# Deconvoluting Convolutions

DATA SCIENCE MEETUP

**APRIL 2018** 

## Topics

#### The 2018 Data Science Bowl

#### Puppy bowl

- Image processing basics
- The simple approach

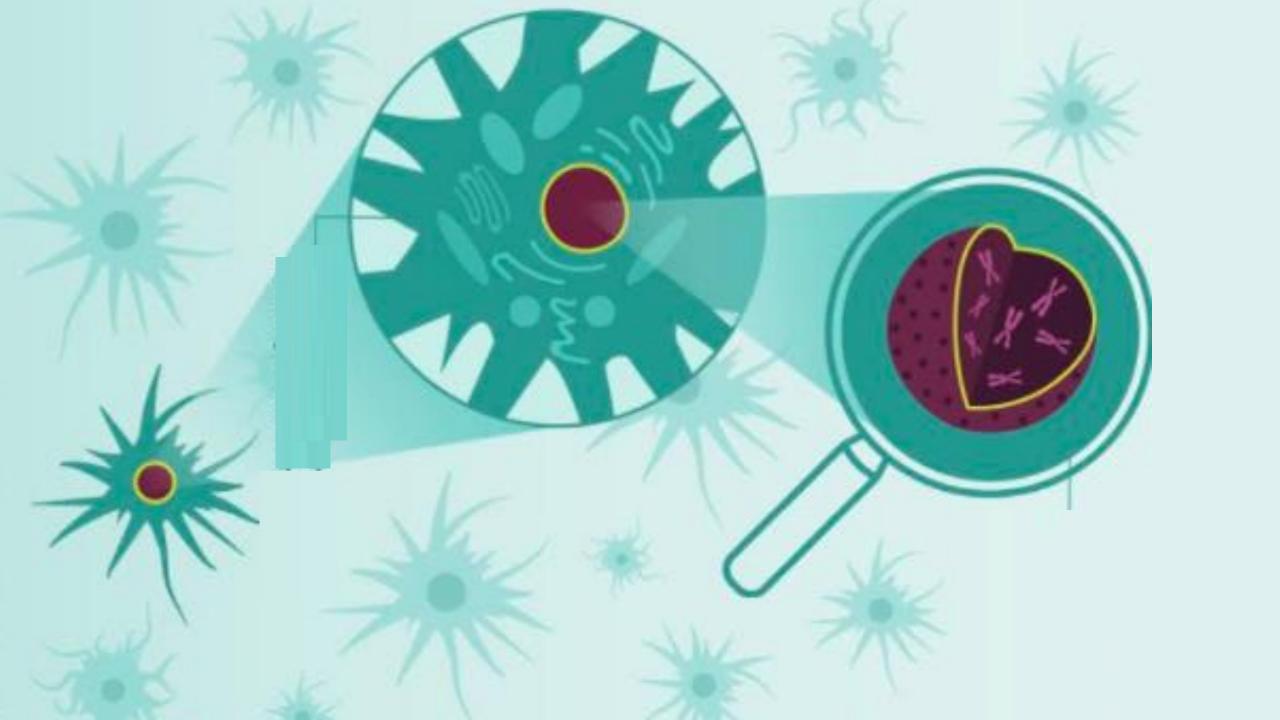
#### Superbowl

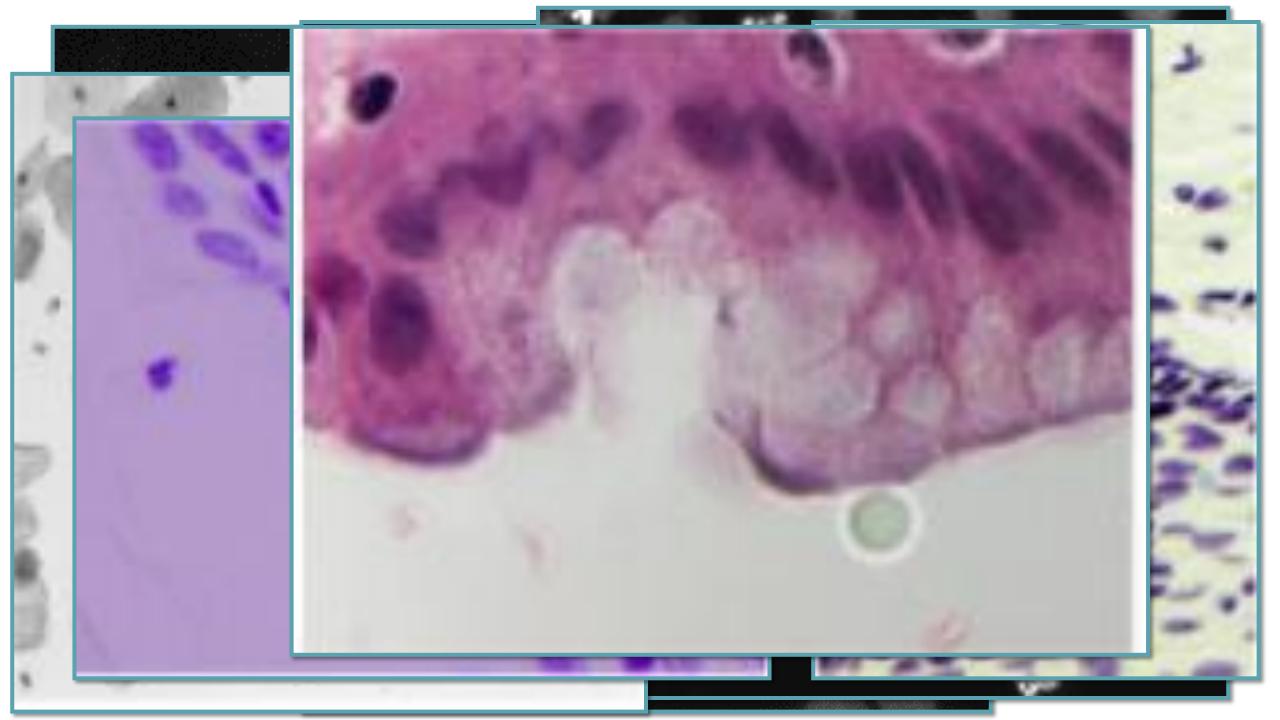
- Feature detection basics
- The U-Net approach

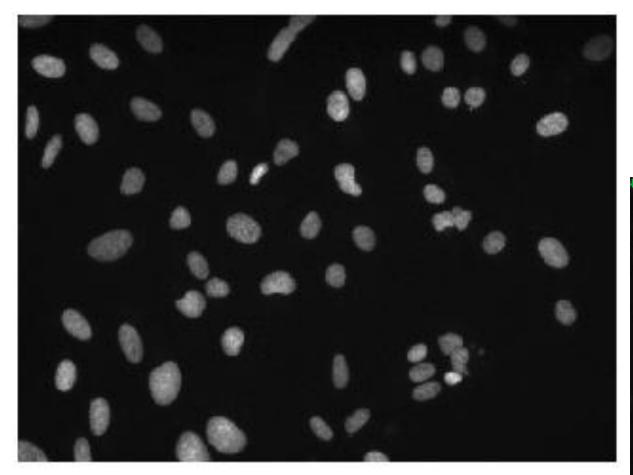
#### Performance



Presented by
Booz | Allen | Hamilton & kaggle\*

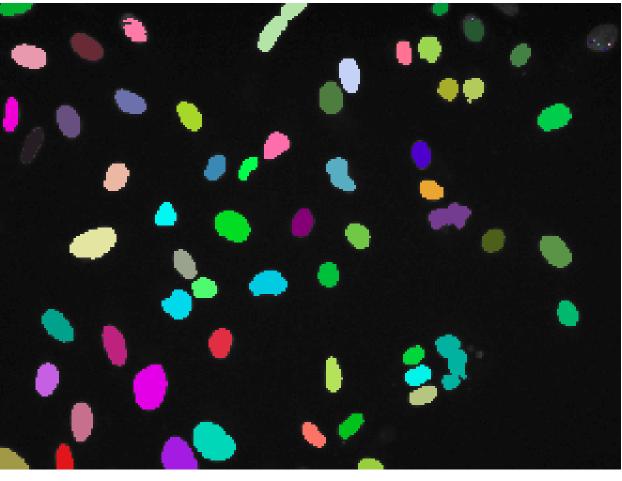






## **Competition metric:**Intersection of the Union

#### Competition goal: Separate mask for each nucleus



## Competition challenges

Variety of colors, microscopy types

Variety of sizes and scales

Different background tissue / nuclei types

\*\*Overlapping nuclei\*\*

Small training set (~700)

