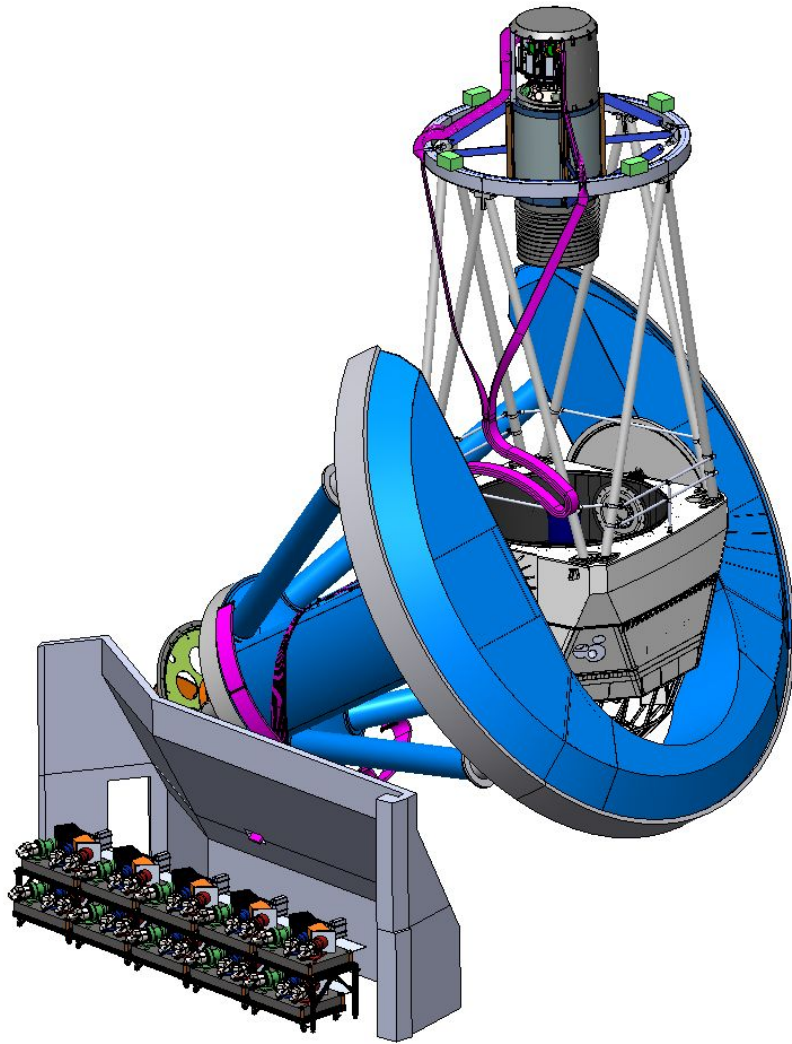


Deep Learning for Cosmic Ray Identification

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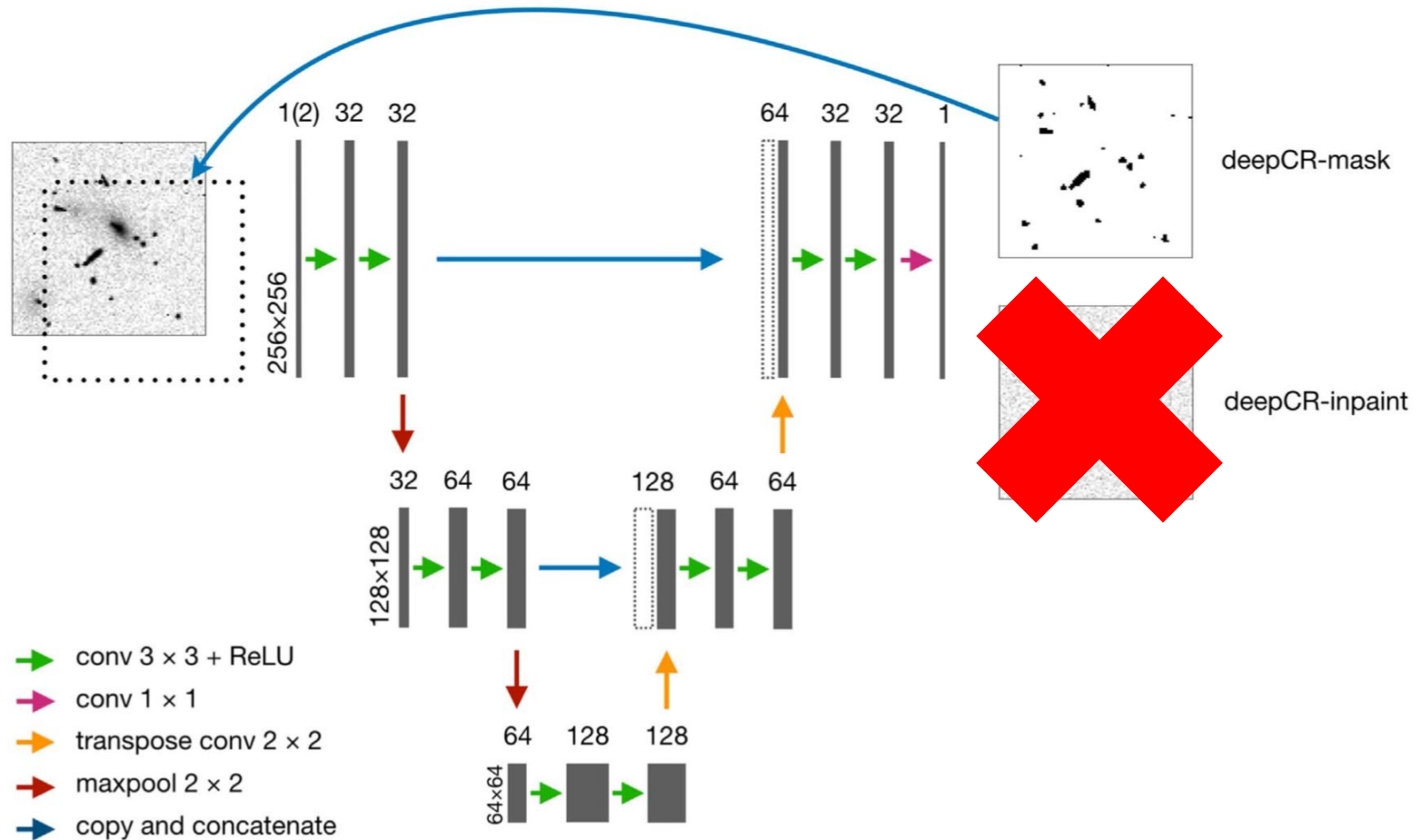
Motivation

- SDSS method is “good” but not the best
 - Relies heavily on tweaking quixotic parameters for optimal results
 - Nsig, cfudge, c2fudge
 - Dependent on exposure PSFs
 - Can sometimes miss cosmics that are dim
 - Can easily overestimate cosmic footprint
- Fully Convolutional Neural Network (CNN) could alleviate previous problems by being trained to compensate for features like fibers
 - Only one tunable parameter of obvious intent (probability threshold)
 - “Black box” nature is a downside
- Deep learning for cosmics has been successfully applied on images taken on the HST



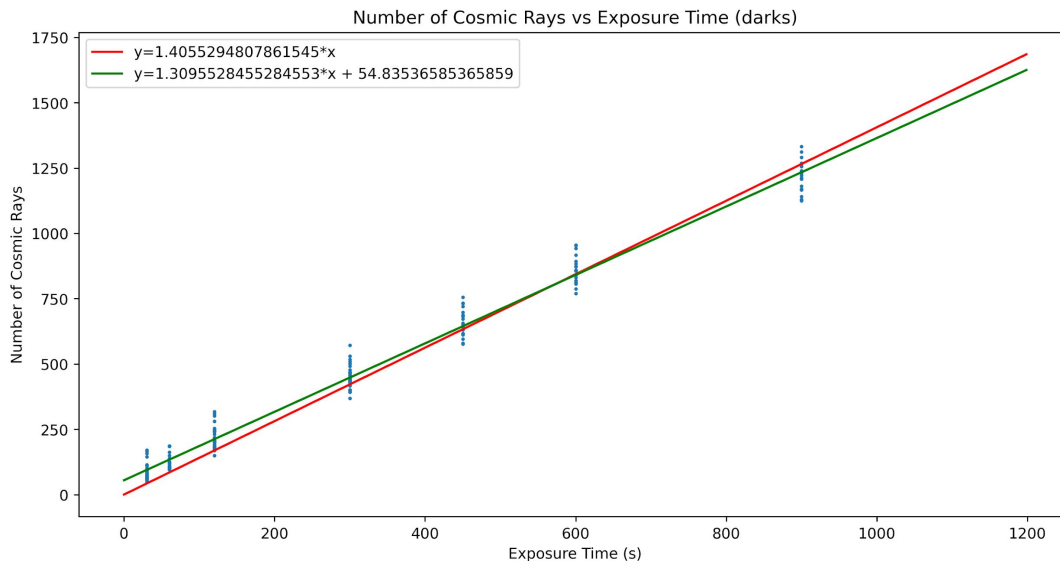
Model

- CNN architecture defined in deepCR (Zhang & Bloom 2020)



