

Neural network particle picking and denoising with Pick more of anything

Alex J. Noble Topaz Workshop at SEMC!

Mar 8, 2023

Topaz Picking: Nature Methods

Topaz Denoising: Nature Communications

http://cb.csail.mit.edu/cb/topaz



Massachusetts Institute of Technology





Tristan Bepler





Workshop Goals=)

- 1. Understand how Topaz can help you
- Get hands-on Topaz experience so you can get better cryoEM structures!

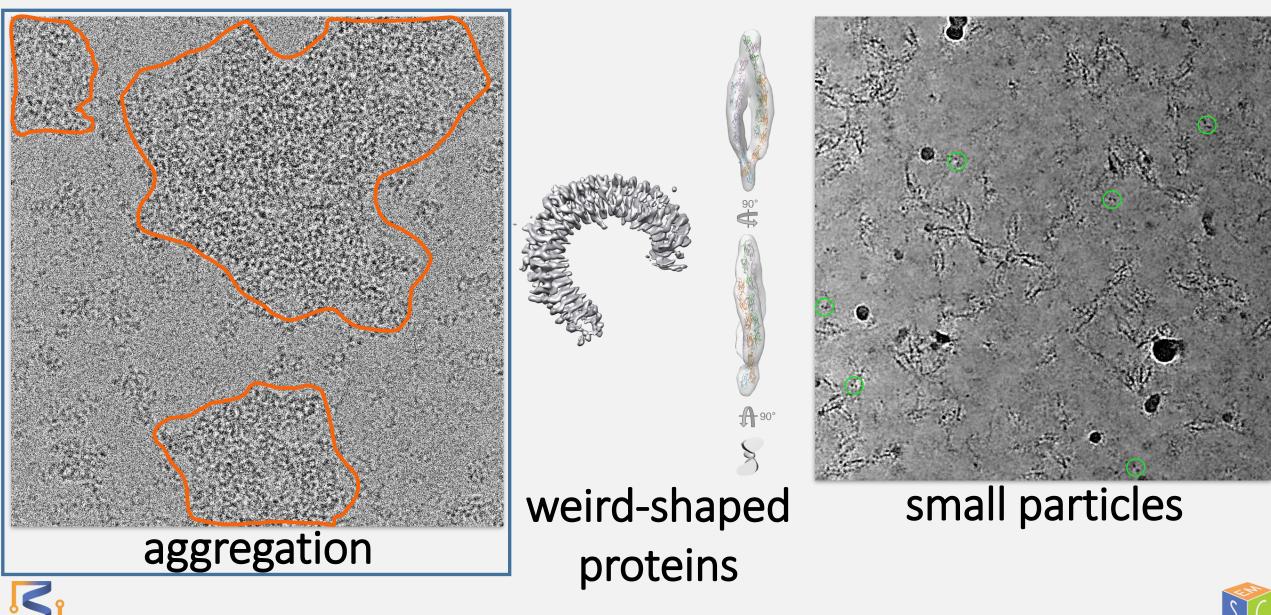






Common problems in cryoEM

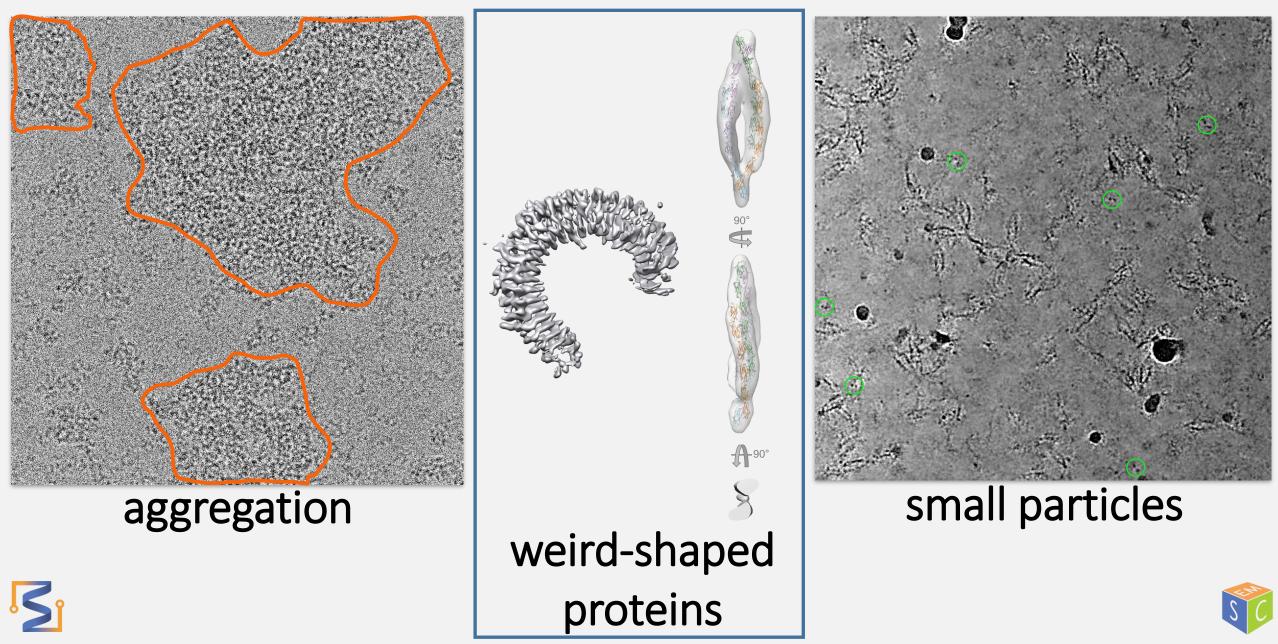






Common problems in cryoEM

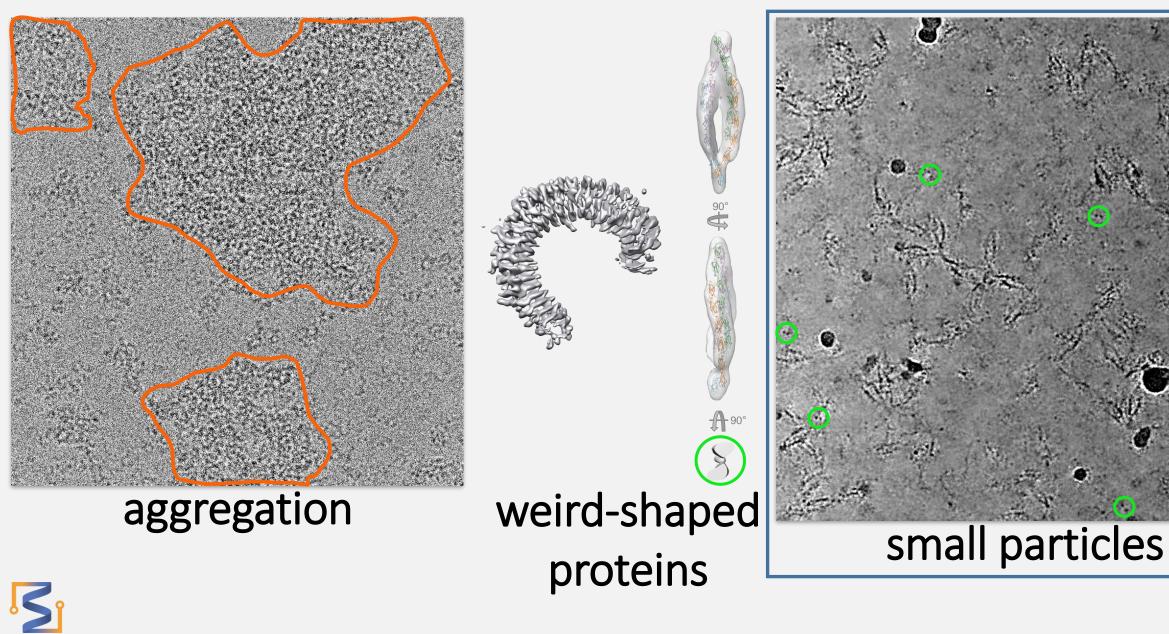






Common problems in cryoEM









Conceptual Topaz Overview

- How TOPAZ picking is beneficially different
- What problems TOPAZ solves
- Examples
- How can *denoising* help you?