Errors in training set

## Topics

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#### **Puppy bowl**

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#### Superbowl

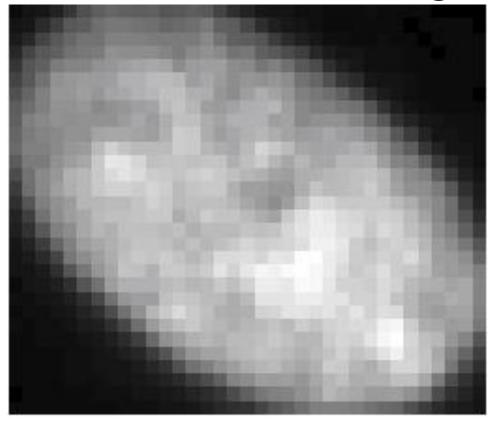
- Feature detection basics
- The U-Net approach

Performance



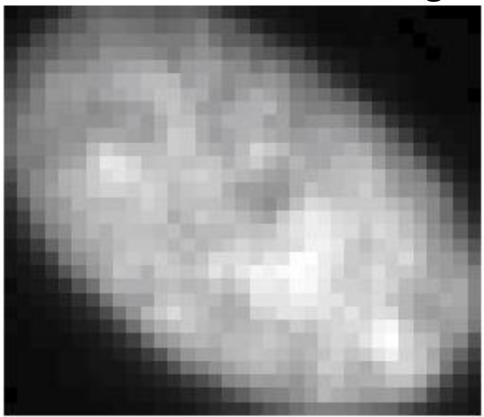
## Image: Intensity data with meaningful order

One cell from train image

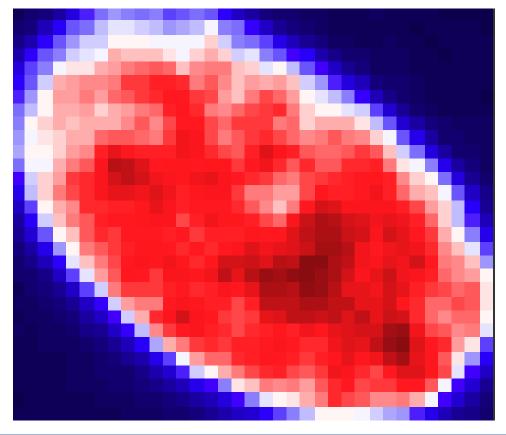


## Image: Intensity data with meaningful order

One cell from train image

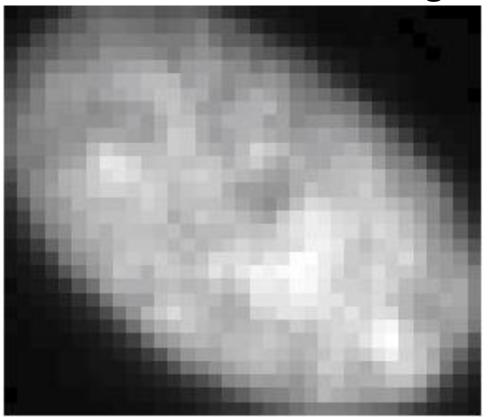


Data with 3 color channels

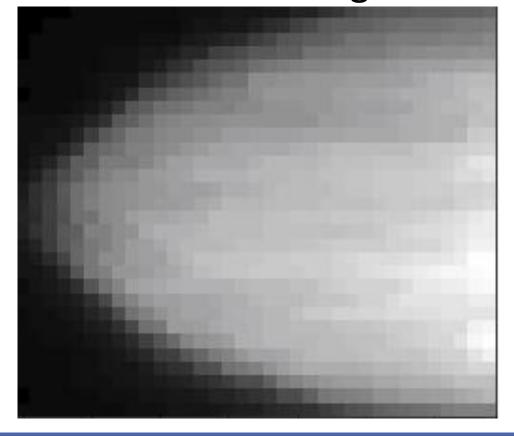


## Image: Intensity data with meaningful order

One cell from train image



Data sorted along rows



## Topics

#### The 2018 Data Science Bowl

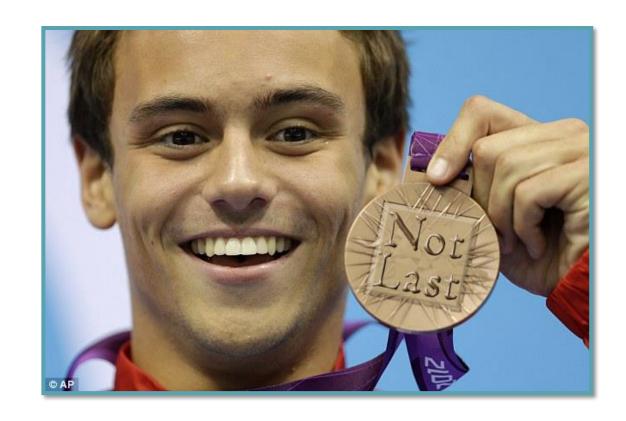
#### **Puppy bowl**

- Image processing basics
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#### Superbowl

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Performance



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## Stephen Bailey Teaching notebook for total imaging newbies

352 voters

last run 2 months ago · Python notebook · 18866 views using data from 2018 Data Science Bowl · ● Public



 ${\color{red}Notebook} \quad \textbf{Code} \quad \textbf{Data} \ (1) \quad \textbf{Output} \ (1) \quad \textbf{Comments} \ (46) \quad \textbf{Log} \quad \textbf{Versions} \ (14) \quad \textbf{Forks} \ (118) \quad \textbf{Options} \quad \textbf{Fork} \ \textbf{Notebook}$ 

**Edit No** 

Tags

Add Tag

Notebook

This kernel will implement classical image techniques and will hopefully serve as a useful primer to people who have never worked with image data before. Ultimately, we will develop a simple pipeline using scipy and numpy (and a little bit of

## Competition challenges

Small training set (~700)

Variety of colors, microscopy types

Variety of sizes and scales

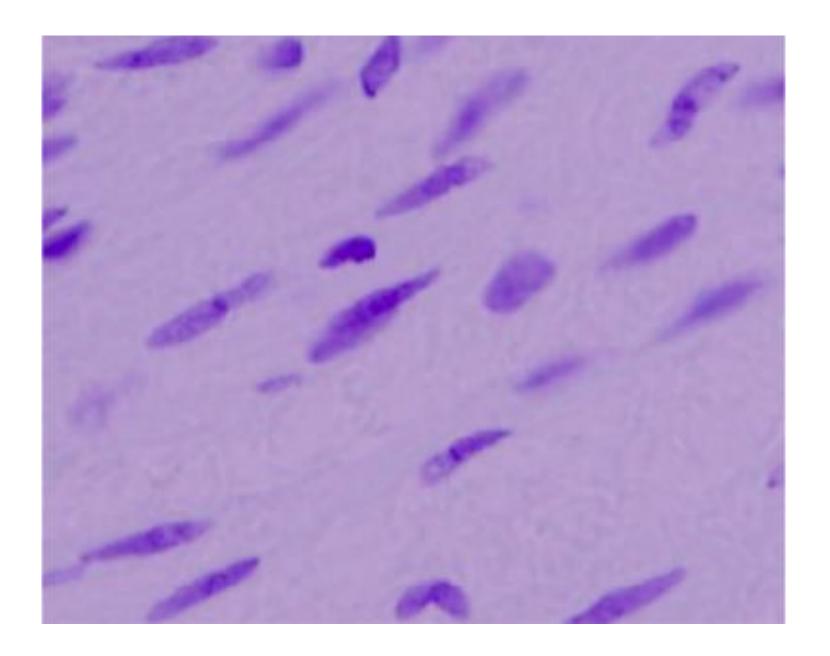
Different background tissue

Overlapping nuclei

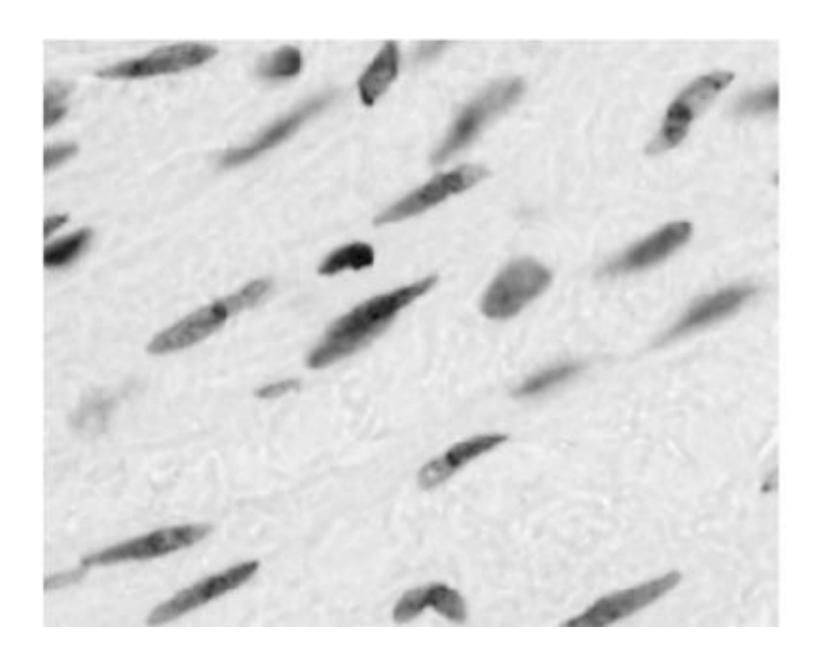
## Competition challenges

- Small training set (~700)
- Variety of colors, microscopy types
- Variety of sizes and scales
- Different background tissue
- **Overlapping nuclei**

Step one: Convert to grayscale image.