Data

- Generate training images using “clean” images
 - Median of multiple exposures of identical tiles
 - Currently using R-band exposures from SV0 (3/14/20-3/15/20)
- Simulated noise added to training images
 - Noise picked from Gaussian with $\sigma \sim \sqrt{1/\text{median_ivar}}$ and $\mu \sim 0$
- Cosmics from 5 minute calibration darks 01/13/2021-01/21/2021
 - $\sim 41\text{k}$ unique cosmics

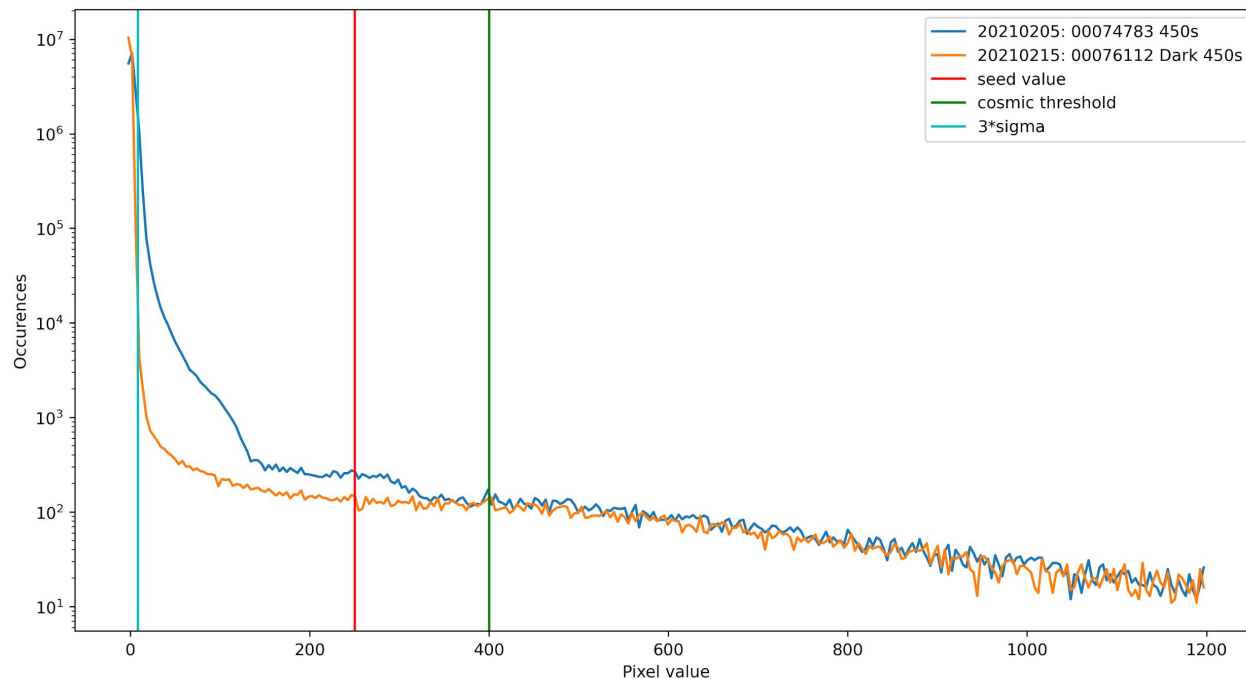


- Simulate number of cosmics via simulating exposure times
 - Approx. linear relationship between exposure time and num of cosmics
 - Num cosmics = $\sim 1.4 * \text{exposure time}$

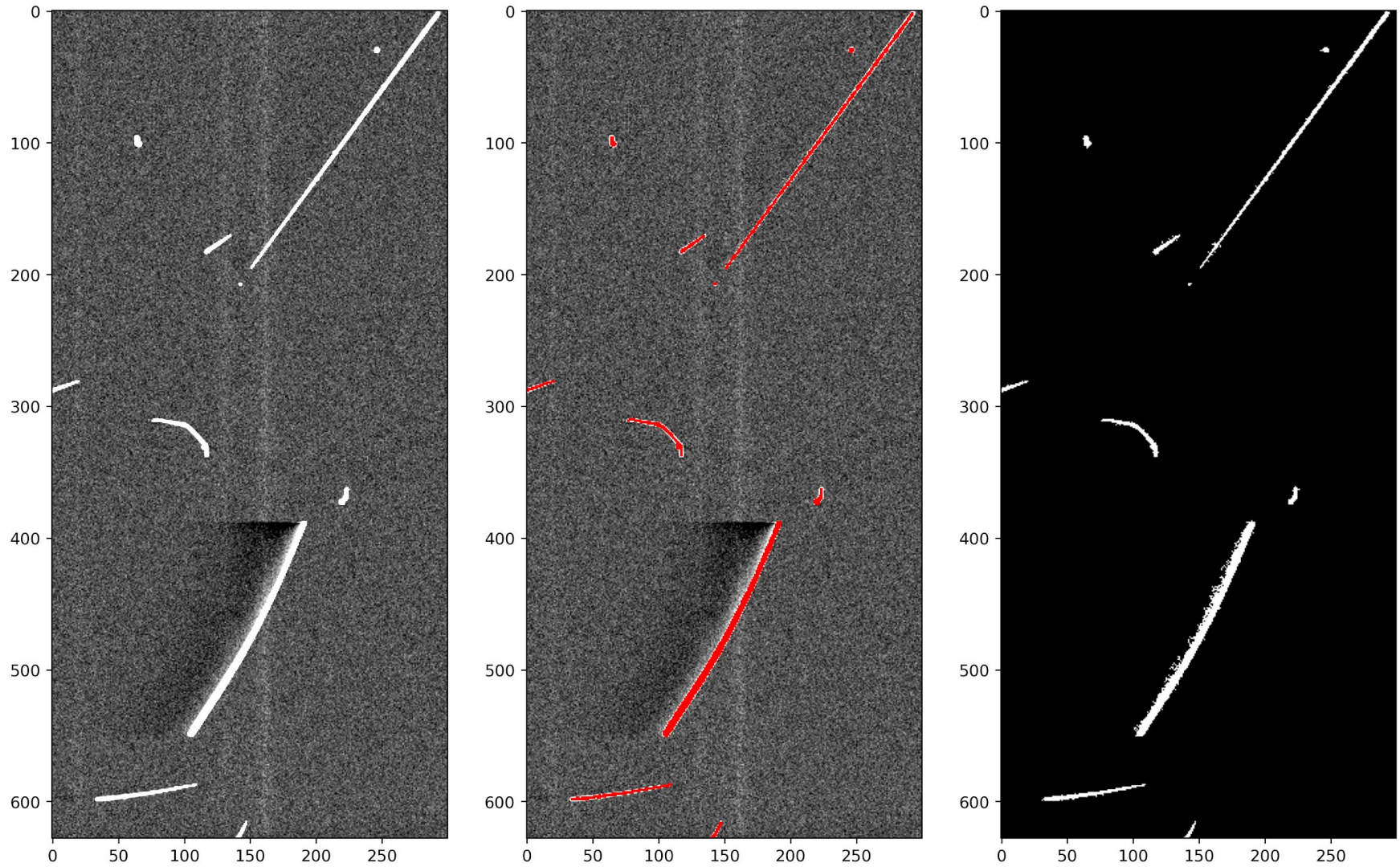


Extracting Cosmics

- Cosmics are extracted from darks
 - From histogram analysis everything above pixel value ~ 400 is a cosmic ray
- Can use a similarly high value (250) as a “seed” for cosmics
- Flood fill outwards from seed values until pixels drop below 3 sigma of a clean dark (sigma $\sim 1-3$)