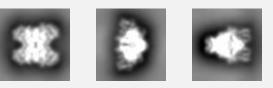






Current particle picking methods

- Historically, particle picking =
 - Template matching
 - Rotational averaging
 - Difference of Gaussians



- Newer methods use positive-negative convolutional neural networks (e.g. crYOLO, Warp, DeepPicker)
 - TOPAZ is different positive-unlabeled

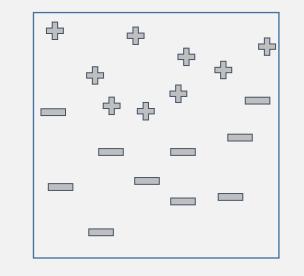


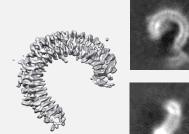


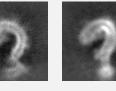


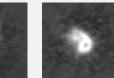
What is a *positive-unlabeled* framework?

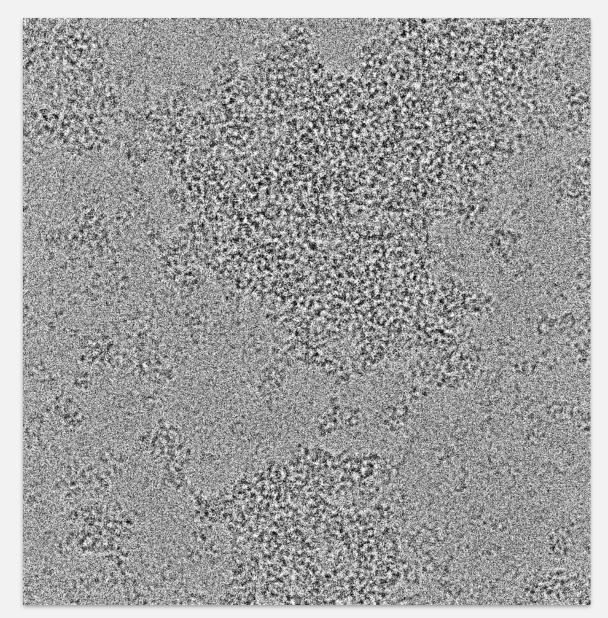










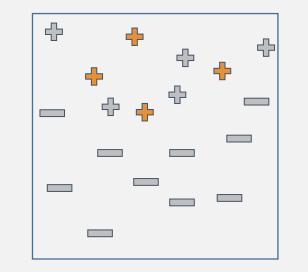


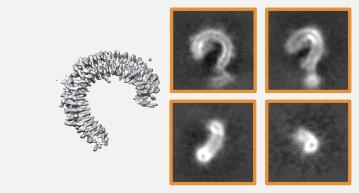


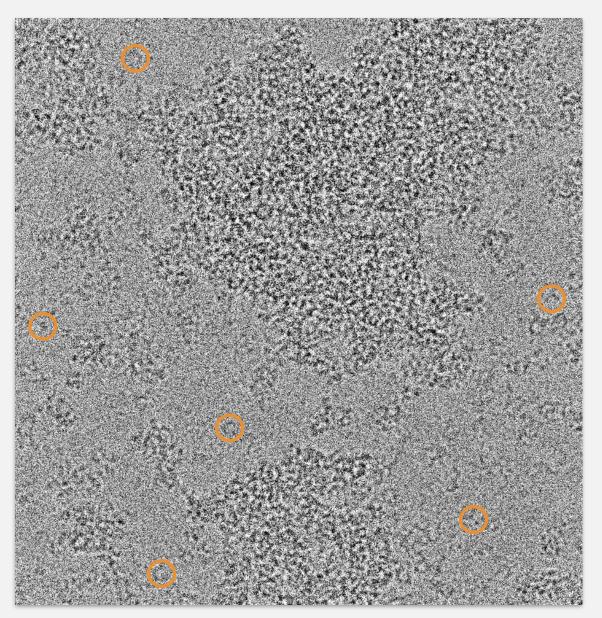


What is a *positive-unlabeled* framework?







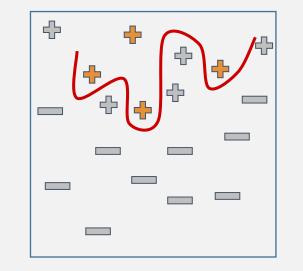


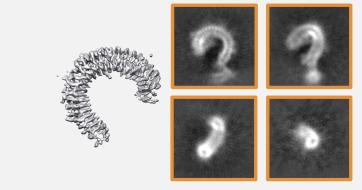


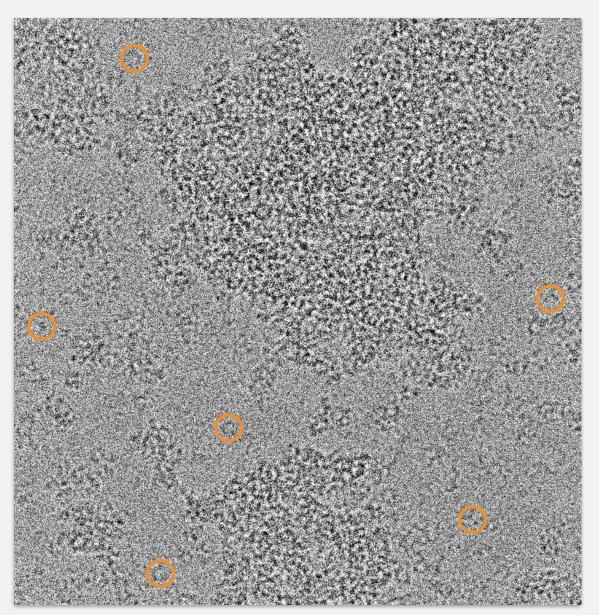


What is a *positive-unlabeled* framework?





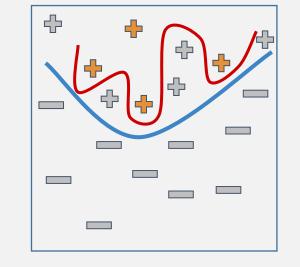


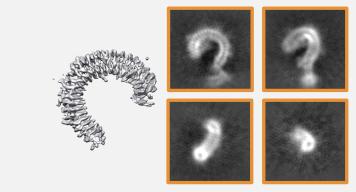


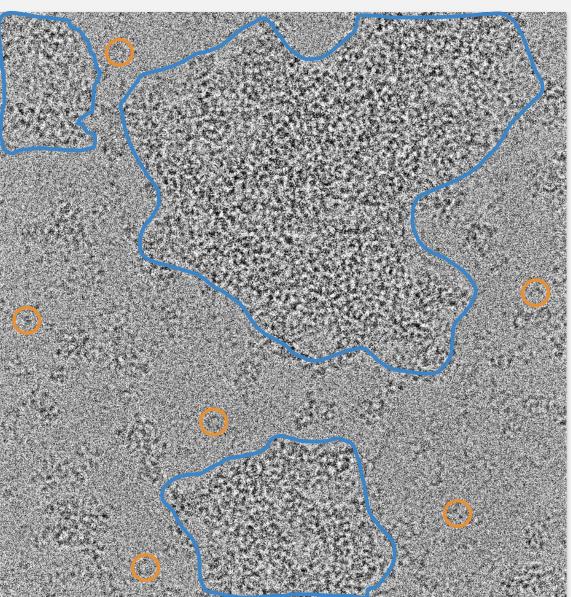
















Problems TOPAZ solves

- Assumes **sparsely labeled** training data (positive-unlabeled)
- Pick any size & shape particles
- Picks more real particles than other pickers
- Very high ratio of true positives to false positives
 - This *reduces bias* in classification filtering
- Centers particles well (surprisingly important!)