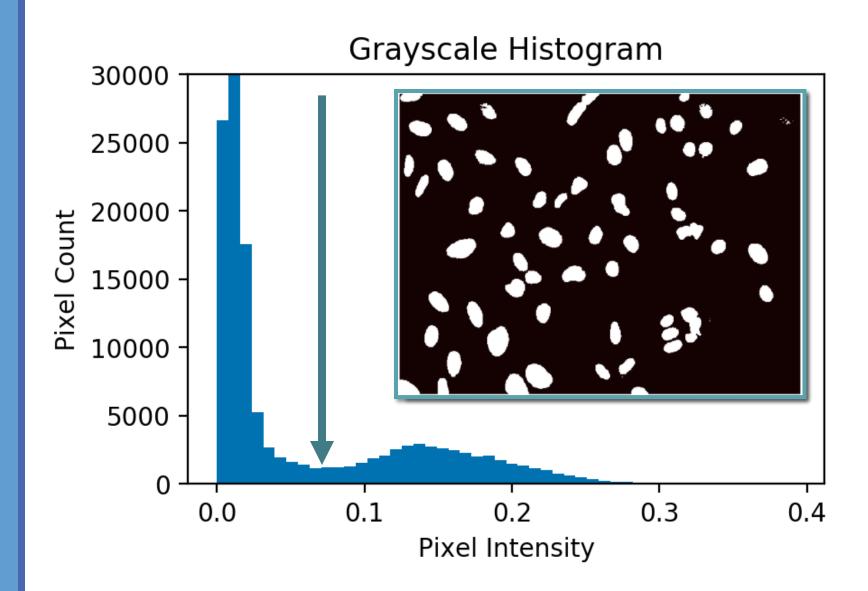
Step one: Convert to grayscale image.



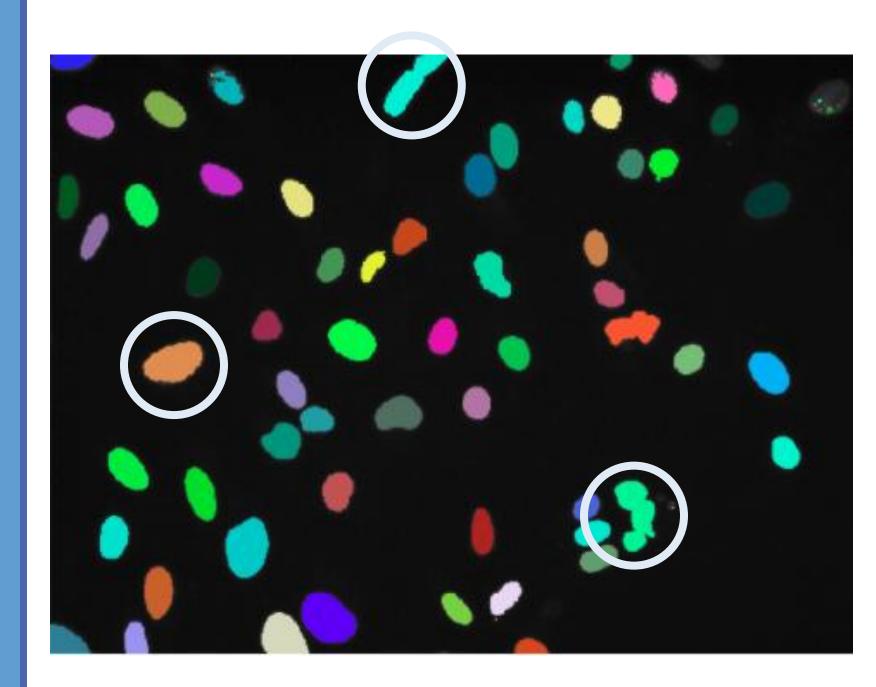
#### Step two: Threshold background

Assume there are two pixel types in the image:

- Nuclei
- Background.



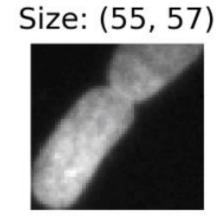
Step three: Separate individual objects



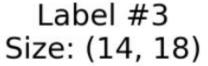
#### Step four: Post-process individual objects

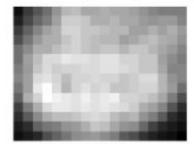
Eliminate tiny objects

Label #1 Size: (14, 39)

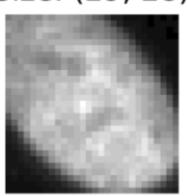


Label #2





Label #4 Size: (29, 28)



Label #5 Size: (1, 1)



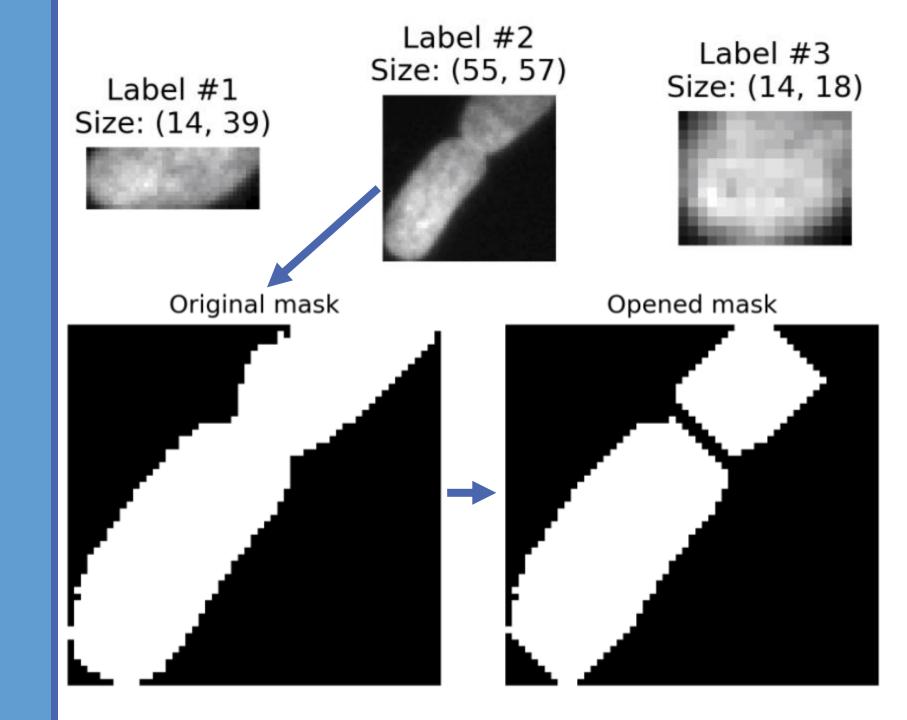
Label #6 Size: (1, 1)



