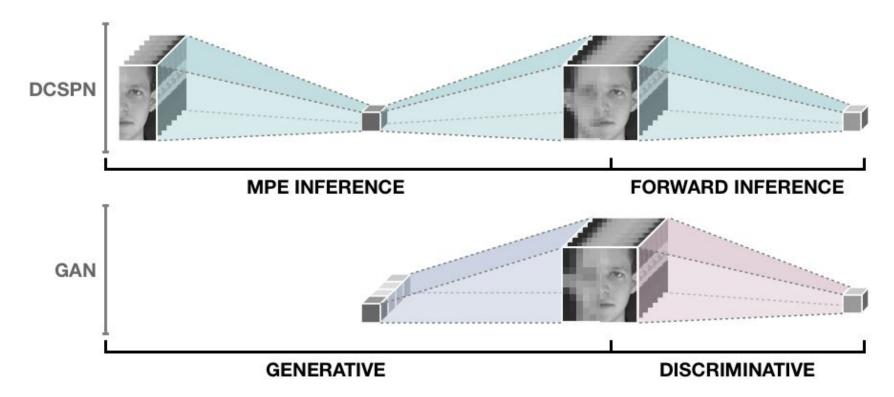


DCSPNs yields an MSE score of 651



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

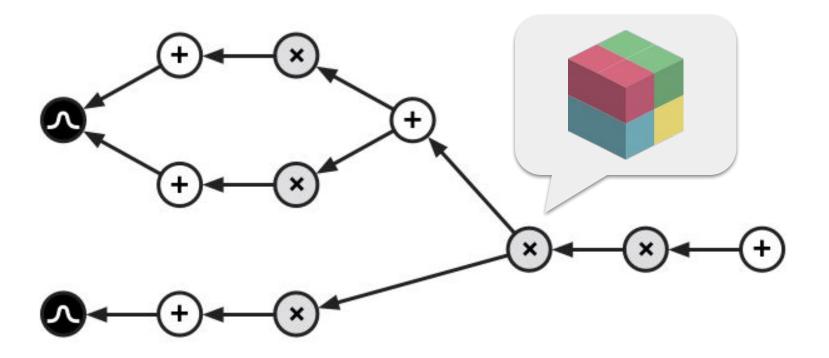
- serve as a **regularization** technique
- alleviate vanishing gradient



# 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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