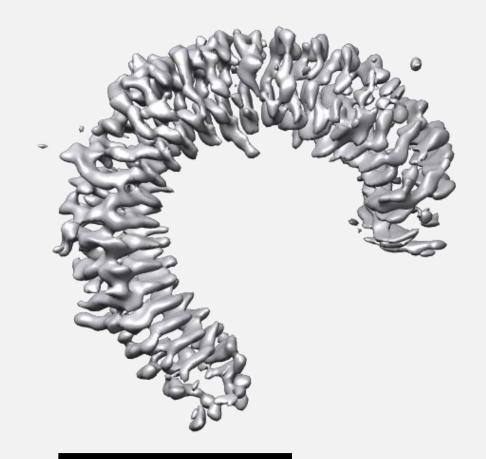
Ok great, how well does TOPAZ actually work??







- 105 kDa
- non-globular
- asymmetric
- aggregates









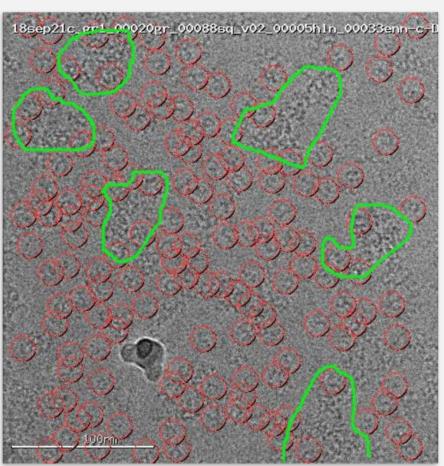


- - •

- asymmetric
- non-globular <u>aggregates</u>

	Front	Oblique	Side	Тор	Junk
Topaz	43% (435k)	20% (195k)	14% (144k)	23% (231k)	0
Template	64%	14%	14%	3%	5%
	(401k)	(86k)	(90k)	(17k)	(33k)
DoG	59%	14%	7%	6%	14%
	(456k)	(104k)	(50k)	(43k)	(118k)

105 kDa









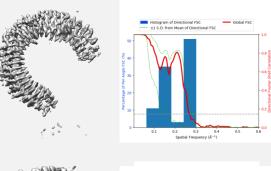


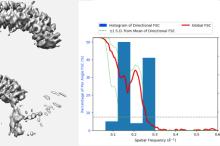
- asymmetric
- aggregates

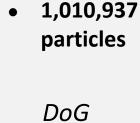
	Front	Oblique	Side	Тор	Junk
Topaz	43% (435k)	20% (195k)	14% (144k)	23% (231k)	0
Template	64%	14%	14%	3%	5%
	(401k)	(86k)	(90k)	(17k)	(33k)
DoG	59%	14%	7%	6%	14%
	(456k)	(104k)	(50k)	(43k)	(118k)

105 kDa

non-globular



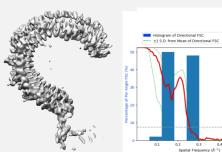




Topaz

3.70 Å

3.86 Å 770,263 particles



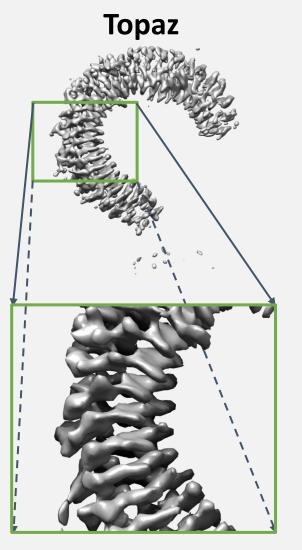
Template 3.92 Å 627,533 particles

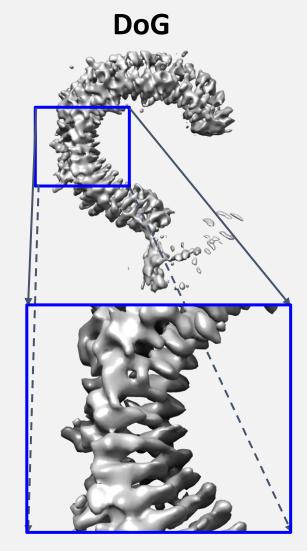












Template

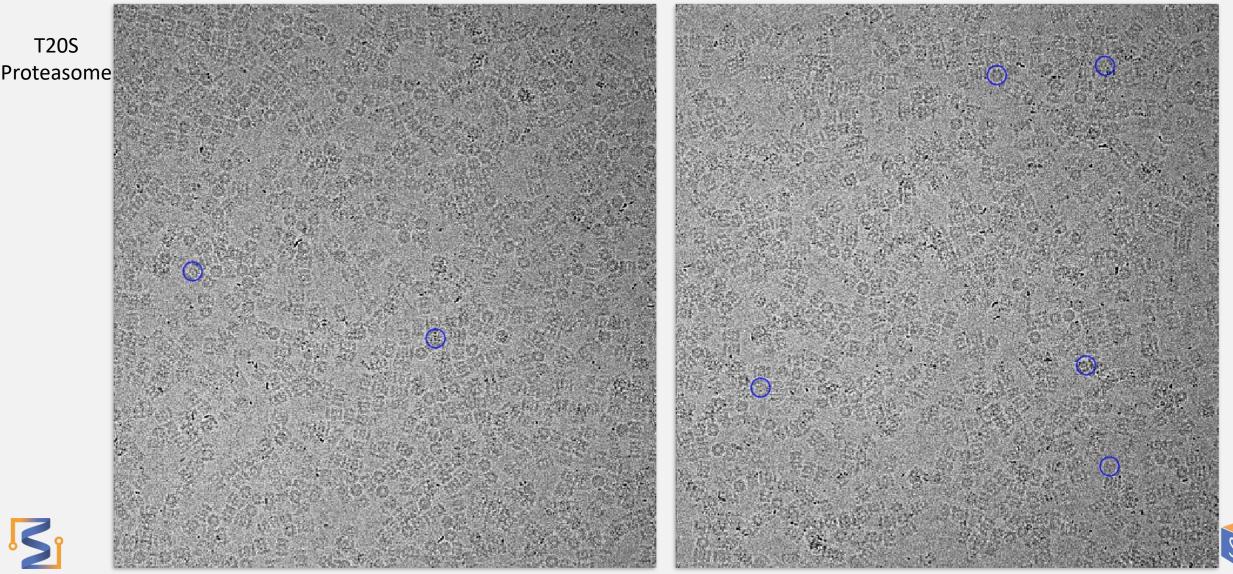
C Topaz particles *uniquely* resolve secondary structure *w/o curation*





- How sparse can we pick for training?
- Pick ~100 1,000 particles this sparsely:

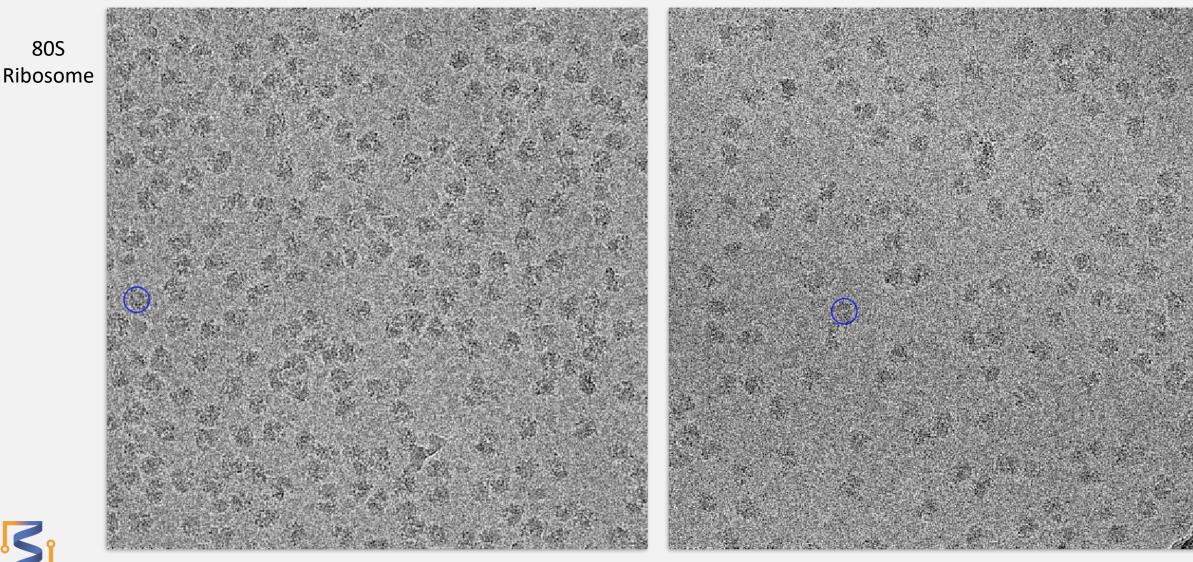
• *abeled* particles

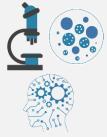




- How sparse can we pick for training?
- Pick ~100 1,000 particles this sparsely:

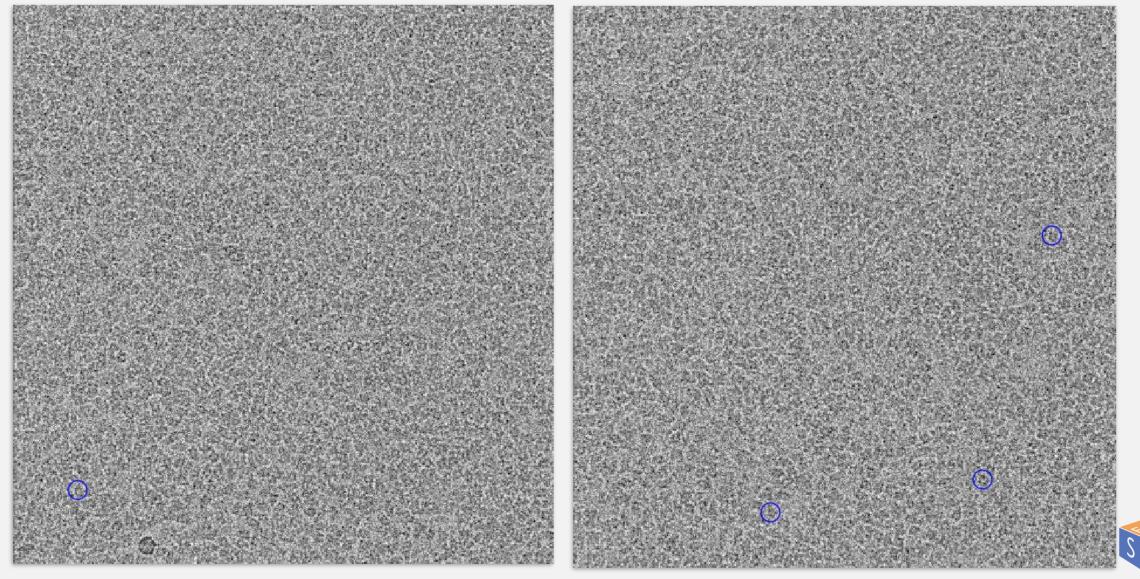
• *abeled* particles





How sparse can we pick for training? Pick ~100 – 1,000 particles this sparsely: O= labeled particles

Aldolase

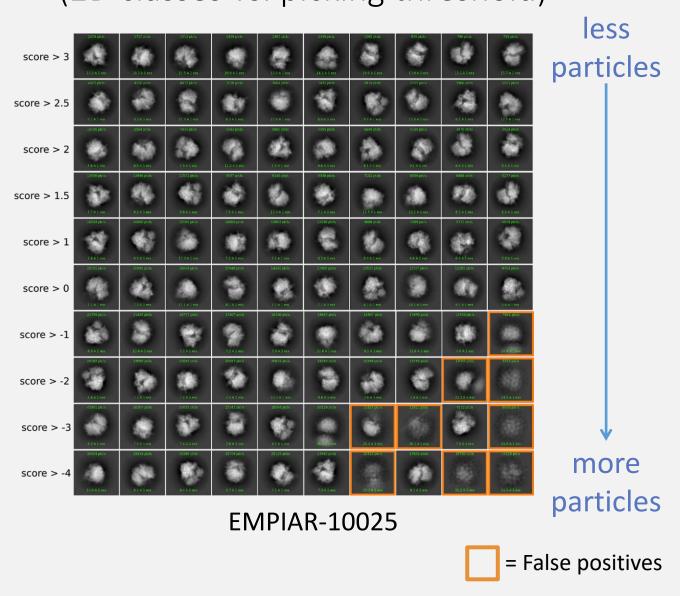






TOPAZ ranks particles well, avoids junk (2D classes vs. picking threshold)

80S Ribosome



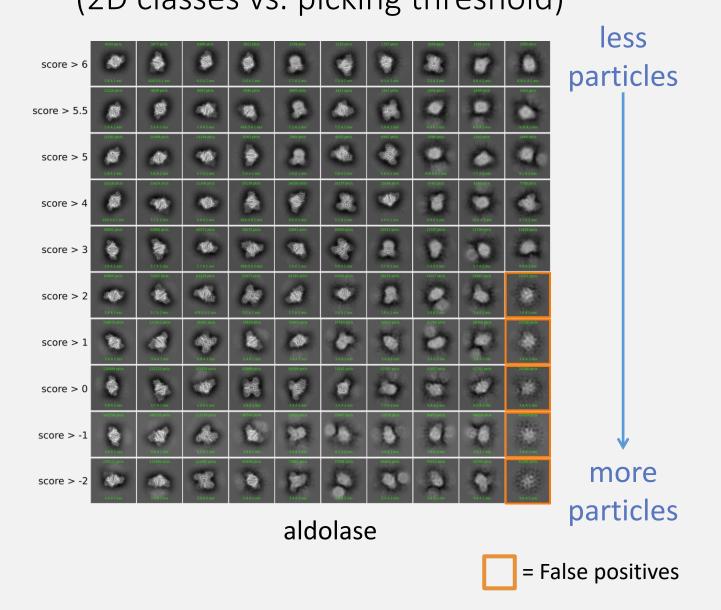






TOPAZ ranks particles well, avoids junk (2D classes vs. picking threshold)