Extracting Cosmics



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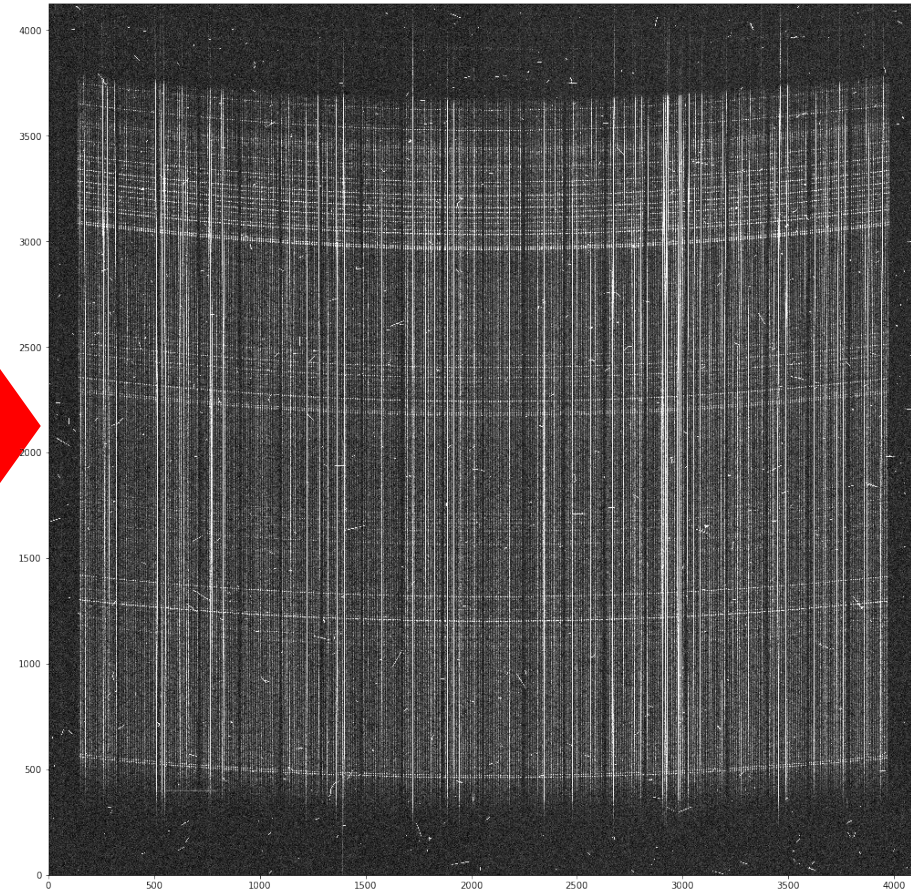
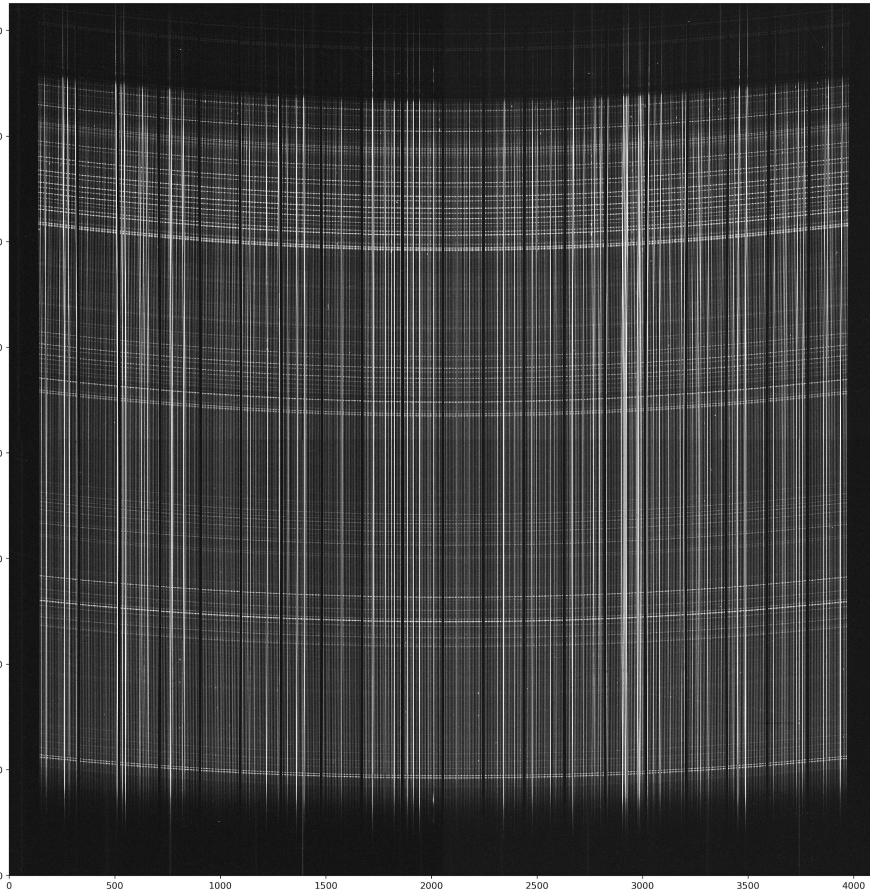
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Slide 6

Data

Median of Tile ID #66003



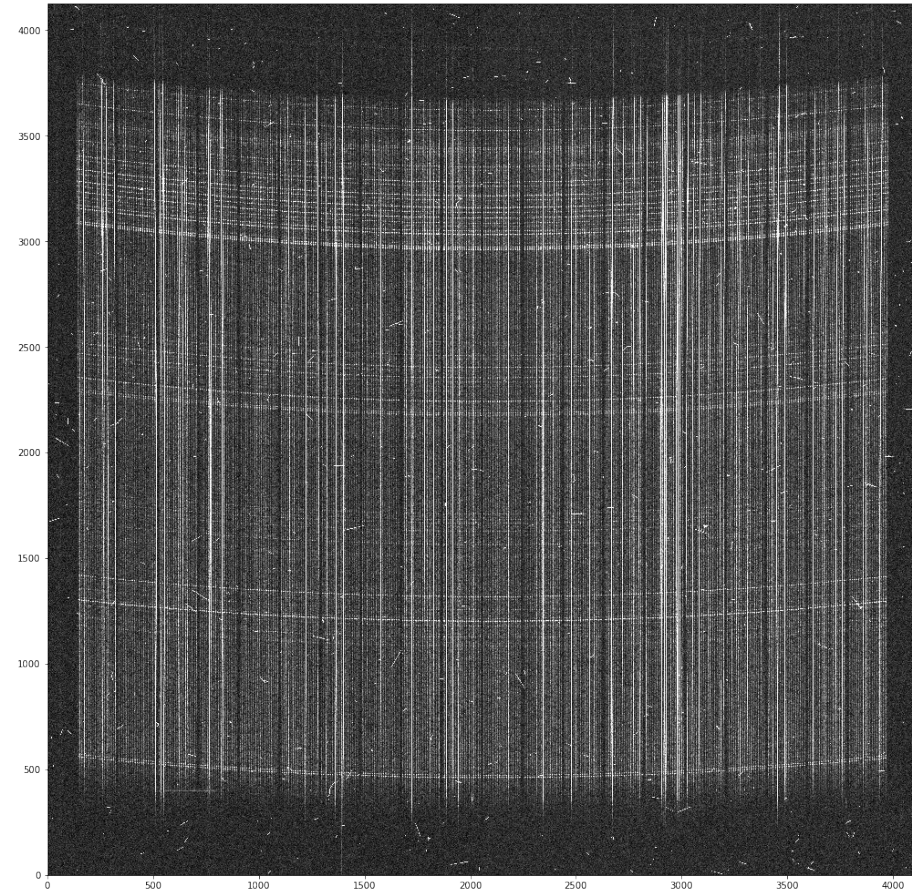
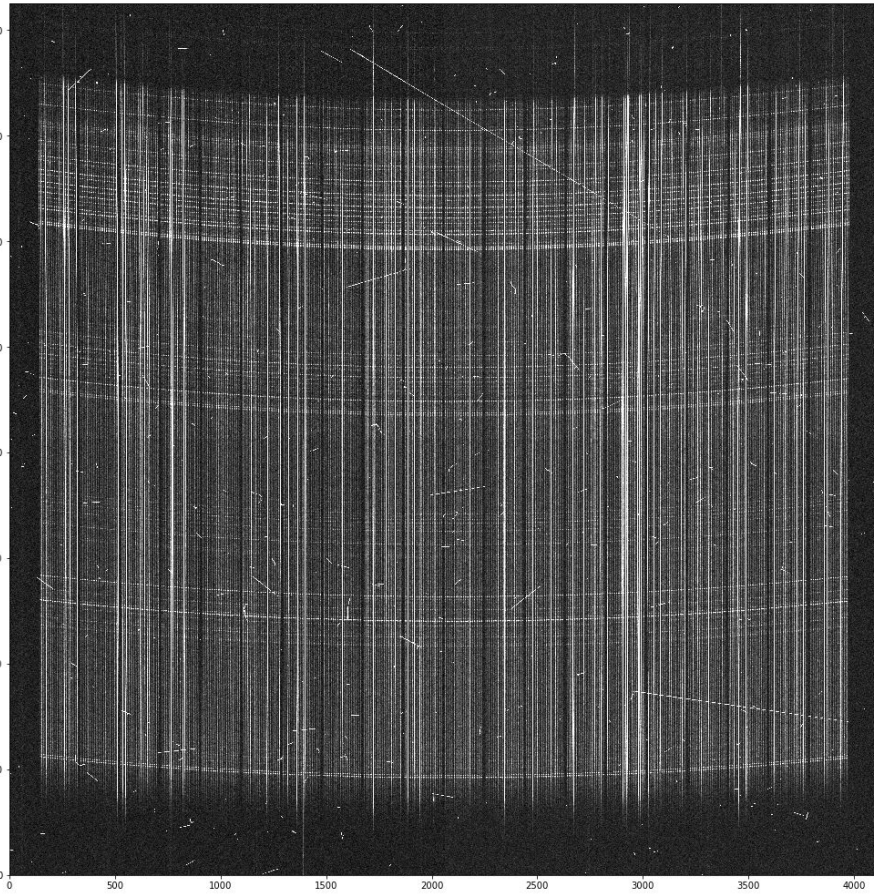
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Slide 7