Step four: Post-process individual objects

Eliminate tiny objects

Open connected objects





## Topics

#### The 2018 Data Science Bowl

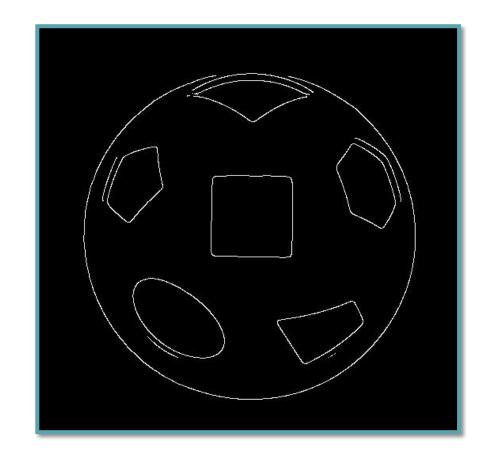
#### Puppy bowl

- Image processing basics
- The simple approach

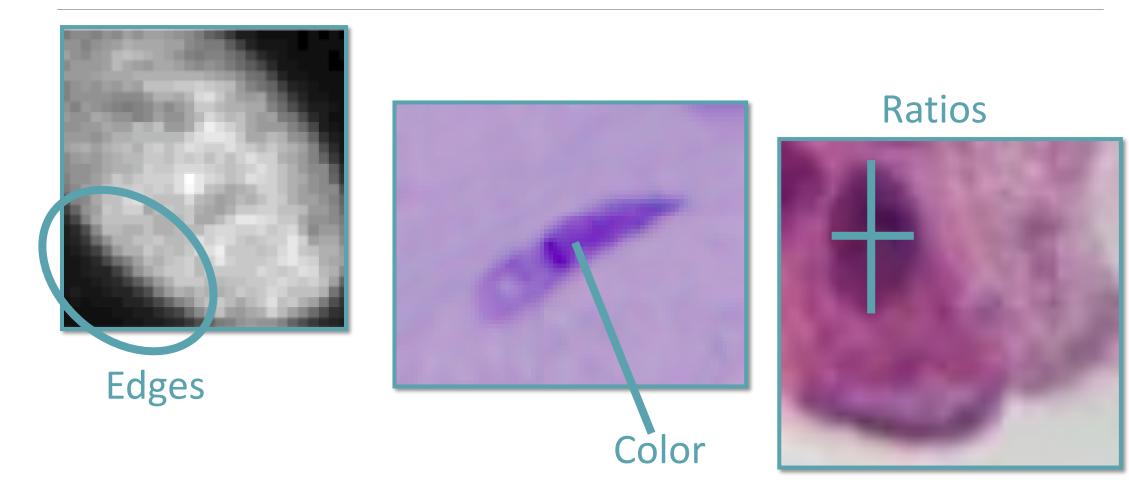
#### Superbowl

- Feature detection basics
- The U-Net approach

Performance

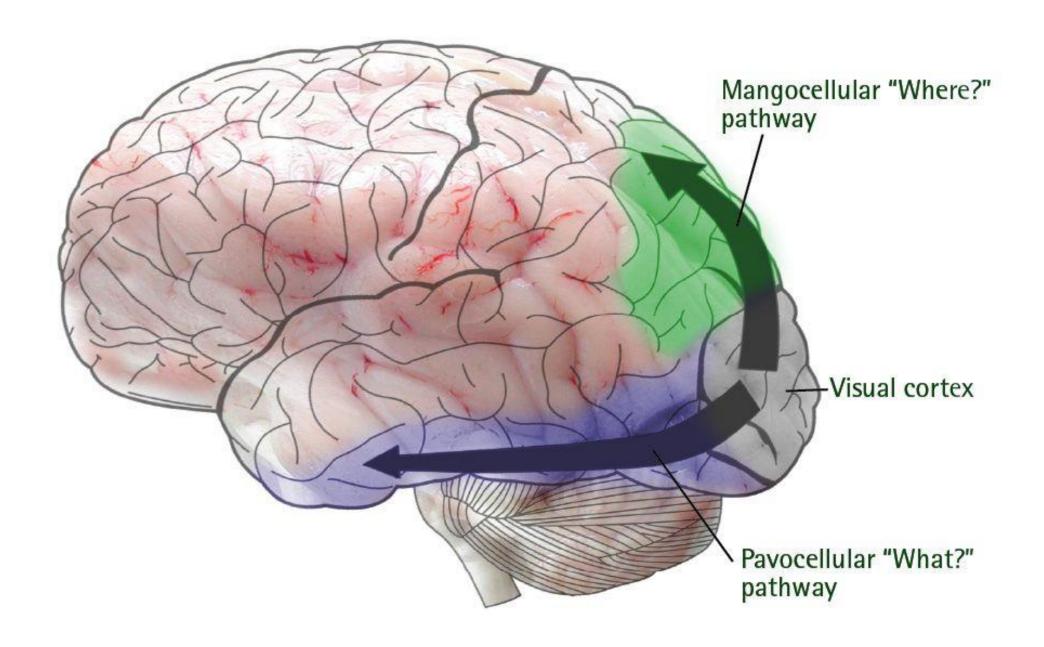


## Humans recognize objects from patterns





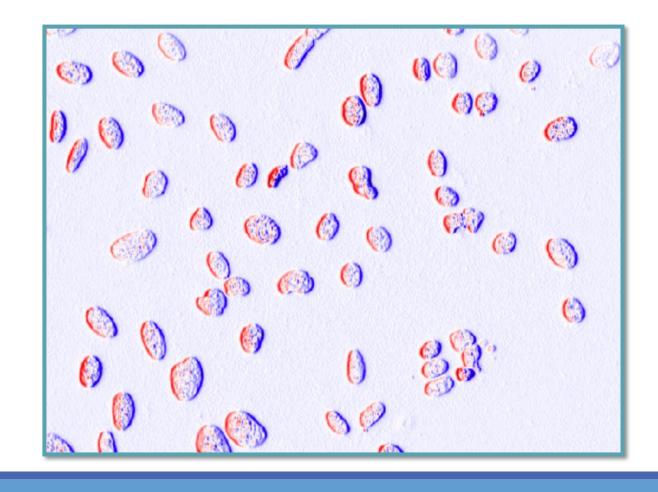
https://www.youtube.com/watch?v=IOHayh06LJ4



## Convolution: Weighting an image by a pattern.

Horizontal Edges 3 x 3

1	0	-1
1	0	-1
1	0	-1



## Convolution sums the element-wise product of an image window and filter

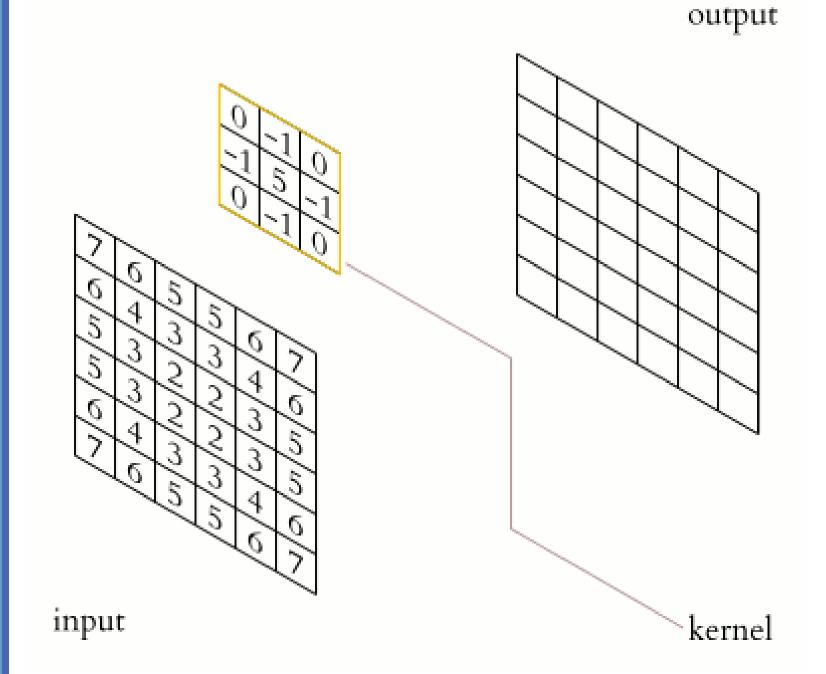
#### **Image Window**

5	4	3
5	4	3
5	4	3

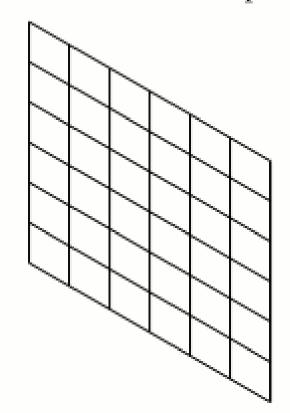
#### Filter

1	0	-1
1	0	-1
1	0	-1

A separate convolution is performed for each pixel.