Aldolase

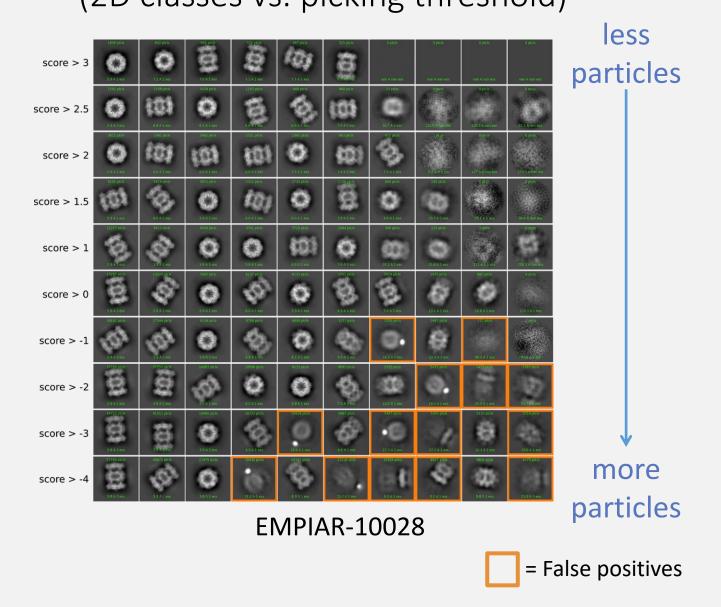






TOPAZ ranks particles well, avoids junk (2D classes vs. picking threshold)

T20S Proteasome

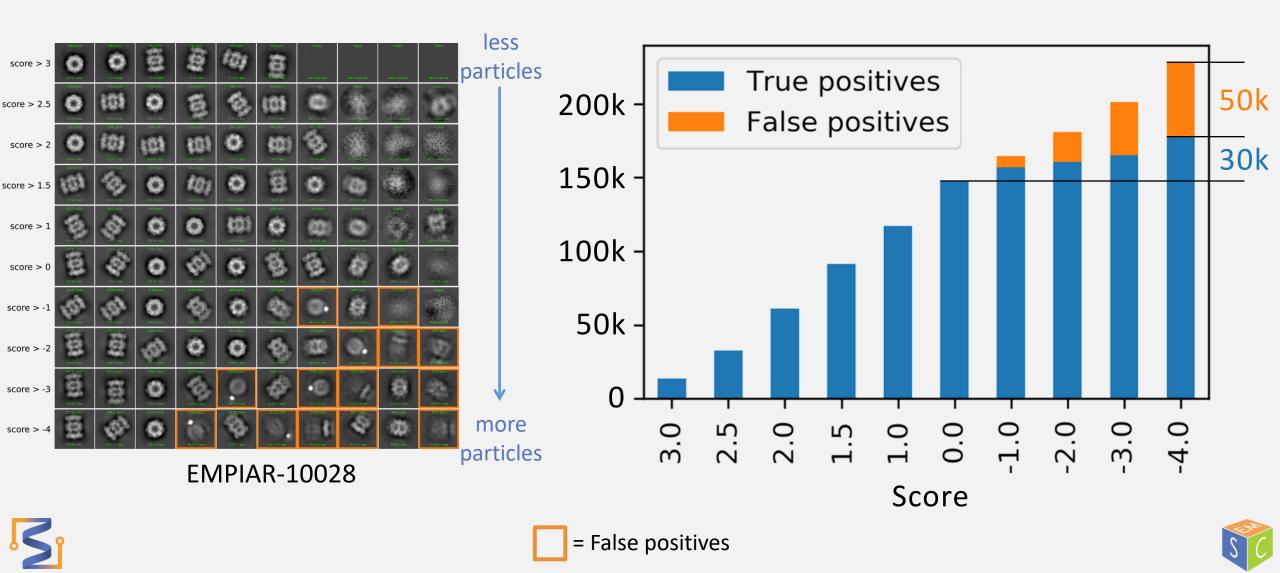






TOPAZ ranks particles well, avoids junk

(Some good particles have negative scores)