Data



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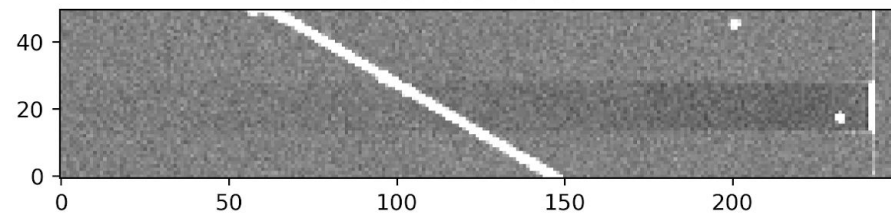
Slide 8

Dark Trails

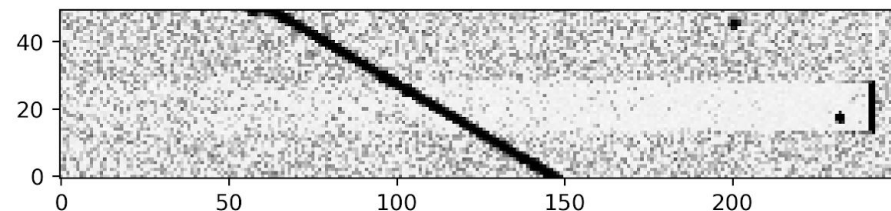
- In current preproc pipeline dark trails are corrected before identifying cosmoics
- Training data does not correct dark trails (yet)
- More important for SDSS algorithm which requires ivar
 - CNN does not use ivar

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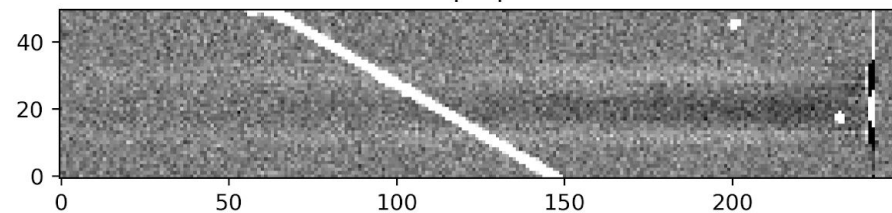
bias-subtracted