output



input

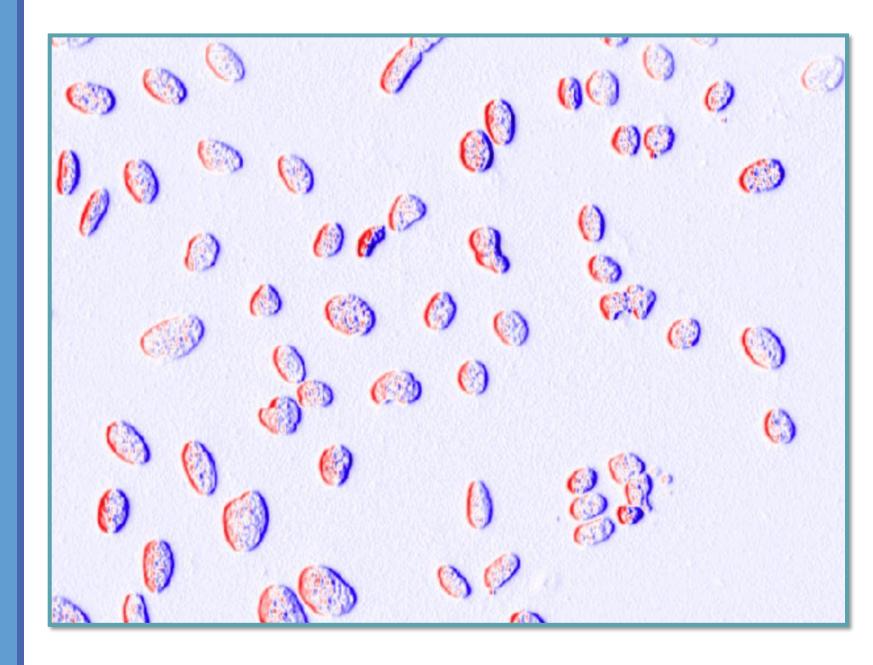
A separate

convolution is

performed for each pixel.

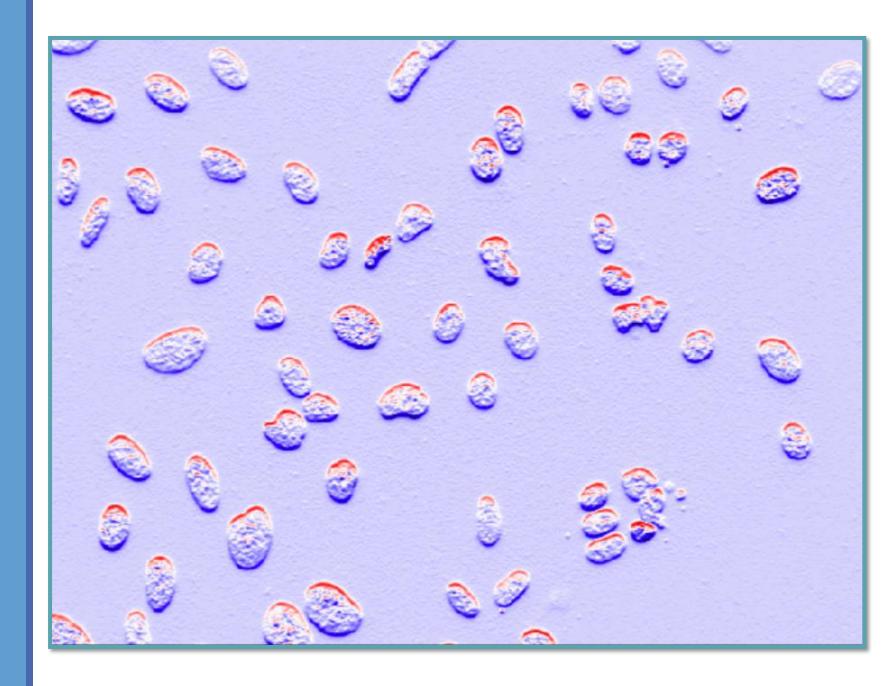
### Results: Horizontal Edges

1	0	-1
1	0	-1
1	0	-1



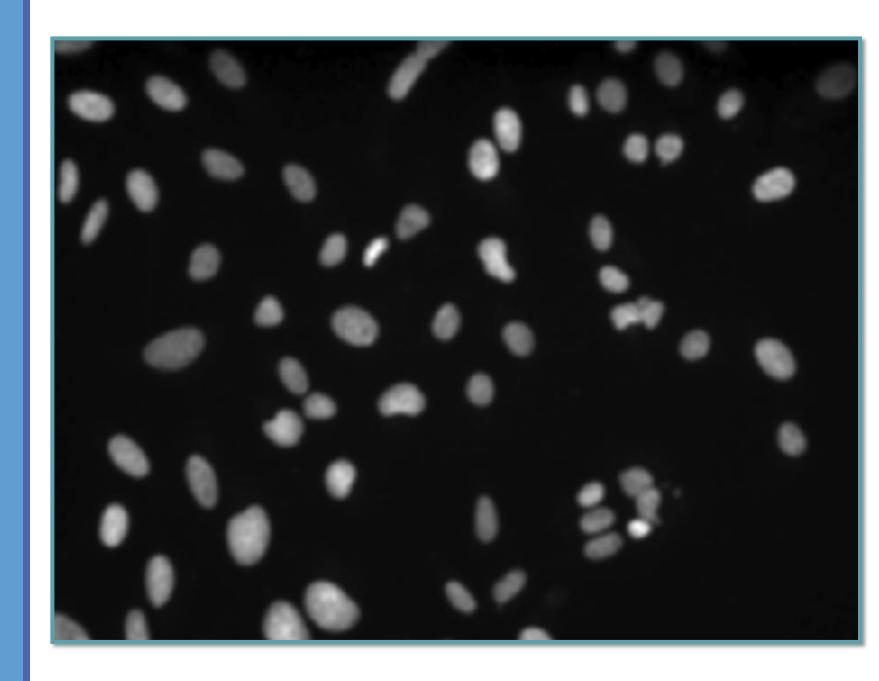
### Results: Vertical Edges

1	1	1
0	0	0
-1	-1	-1



### Results: Mean Filter

1	1	1
1	1	1
1	1	1

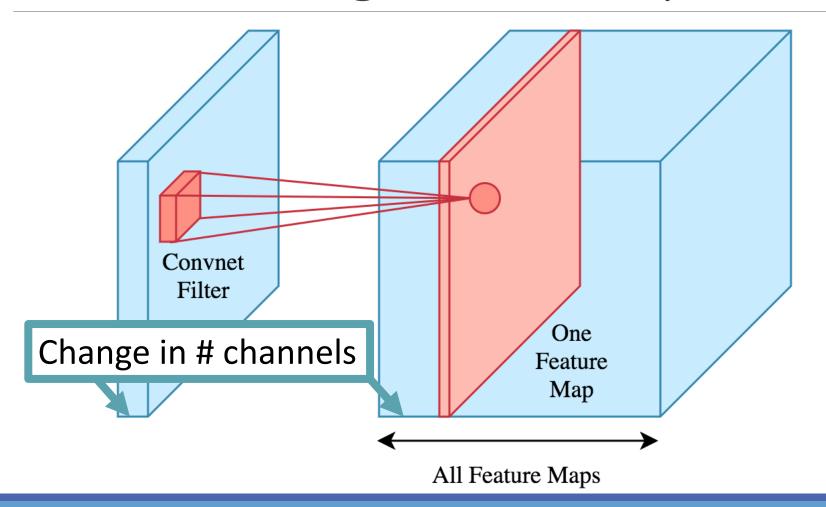


## Convolve image with multiple filters



Input

## Convolve image with many filters



- Horiz. edges
- Vert. edges
- Diag. edges
- Flat areas
- Smooth areas
- High color
- ...

#### Convolutional neural networks

Don't impose filter weights... learn them!