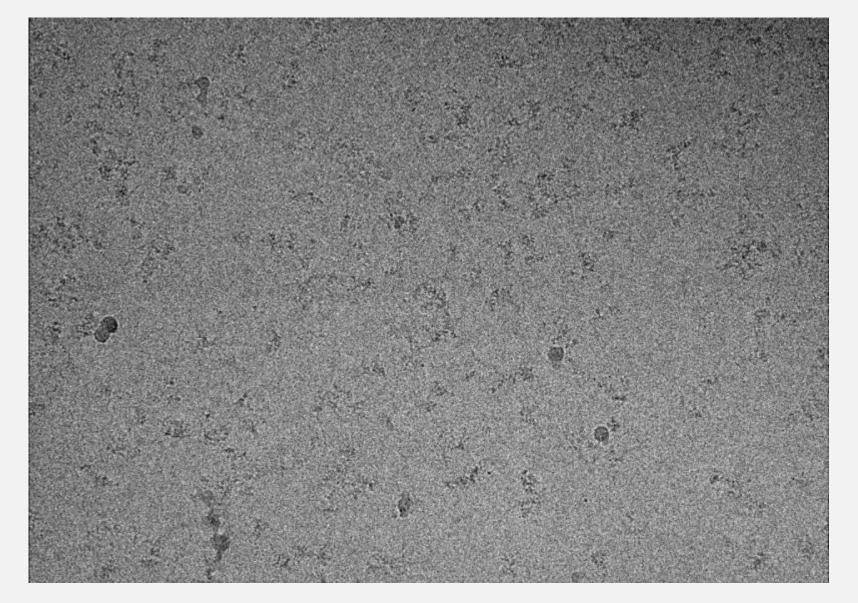
COVID-19 picking successes









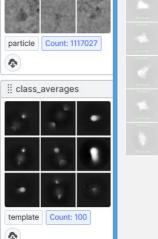




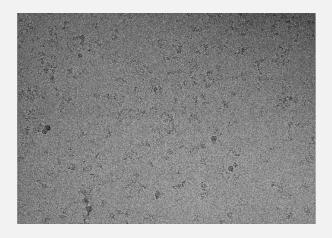


Template & blob picking 1.1m initial particles

6.7.A 1 esc 6.8.A 1 esc 6.0.A 1 esc 7.3.A 1 esc 6.7.A 1 esc 6.9.A 1 esc 7.1.A 1 esc 5.9.A 2 esc 7.4.A 3 esc 1.5071 ptcls 1.5399 ptcls 1.5348 ptcls 1.5249 ptcls 1.5107 ptcls 1.5099 ptcls 1.4997 ptcls 1.49920 ptcls 6.6.A 1 esc 9.1.A 3 esc 6.5.A 3 esc 7.0.A 2 esc 5.9.A 1 esc 7.5.A 3 esc 8.2.A 3 esc 7.2.A 2 esc 1.4431 ptcls 9.1.A 3 esc 6.5.A 3 esc 7.0.A 2 esc 6.7.A 2 esc 7.5.A 3 esc 8.2.A 3 esc 7.2.A 2 esc 1.4431 ptcls 1.4180 ptcls 1.4032 ptcls 1.4020 ptcls 1.4017 ptcls 1.4009 ptcls 1.3079 ptcls 1.3997 ptcls 1.394 ptcls 8.4.A 1 esc 8.0.A 3 esc 7.1.A 3 esc 1.00.A 3 esc 7.2.A 3 esc 3.3.6.3 esc 1.3.5.A 3 esc 1.3.5.A 3 esc	6.8 A 3 ess 3.4752 ptcls 7.7 A 3 ess 3.3765 ptcls	particle Count: 11170
6.7 A 1 ess6.6 A 1 ess0.6 A 1 ess7.3 A 1 ess6.7 A 1 ess6.9 A 1 ess7.1 A 1 ess5.9 A 2 ess7.4 A 3 ess15671 ptcls15399 ptcls15349 ptcls15349 ptcls15249 ptcls15107 ptcls15099 ptcls14997 ptcls14920 ptcls6.0 A 1 ess9.1 A 3 ess6.5 A 3 ess7.0 A 2 ess5.9 A 1 ess6.7 A 2 ess7.3 A 3 ess8.2 A 3 ess7.2 A 3 ess14431 ptcls9.1 A 3 ess6.5 A 3 ess7.0 A 2 ess5.9 A 1 ess6.7 A 2 ess7.3 A 3 ess8.2 A 3 ess7.2 A 3 ess14431 ptcls14380 ptcls14032 ptcls14026 ptcls14017 ptcls14009 ptcls13670 ptcls13562 ptcls13394 ptcls8.8 A 1 ess8.0 A 3 ess7.1 A 3 ess10.0 A 3 ess7.2 A 3 ess8.1 A 3 ess7.3 A 3 ess8.4 A 3 ess13.5 A 3 ess	6.8 A 3 ess 14752 ptcls 7.7 A 3 ess	class_averages
15671 ptcls 15399 ptcls 15348 ptcls 15249 ptcls 15167 ptcls 15111 ptcls 15099 ptcls 14997 ptcls 14920 ptcls	14752 ptds 7.7 A 3 ess	ii class_averages
6.0 A 1 ess 9.1 A 3 ess 6.5 A 3 ess 7.0 A 2 ess 5.9 A 1 ess 6.7 A 2 ess 7.3 A 3 ess 82.2 A 3 ess 7.2 A 3 ess 14431 ptclk 9.1 A 3 ess 14.3 2 ptcl s 1402 ptcl s 1401 ptcl s 1.400 ptcl s 1.362 ptcl s 1.3394 ptcl s <td>7.7 A 3 ess</td> <td>ii class_averages</td>	7.7 A 3 ess	ii class_averages
6.0 A 1 ess 9.1 A 3 ess 6.5 A 3 ess 7.0 A 2 ess 5.5 A 1 ess 6.7 A 2 ess 7.5 A 3 ess 8.2 A 3 ess 7.2 A 3 ess 14431 ptcls 14300 ptcls 14032 ptcls 14026 ptcls 14017 ptcls 14009 ptcls 13679 ptcls 13562 ptcls 13394 ptcls 8.4 A 1 ess 8.0 A 3 ess 7.1 A 3 ess 10.0 A 3 ess 7.2 A 3 ess 8.1 A 3 ess 7.5 A 3 ess 8.4 A 3 ess 11.5 A 3 ess	7.7 A 3 ess	
6.0 A 1 ess 9.1 A 3 ess 6.5 A 3 ess 7.0 A 2 ess 5.9 A 1 ess 6.7 A 2 ess 7.5 A 3 ess 82.A 3 ess 7.2 A 3 ess 1 4431 ptcls 1 4380 ptcls 1 4020 ptcls 1 4017 ptcls 1 4009 ptcls 1 3607 ptcls 1 3567 ptcls 1 3394 ptcls 8.4 A 1 etss 8.0 A 3 ess 7.1 A 3 ess 1 0.0 A 3 ess 7.2 A 3 ess 6.1 A 3 ess 7.3 A 3 ess 1 3.5 A		
B.4 Å 1 ess B.0 Å 3 ess 7.1 Å 3 ess 20.0 Å 3 ess 7.2 Å 3 ess 8.1 Å 3 ess 7.5 Å 3 ess 8.4 Å 3 ess 13.5 Å 3 ess	33265 ptels	
B.4 A 1 ess B.0 A 3 ess 7.1 A 3 ess 10.0 A 3 ess 7.2 A 3 ess 8.1 A 3 ess 7.5 A 3 ess 8.4 A 3 ess 11.5 A 3 ess		
B.4 A 1 ess B.0 A 3 ess 7.1 A 3 ess 10.0 A 3 ess 7.2 A 3 ess 8.1 A 3 ess 7.5 A 3 ess 8.4 A 3 ess 11.5 A 3 ess		
	6.5 A 1 ess	
13061 ptcls 12993 ptcls 12418 ptcls 12113 ptcls 11557 ptcls 11482 ptcls 11370 ptcls 11174 ptcls	10975 ptcls	template Count: 100
7.1 A 3 ess 7.5 A 3 ess 7.4 A 3 ess 8.2 A 3 ess 7.8 A 2 ess 7.1 A 3 ess 8.2 A 3 ess 7.8 A 1 ess 7.2 A 3 ess 10912 ptc/s 10768 ptc/s 10768 ptc/s 10086 ptc/s 19081 ptc/s 10055 ptc/s 9838 ptc/s 9835 ptc/s 9730 ptc/s	6.2 A 1 ess 9671 ptcls	
1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1	
7.9 A 1 css 7.2 A 3 css 8.0 A 3 css 6.5 A 1 css 7.2 A 2 css 6.8 A 2 css 9.5 A 1 css 6.7 A 1 css 7.5 A 2 css	6.7 A 1 ess	
9657 ptcls 9178 ptcls B877 ptcls 8743 ptcls 8675 ptcls 8538 ptcls 8404 ptcls 8403 ptcls 8398 ptcls	8351 ptcls	
1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1		
62A2 css 72A3 css 59A2 css 59A1 css 7.6A3 css 6.0A3 css 7.4A2 css 6.1A3 css 8.0A2 css	5.9 A 2 ess	
8331 ptris 8325 ptris 8323 ptris 8235 ptris 8210 ptris 8201 ptris 8111 ptris 8032 ptris 8028 ptris	7918 ptcls	
🗶 - 100 100 100 100 100 100 100 100 100 1	Sie	
7.3 A 2 ess 7.7 A 3 ess 5.9 A 3 ess 7.1 A 2 ess 5.9 A 1 ess 7.4 A 1 ess 5.9 A 3 ess 6.9 A 1 ess 6.3 A 3 ess	7.6 A 3 ess	