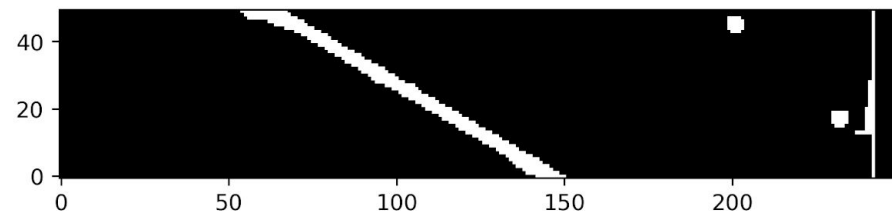
ivar



full preproc

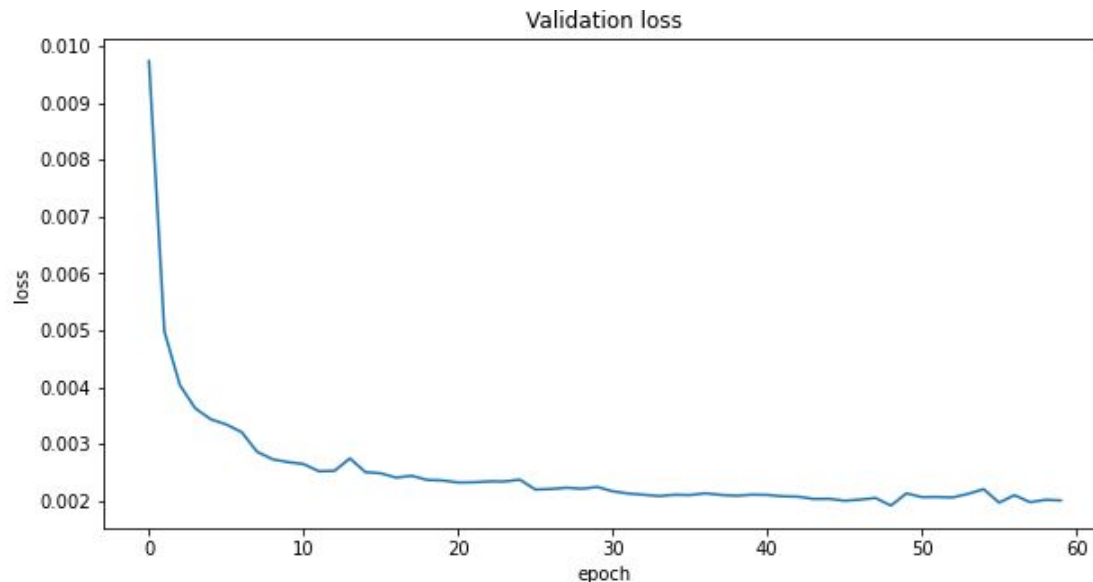


mask

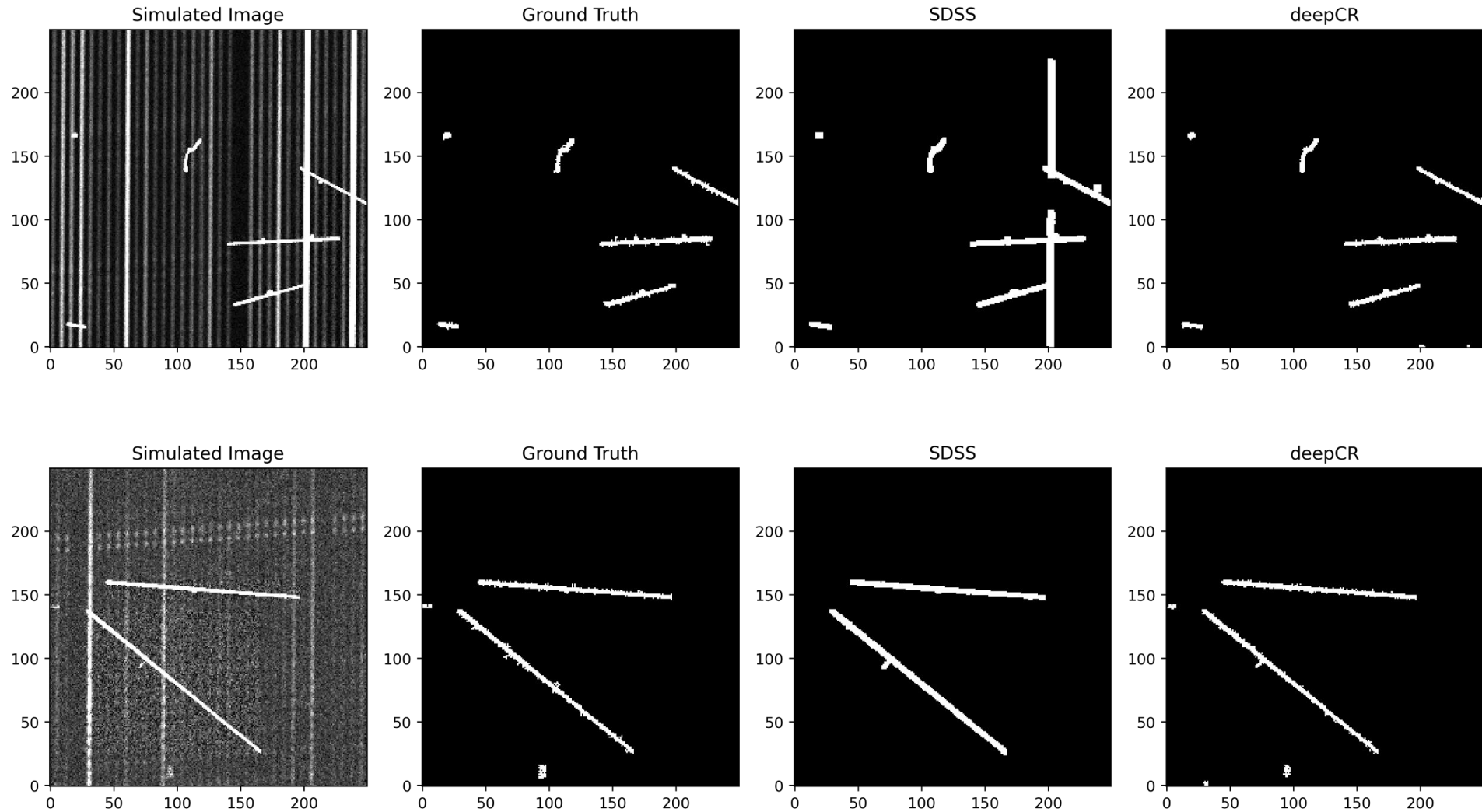


Training

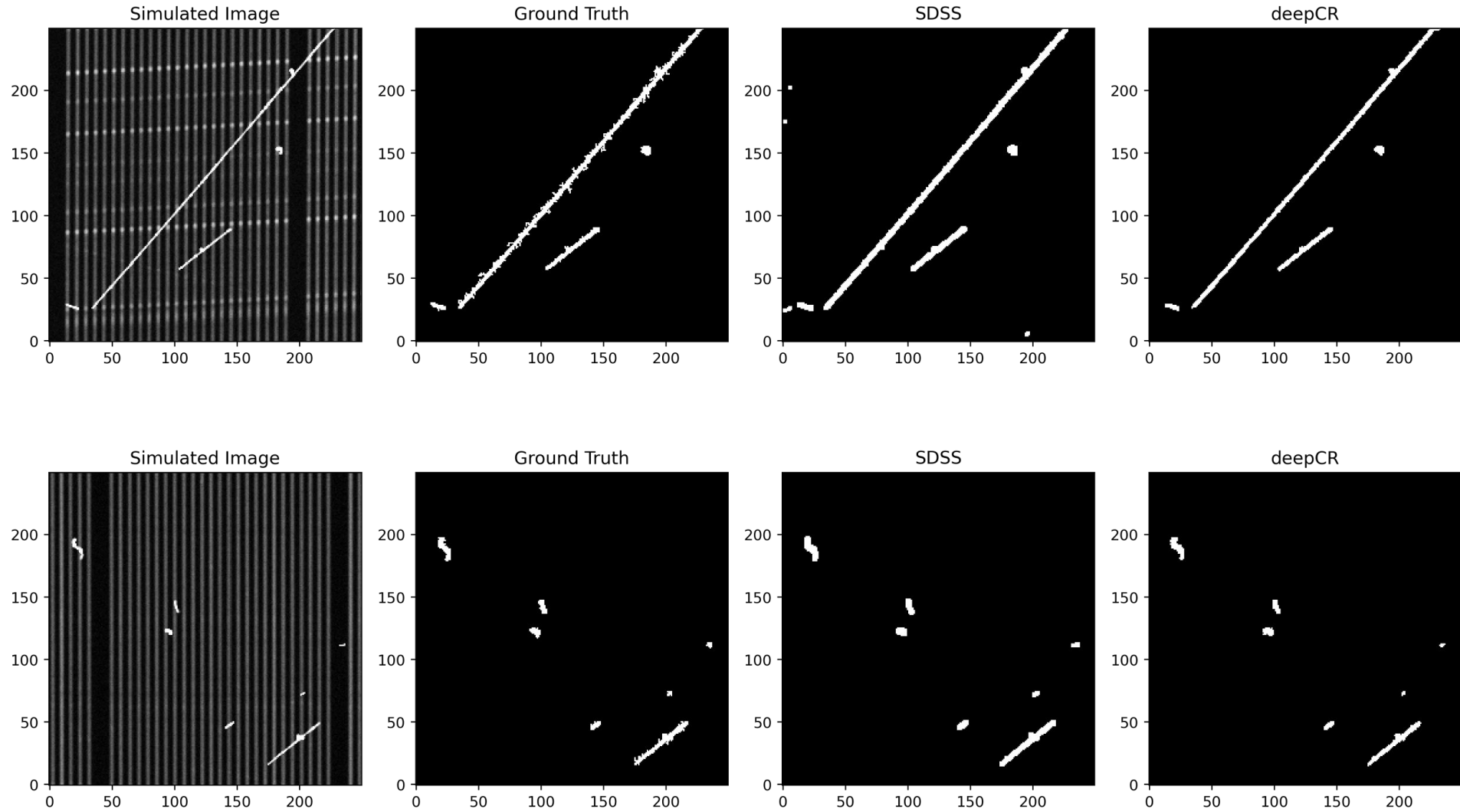
- Images are cut into overlapping 256x256 patches
 - 10 training images -> 2404 patches, 1803 (75%) of which are used for training
- Network outputs “probability map”
 - > 0.5 probability threshold identified as a cosmic
 - Tunable parameter
- Train for 60 epochs
 - Batch normalization statistics frozen after 24 epochs



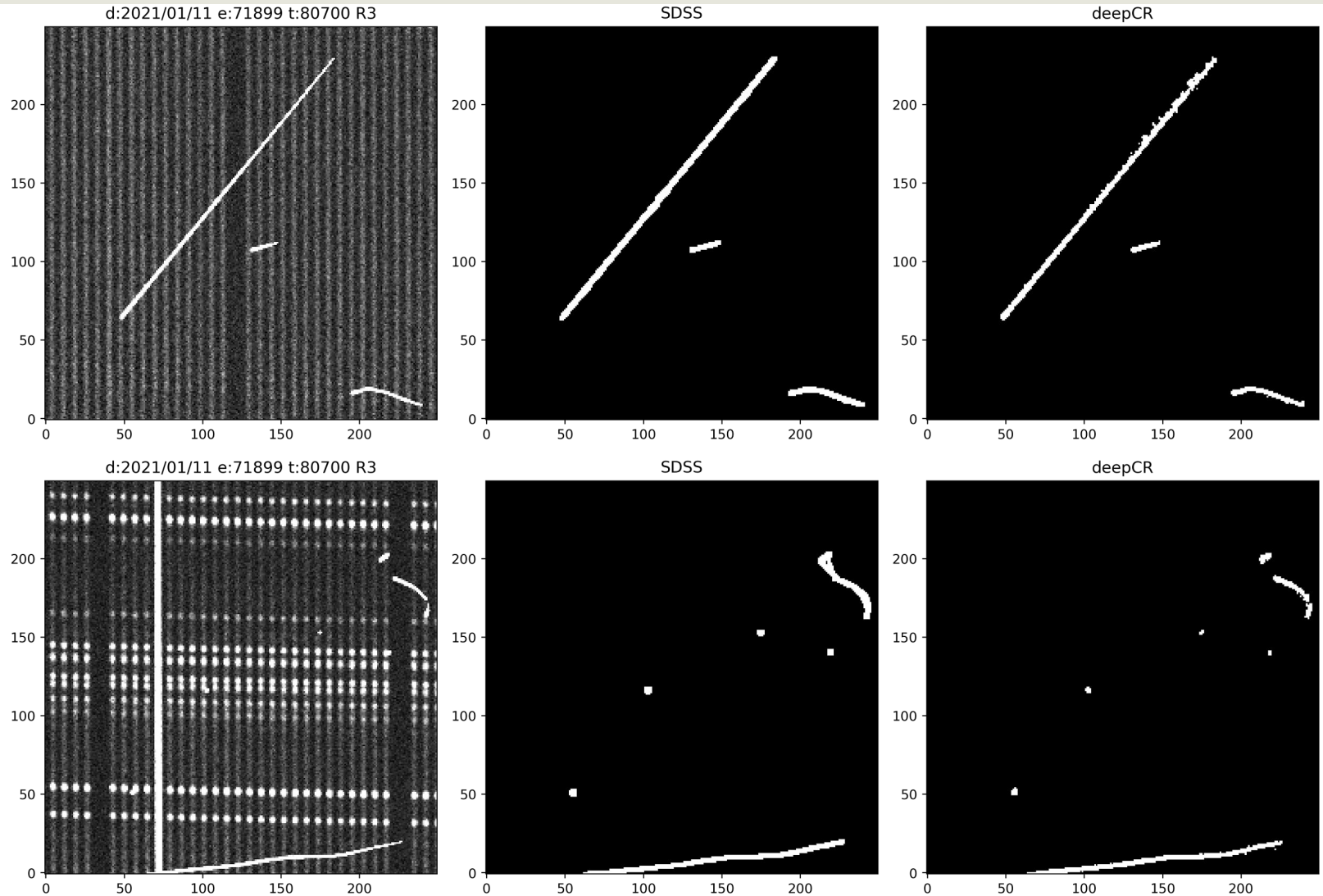
Comparison (Simulated Data)