Horizontal Edges 3 x 3

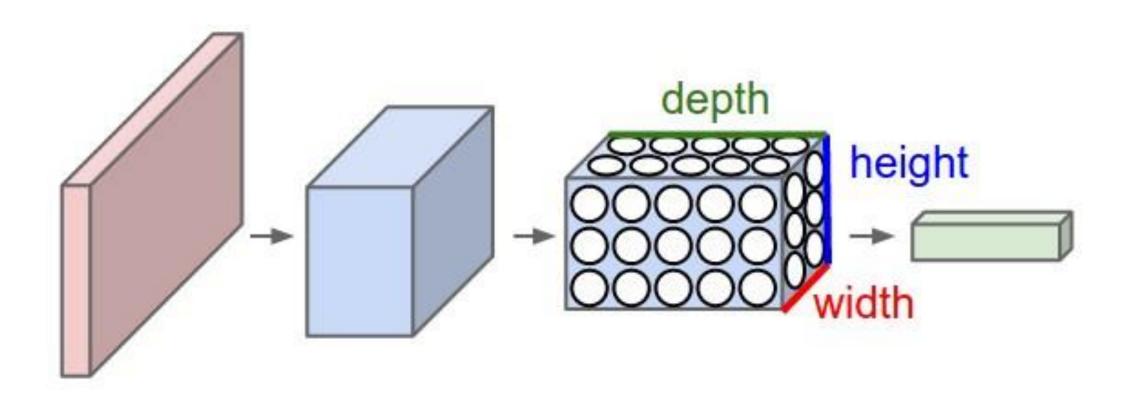
1	0	-1
1	0	-1
1	0	-1

Conv2D Weights [0] 3 x 3

1.2	-0.3	-1.3
1.8	0.1	-1.6
1.1	0.2	-0.4

#### Forward Propagation $\mathbf{Z}_1 = s(\mathbf{X} * \mathbf{W}_1)$ $\mathbf{Z}_2 \ \mathbf{U}_2^1$ W, PREDICTED TARGET LABEL LABEL **PROBABILITIES** IMAGE Cost SOFT-MAX CONVOLUTION HIDDEN **OUTPUT LAYER** IMAGE MASKS LAYER Computation **Backward Propagation**

# Rule of thumb: Layers get more compact but deeper.



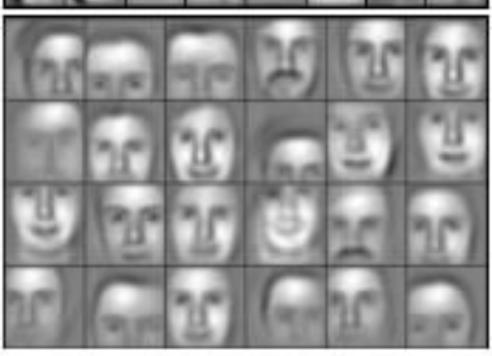
Rule of thumb: Filters become sensitive to higher level features in deeper layers



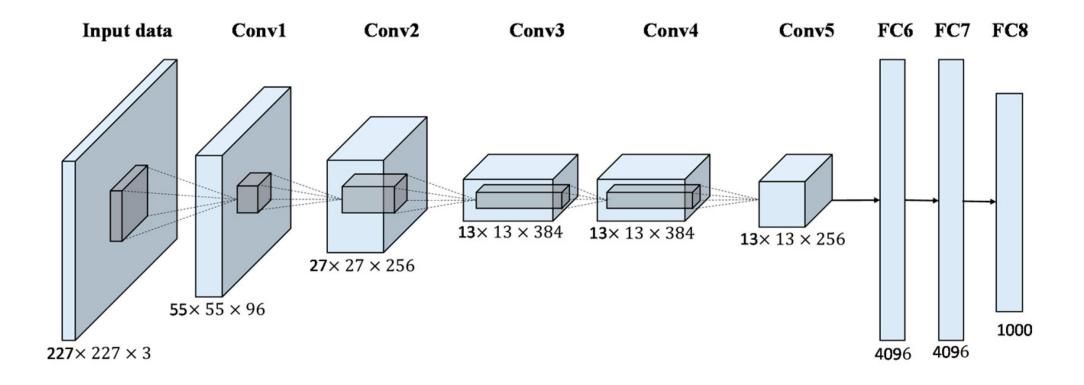
Layer 2



Layer 3



# Rule of thumb: Use a pre-built architecture



# Topics

#### The 2018 Data Science Bowl

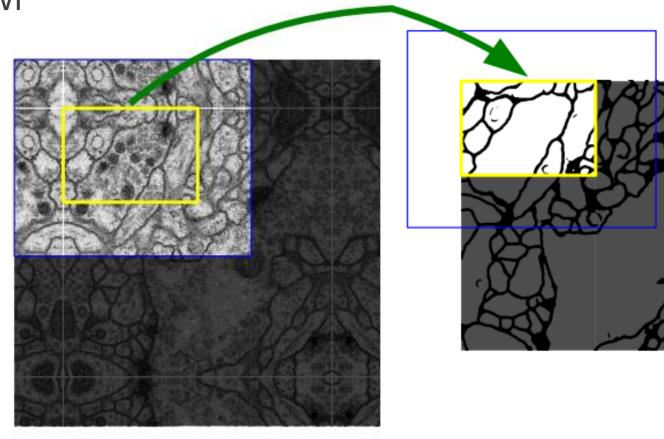
## Puppy bowl

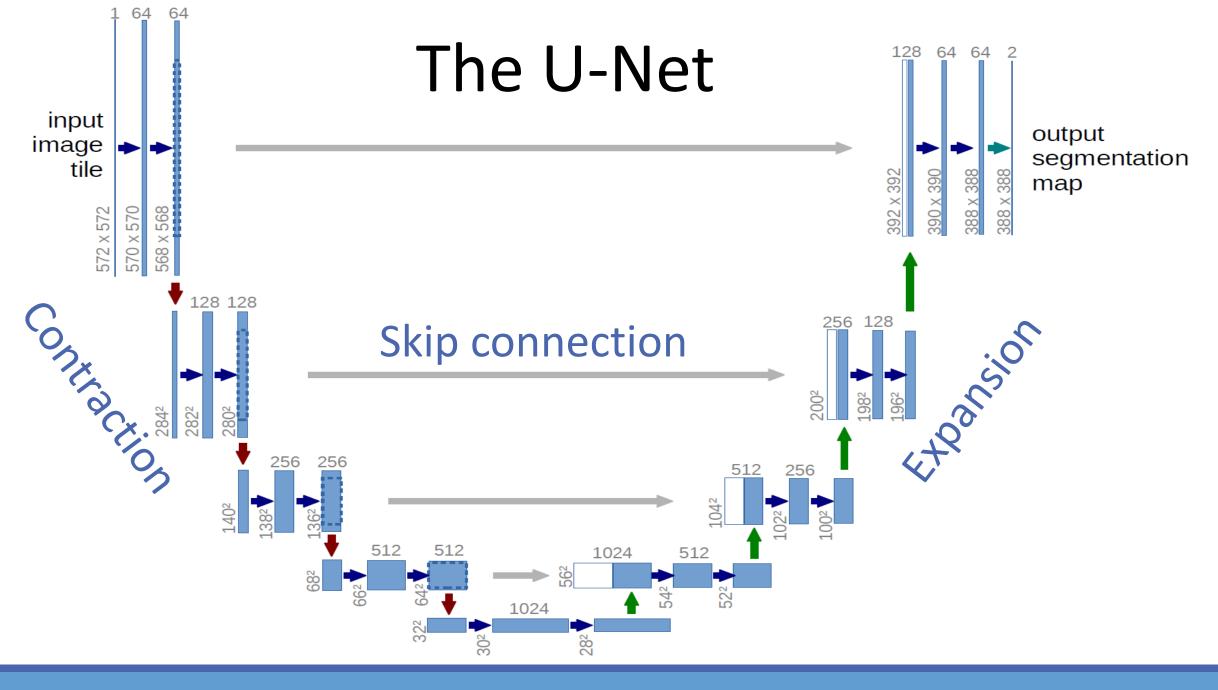
- Image processing basics
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## Superbowl