Template & blob picking 1.1m initial particles

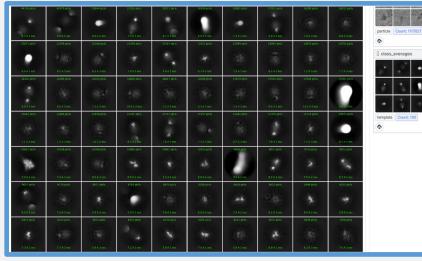
44158 ptcls	41879 ptcls	25644 ptcls	22318 ptcls	18371 ptcls	18309 ptcls	18082 ptcls	17971 ptcls	16190 pttls	16012 ptcls										-	
				•				6.80	100											
6.7 A 1 ess	6.8 A 1 ess	6.6 A 1 ess	73A1ess	6.7 A 1 ess	6.9 A 1 ess	7.1 A 1 ess	5.9 A 2 ess	7.4 A 3 ess	6.8 A 3 ess	particle Count: 1117027										
15671 ptcls	15399 ptcls	15348 ptcls	15249 ptcls	15167 ptcls	15111 ptcls	15099 ptcls	14997 ptcls	14920 ptcls	14752 ptcls	•									-	8. 6. 8.
	A Second	1.00	4			1057	35	190	-55	ii class_averages										
	Coldina -				140	45		1												
6.0 A 1 ess 14431 ptcls	9.1 A 3 ess 14380 ptcls	6.5 A 3 ess 14032 ptcls	7.0 A 2 ess 14026 ptcls	5.9 A 1 ess 14017 ptcls	6.7 A 2 ess 14009 ptcls	7.5 A 3 ess 13679 ptcls	8.2 A 3 ess 13562 ptcls	7.2 A 3 ess 13394 ptcls	7.7 A 3 ess 13265 ptcls											
	and the second	and the second s		Sec. 200	Acres .	1 martine	14			1 1 1									11744 m	
1.1	Sec.	SEA	18	1987	36	-34	1	18 C												
8.4 A 1 ess	8.0 A 3 ess	7.1 A 3 ess	10.0 A 3 ess	7.2 A 3 ess	8.1 A 3 ess	7.5 A 3 ess	8.4 A 3 ess	13.5 A 3 ess	6.5 A 1 855	• •										_
13061 ptcls	12993 ptcls	12418 ptcls	12141 ptcls	12113 ptcls	11557 ptcls	11482 ptcls	11370 ptcls	11174 ptcls	10975 ptcls	template Count: 100	π	r/2			30	3				
1996	-10:				1989 an		1	*		•						<u> </u>	26			
7.1 A 3 ess	7.5 A 3 ess	7.4 A 3 ess	8.2 A 7 ess	7.8 A 2 ess	7.1 A 3 ess	5.2 A 3 ess	7.8 A 1 ess	7.2 A 3 ess	6.2 A 1 ess		۳ د	74	1.1					5 7		- 10 ¹ S
10912 ptcis	10768 ptcls	10280 ptcls	10086 ptcls	10081.ptcls	10055 ptcls	9888 ptcls	9857 ptcls	9710 ptcls	9671 ptcls		Elevation	o 🛃			-	\$				# of images
494	1000	Sing	~		di.				10		Elev	至		-		<	52			# of
100		The second		1 Page 1							$-\pi$:/4 🎦	2.	4		2.2	1			
7.9 A 1 ess 9657 ptcls	7.2 A 3 ess 9178 ptcls	8.0 A 3 css B877 ptcls	6.5 A 1 ess 8743 ptcls	7.2 A 2 ess 8675 ptcls	6.8 A 2 ess 8538 ptcls	9.5 A L ess 8404 ptcls	6.7 A 1 ess 8403 ptcls	7.5 A 2 ess 8398 ptcls	6.7 A 1 ess 8351 ptcls				(?							
	100	100	100	100	1.1		and the		100		-π	$-\pi$		$-\pi/2$ -		π/4	π/2	$2 3\pi/$	4 π	100
	1997	*		1997			1.20	*							Azim	uth		• 1		
6.2 A 2 ess	7.2 A 3 ess	5.9 A 2 ess	5.9 A 1 ess	7.6 A 3 ess	6.0 A 3 ess	7.4 A 2 ess	61A3 ess	8.0 A 2 ess	5.9 A 2 ess				1.	3k f	ina	l pa	art	ICle	es	
8351 ptcls	8325 ptcls	6323 ptcls	8255 ptcls	8210 ptcls	8201 ptcls	B111 ptcls	8032 ptcls	6028 ptcis	7918 ptcls							•				
5	- 1980 - 1980			*	70	R.C.	*	- 302.	Site.											NCCAT
7.3 A 2 ess	7.7 A 3 ess	5.9 A 3 ess	7.1 A 2 ess	5.9 A 1 ess	7.4 A 1 ess	5.9 A 3 ess	6.8 A 1 ess	6.3 A 3 ess	7.6 A 3 ess											
																				- Com