Comparison (Simulated Data)

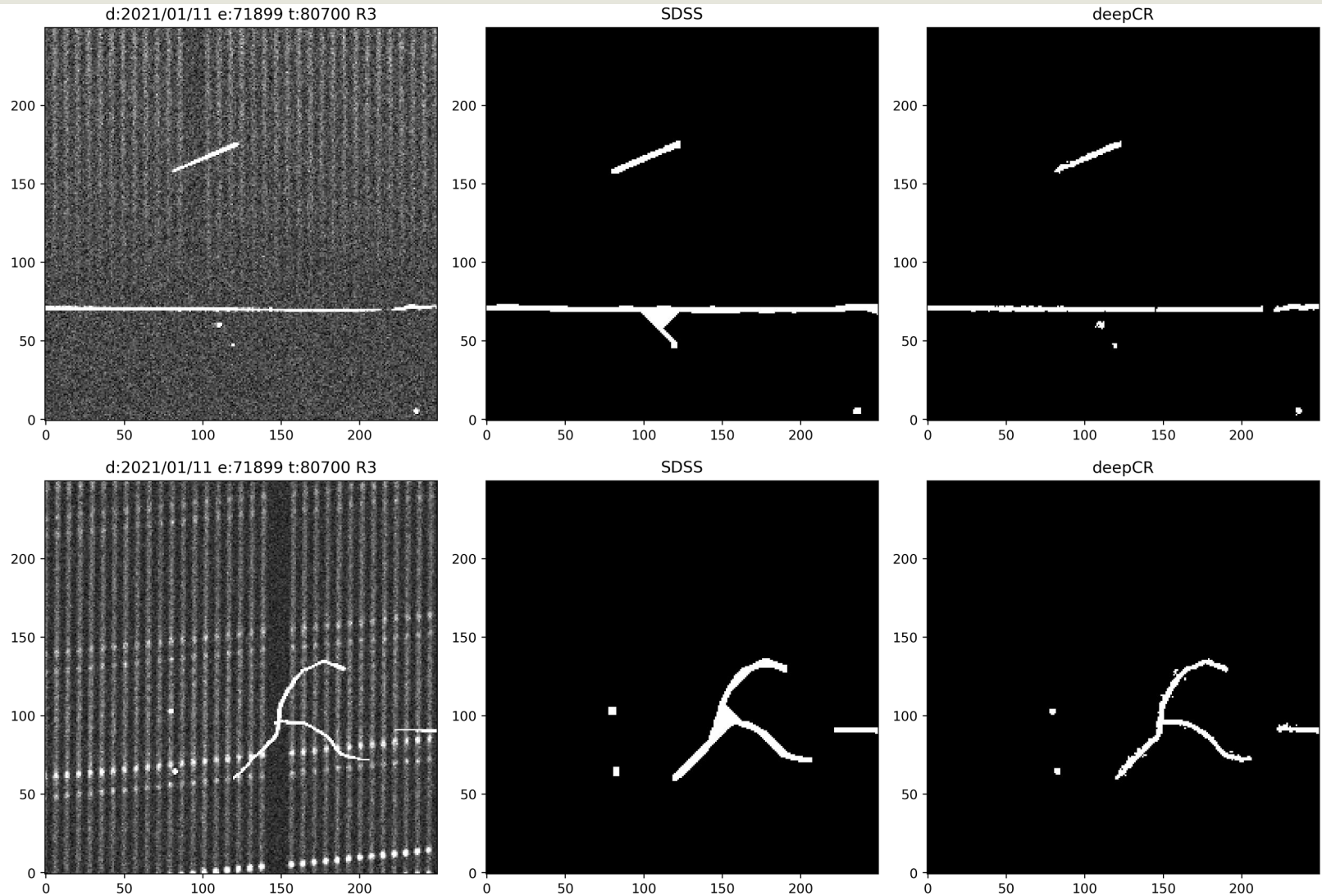


Comparison (Real Data 2021/01/11)



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Comparison (Real Data 2021/01/11)



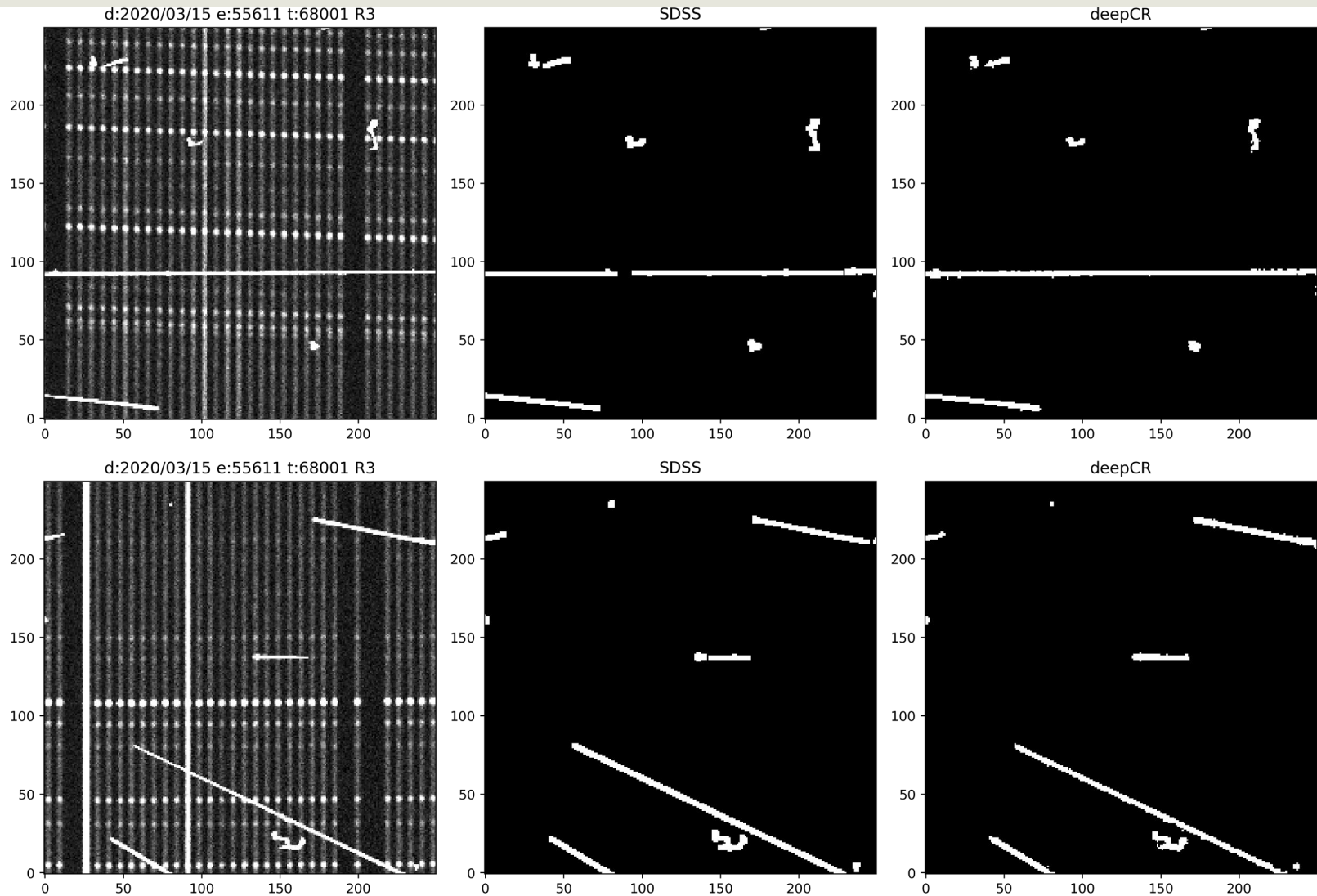
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Slide 14