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Performance





#### Convolutions

- 3 x 3 Filter Size
- "Valid" padding

**Max Pooling** 

**Up-convolutions** 

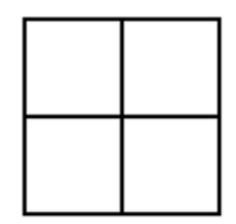
## Convolutions

- 3 x 3 Filter Size
- "Valid" padding

## **Max Pooling**

**Up-convolutions** 

1	3	2	9
7	4	1	5
8	5	2	з
4	2	1	4



#### Convolutions

- 3 x 3 Filter Size
- "Valid" padding

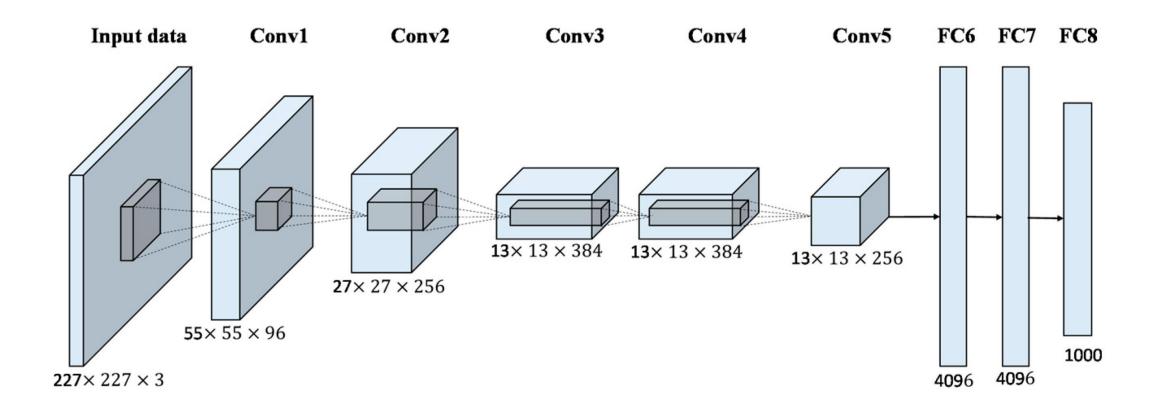
## **Max Pooling**

**Up-convolutions** 

1	m	2	9
7	4	1	5
8	5	2	3
4	2	1	4

7	9
8	

# Convolutions change depth, Pooling changes height / width

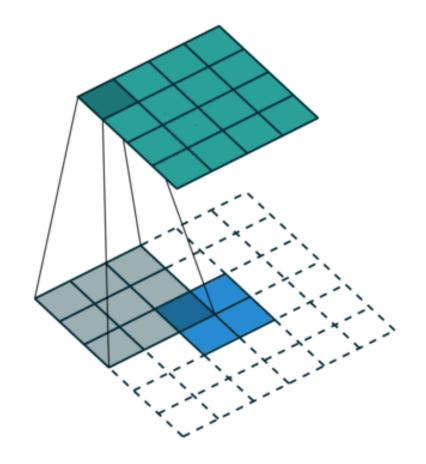


## Convolutions

- 3 x 3 Filter Size
- "Valid" padding

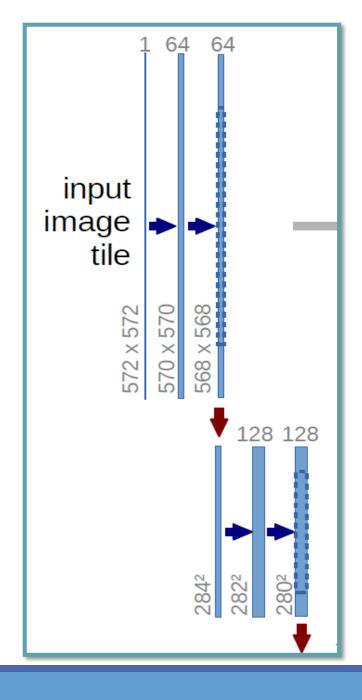
**Max Pooling** 

**Up-convolutions** 



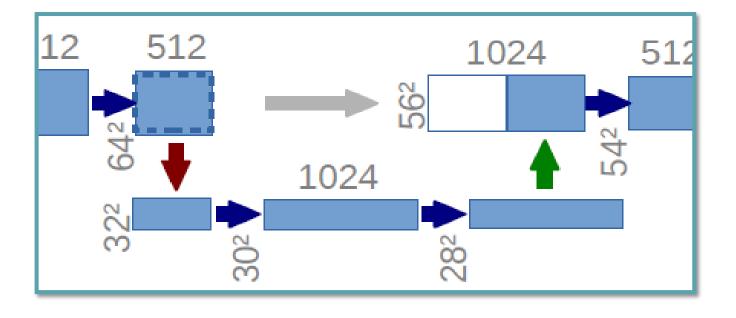
## Contraction Path

Layer	Area	Depth
Input	572 <sup>2</sup>	1
Conv1	570 <sup>2</sup>	64
Conv2	568 <sup>2</sup>	64
MaxPool1	284 <sup>2</sup>	64
Conv3	282 <sup>2</sup>	128
Conv4	280 <sup>2</sup>	128
MaxPool2	140 <sup>2</sup>	128



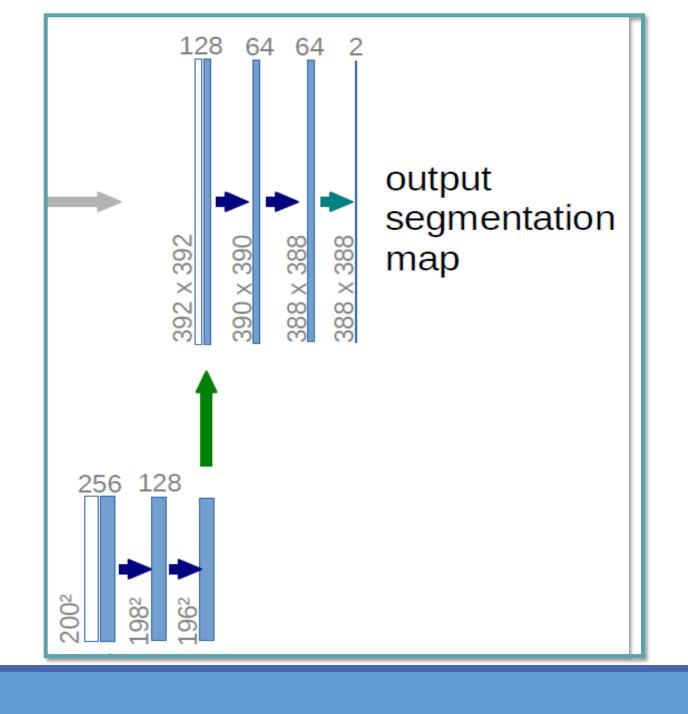
## Basin

Layer	Area	Depth
MaxPool4	32 <sup>2</sup>	512
Conv9	$30^{2}$	1024
Conv10	28 <sup>2</sup>	1024
UpConv1	56 <sup>2</sup>	512



# **Expansion Path**

Layer	Area	Depth
UpConv3	200 <sup>2</sup>	256
Conv15	198 <sup>2</sup>	128
Conv16	196 <sup>2</sup>	128
UpConv4	392 <sup>2</sup>	128
Conv17	390 <sup>2</sup>	64
Conv18	388 <sup>2</sup>	64
Output	388 <sup>2</sup>	2



# Skip Connections



Crops and copies information from earlier in the network to deeper layers Allows final resolution to remain high







Kjetil Åmdal-Sævik Keras U-Net starter - LB 0.277



last run 3 months ago · Python notebook · 63592 views using data from 2018 Data Science Bowl · ● Public



Notebook Code Data (1) Output (2) Comments (126) Log Versions (8) Forks (465)

**Fork Notebook** 

1 You are currently viewing an old version of this script (7/8). View the latest version.

Tags

Notebook

```
# Build U-Net model
inputs = Input((IMG_HEIGHT, IMG_WIDTH, IMG_CHANNELS))
s = Lambda(lambda x: x / 255) (inputs)
c1 = Conv2D(8, (3, 3), activation='relu', padding='same') (s)
c1 = Conv2D(8, (3, 3), activation='relu', padding='same') (c1)
p1 = MaxPooling2D((2, 2)) (c1)
c2 = Conv2D(16, (3, 3), activation='relu', padding='same') (p1)
c2 = Conv2D(16, (3, 3), activation='relu', padding='same') (c2)
p2 = MaxPooling2D((2, 2)) (c2)
```

# Topics

#### The 2018 Data Science Bowl

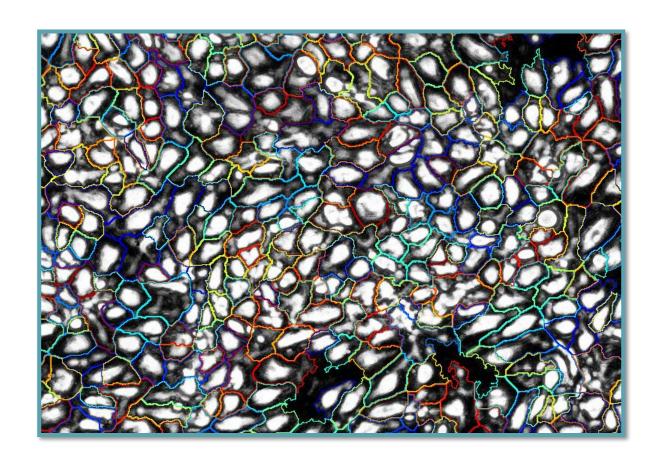
## Puppy bowl

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## **Performance**



# Model performance (0.0 - 0.6)

Approach	<b>Mean Average Precision</b>
1. Vanilla image processing	0.20 - 0.28
2. Vanilla U-Net	0.25 - 0.42
3. Vanilla Mask R-CNN	0.37 - 0.50
4. U-Net + Deep Watershed	0.45 - 0.55
5. Winning model	~ 0.65