Comparison (Real Data 2020/03/15)



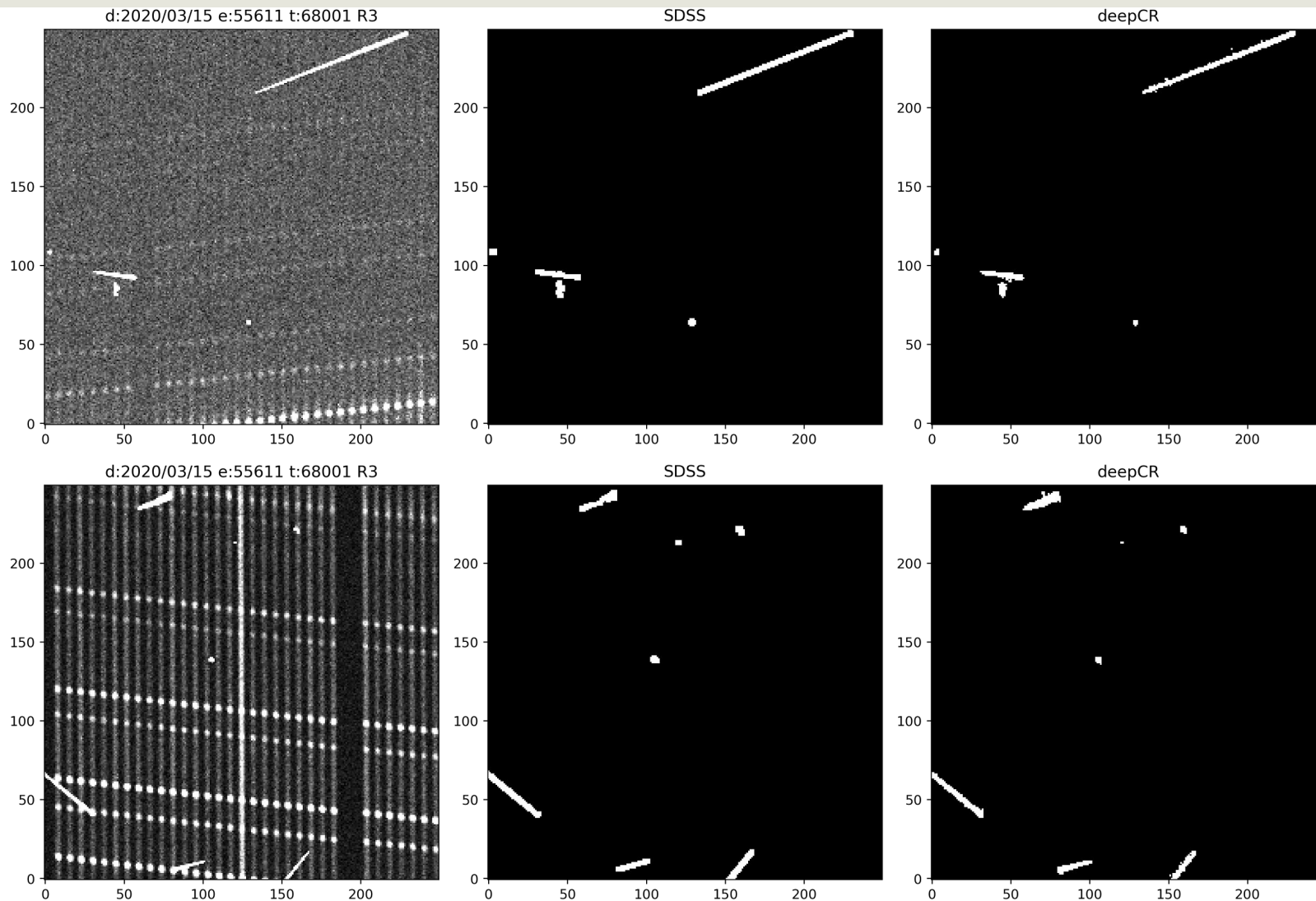
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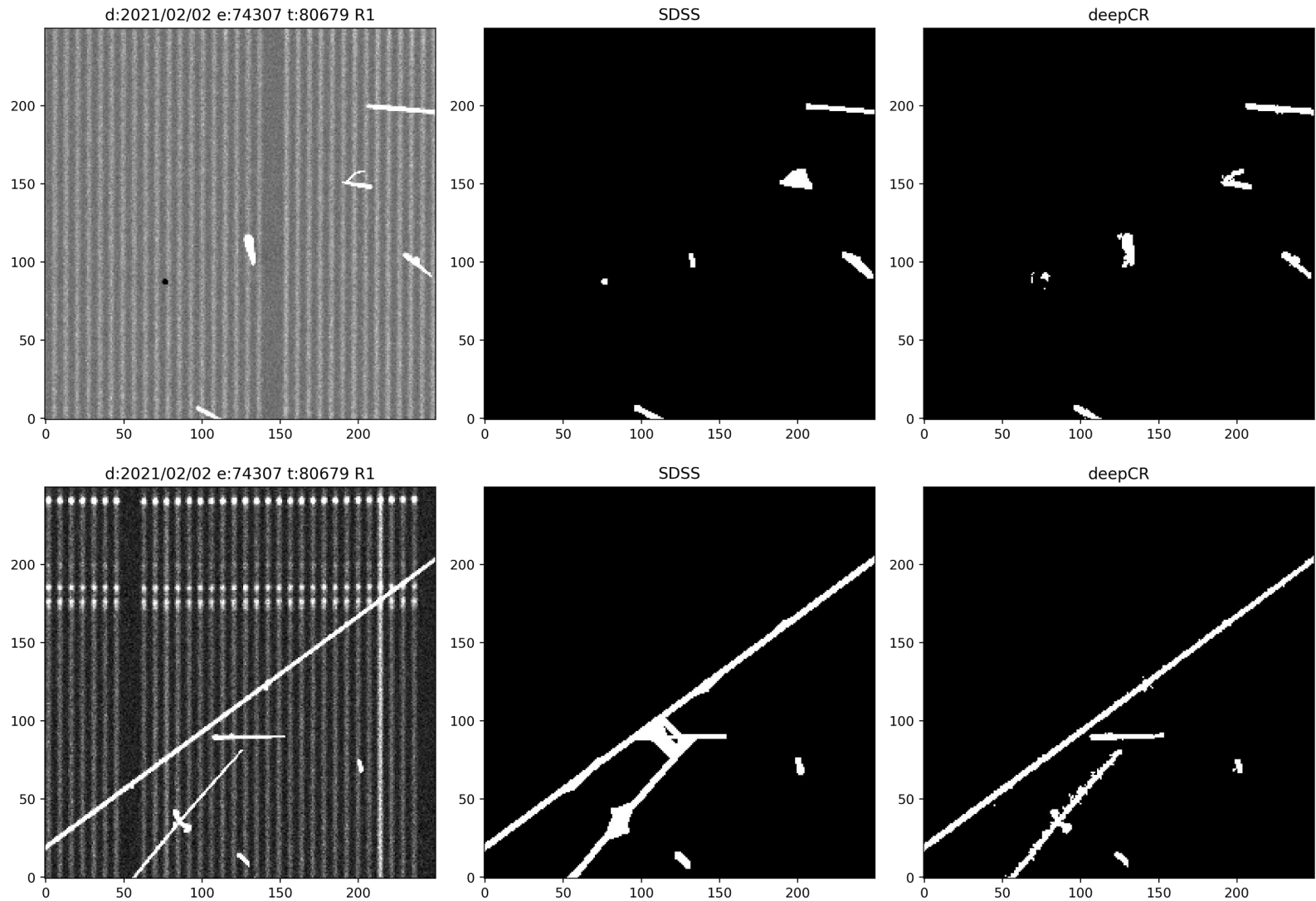
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Slide 15

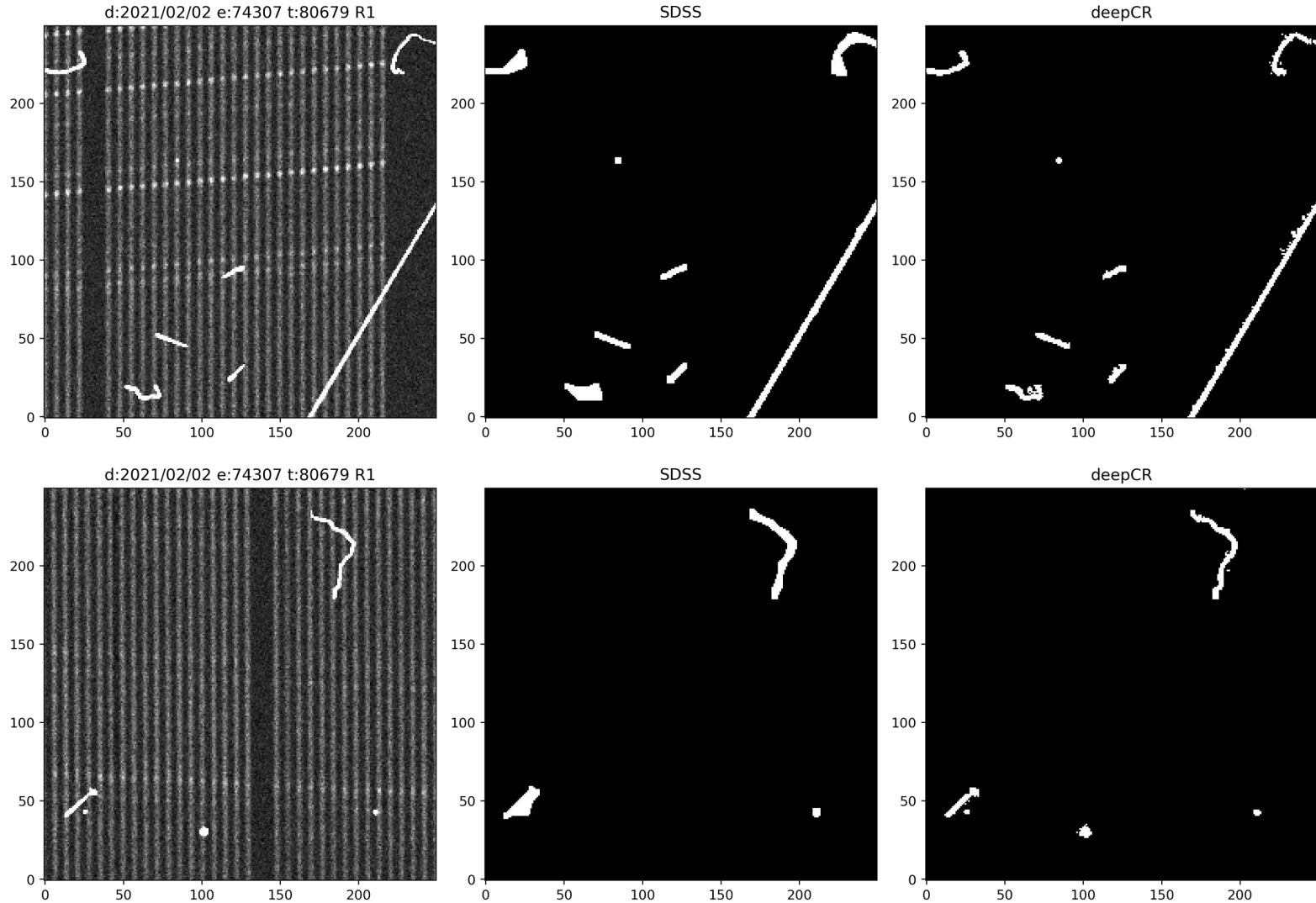
Comparison (Real Data 2020/03/15)



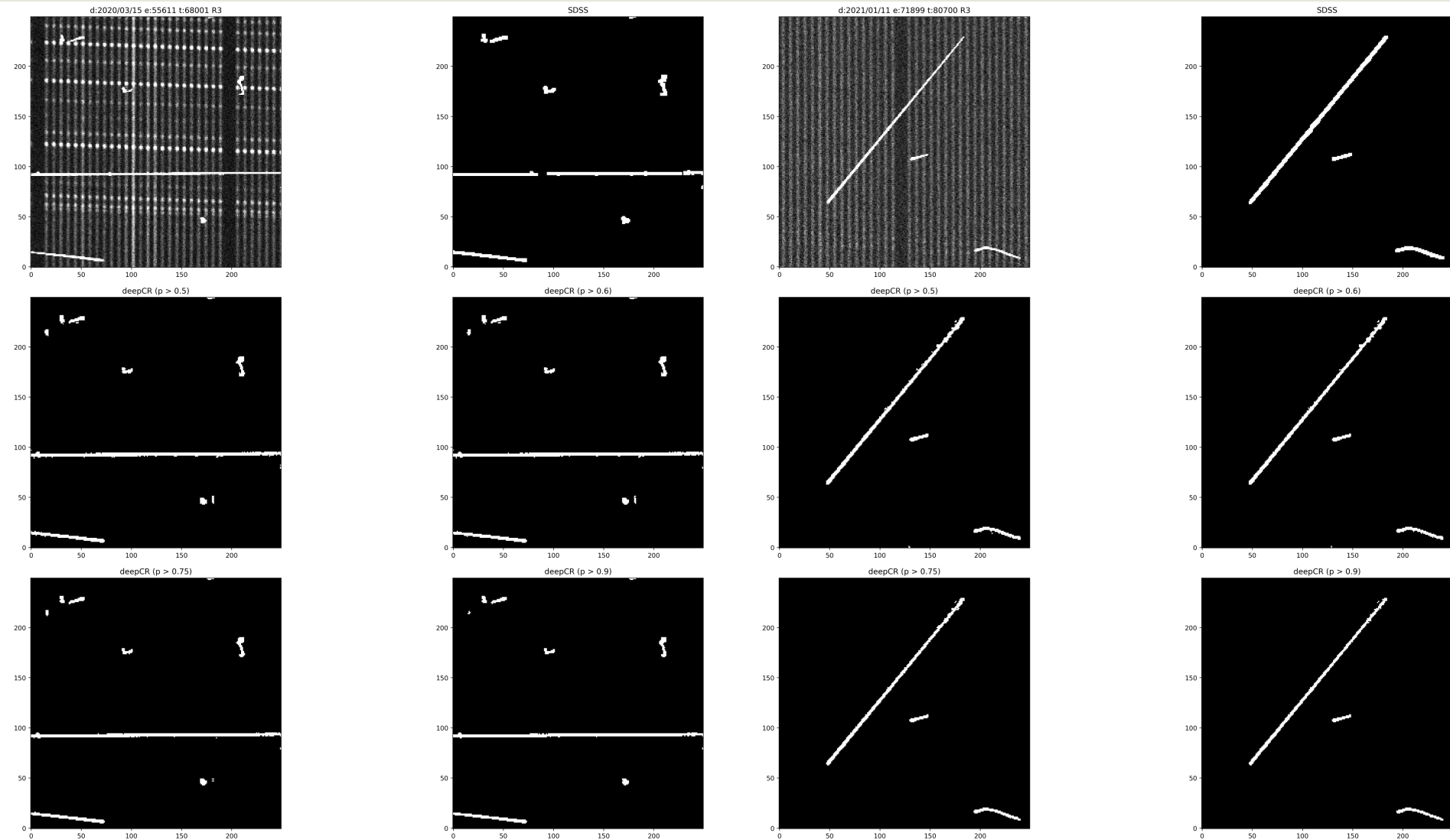
Comparison (Real Data 2021/02/02)



Comparison (Real Data 2021/02/02)



Comparison (Real Data)



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Slide 19

Timing

- ~5s for deepCR impl on low end (NVIDIA Tesla P4) GPU machine
 - Large memory requirement (~fewGB) to process 4k x 4k image at once.
 - Reduced to ~2-4s if we process the image in 16 smaller quadrants
 - Training ~20 minutes
- About 2x as fast on NERSC GPU node
 - NERSC won't give me enough memory to run the whole image :(
 - ~1-1.5s if we process the image in 16 smaller quadrants
- ~45s on my laptop (when nothing else is running)
 - Reduced to ~30s if we process the image in 16 smaller quadrants
 - Training ~40 minutes
- ~5-25s (depends on number of cosmics) for SDSS



Next Steps

- Train individual weights for B and Z band.
- Improve training data to match more how SDSS algorithm “sees” images
- Try and extract spectral data from exposures with cosmic rays marked by deepCR
- Build network independent of deepCR
 - Alternate network configuration may perform better on spectroscopic data
 - Smaller network may have similar performance while being faster
 - Larger network may not sacrifice speed for better cosmic ID