# Insight 1: Data augmentation is critical.

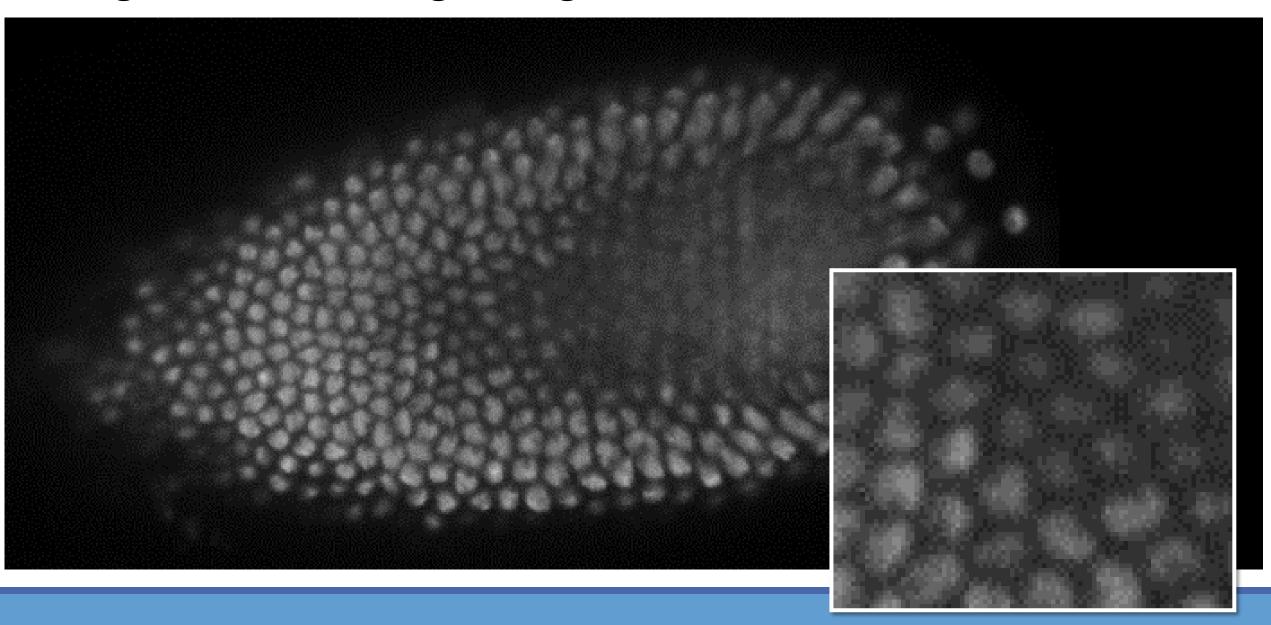
- 1. Add gaussian noise
- 2. Color to gray
- 3. Contrast and brightness
- 4. Random crop
- 5. Mosaics
- 6. Random rotate

## Insight 2: Neural networks don't do it all.

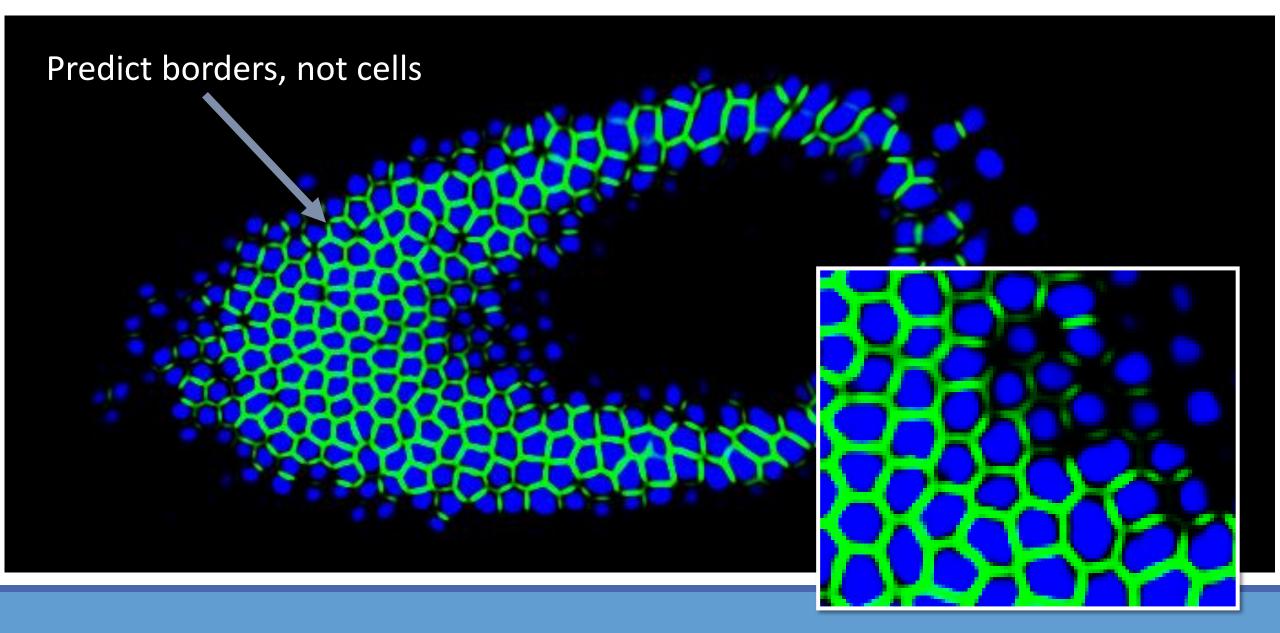
Output of models was treated as "candidate nuclei"... still need to post-process data!

 e.g., Use morphological features such as solidity, circularity, convexity, area, neighbors median, count, etc. to calculate "predicted IOU" for each mask.

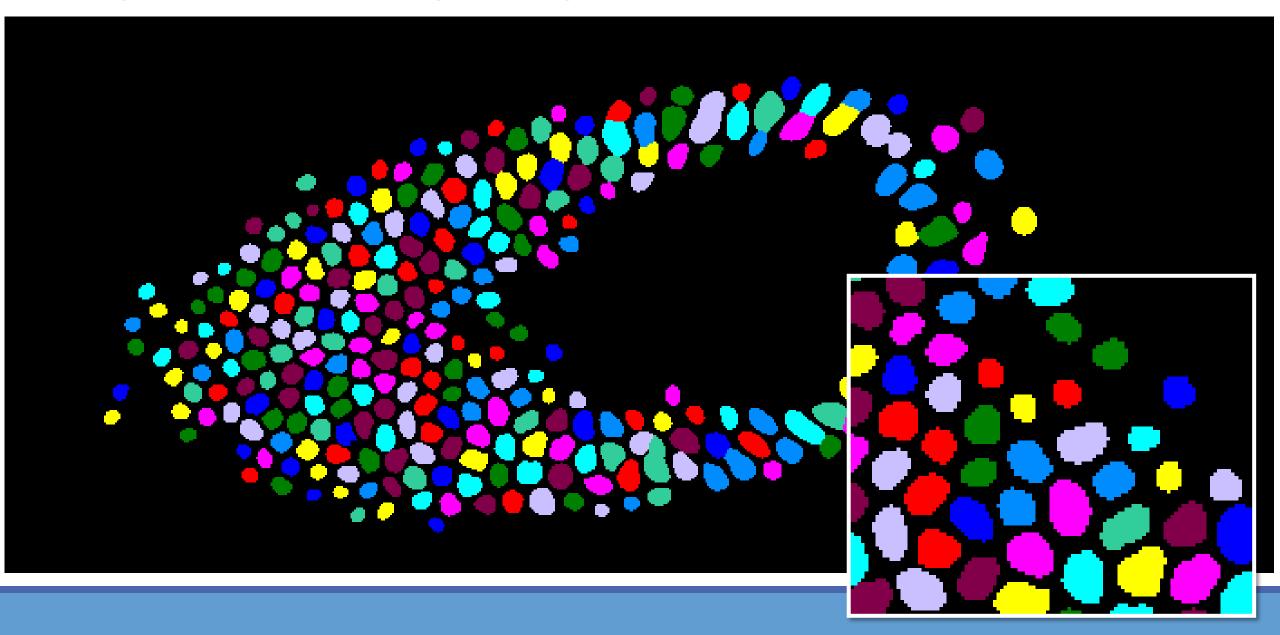
Insight 3: Pick the right target...



## Insight 3: Pick the right target...



Insight 3: Pick the right target...





## For further reference...

- 1. Coursera's Deep learning specialization
- 2. <u>"U-Net: Convolutional Networks for Biomedical Image</u> <u>Segmentation"</u> by Ronneberger, Fischer and Brox
- 3. Kaggle's Data Science Bowl 2018
  - 1. <u>1st Place Solution</u> from *ods.ai*
  - 2. 4<sup>th</sup> Place U-Net + Watershed from *Nuclear Vision*
  - 3. <u>11<sup>th</sup> Place Open Solution from Zheng Li</u>