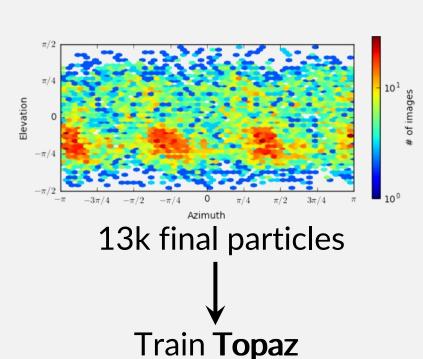






Template & blob picking 1.1m initial particles





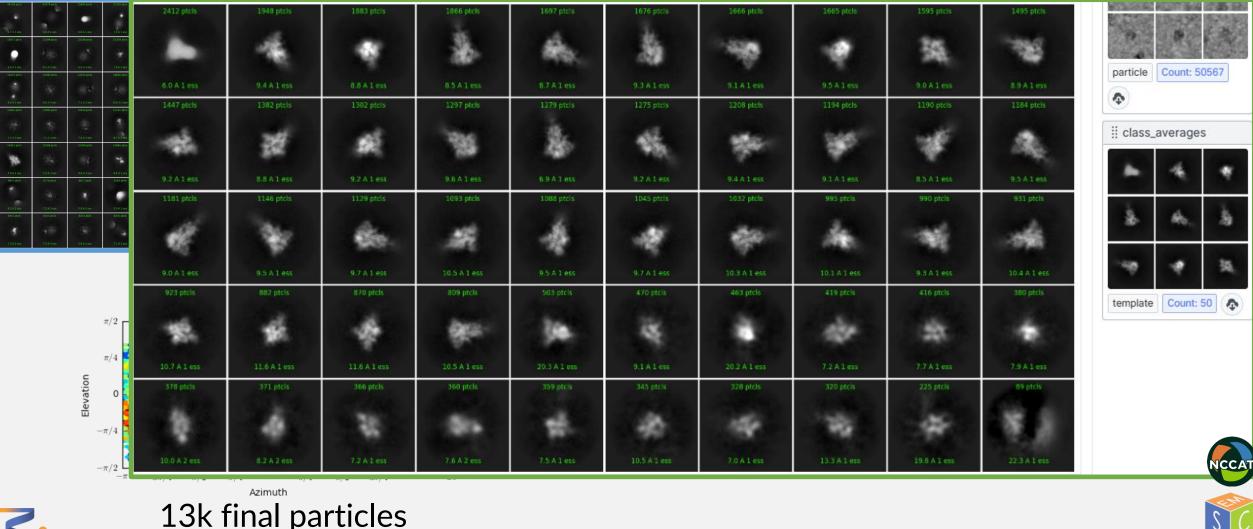






Template & blob picking 1.1m initial particles

Topaz picking 50k initial particles

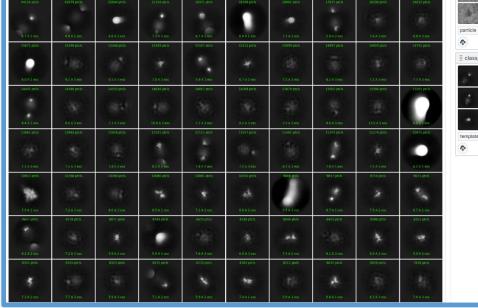


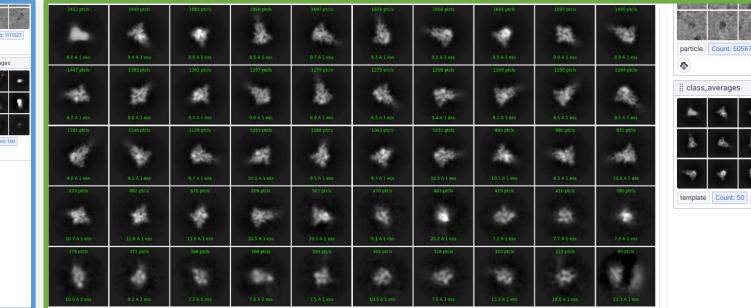


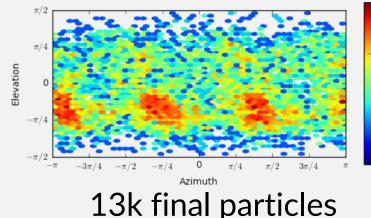


Template & blob picking 1.1m initial particles

Topaz picking 50k initial particles

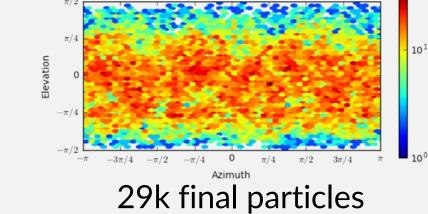


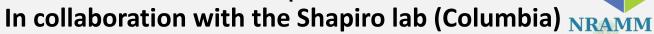




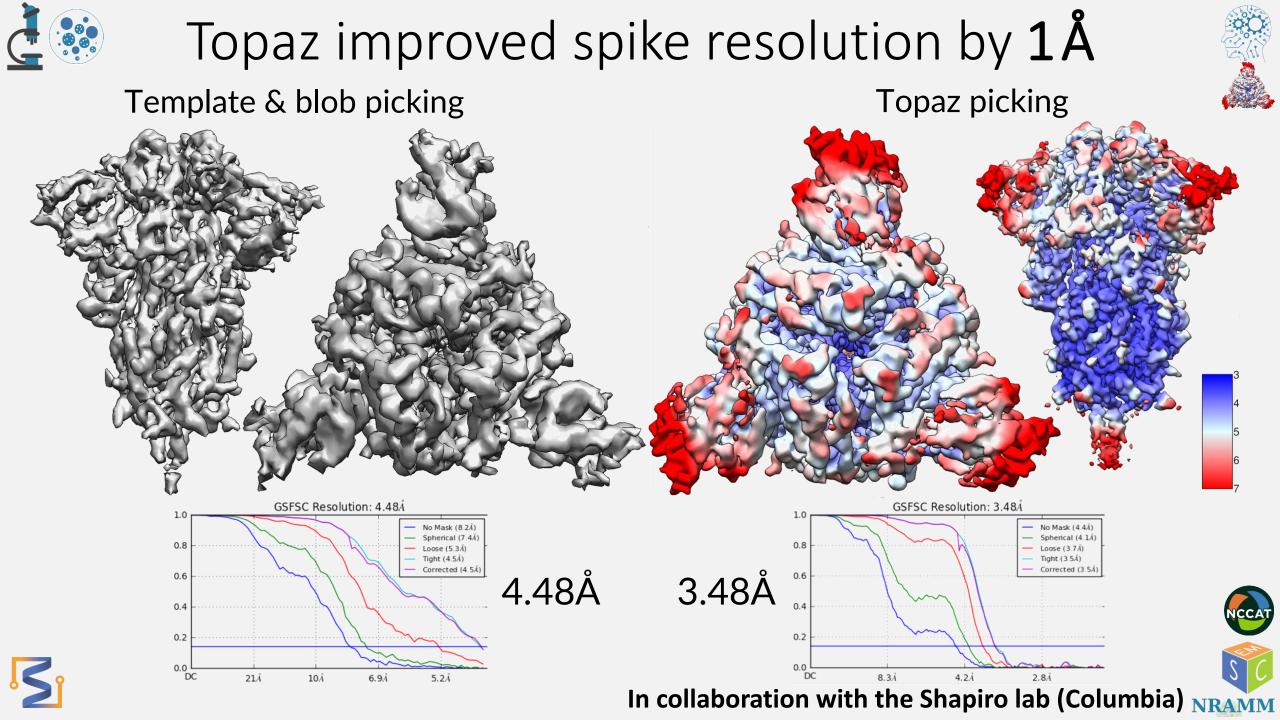
10¹

image









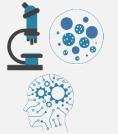




Can we optimize this workflow further?







It all depends on training particles

First workflow

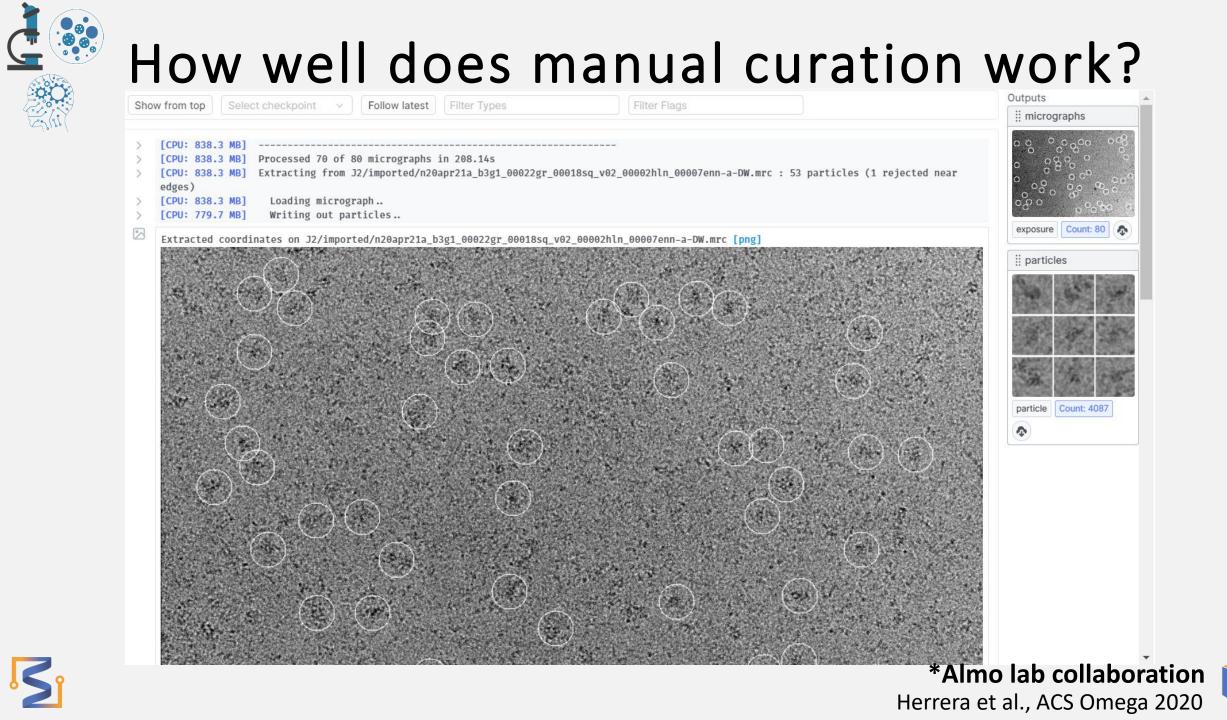
Blob/template pick >> classify >> train Topaz

Better workflow?

Manually curate picks >> classify >> train Topaz

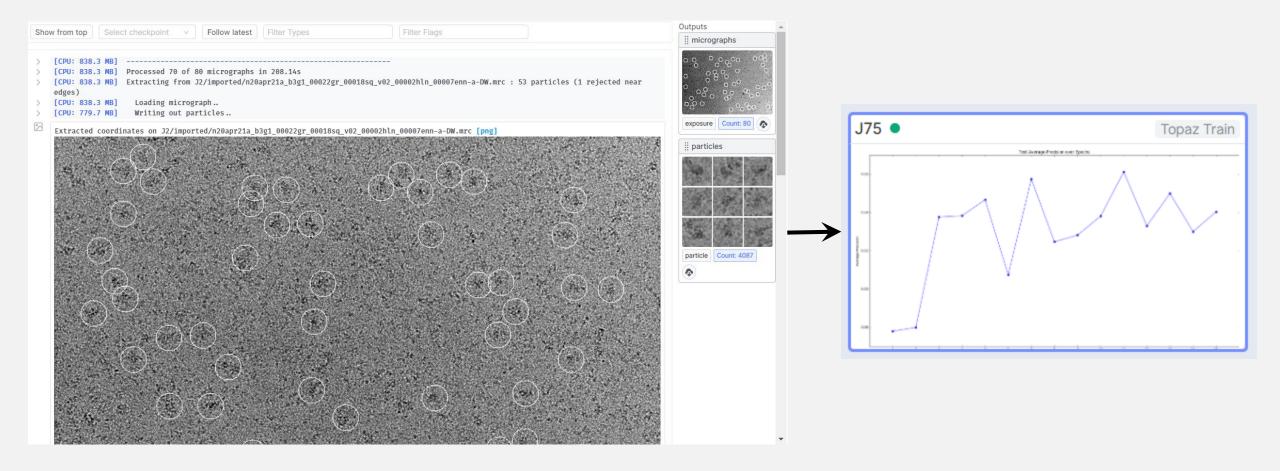








How well does manual curation work?







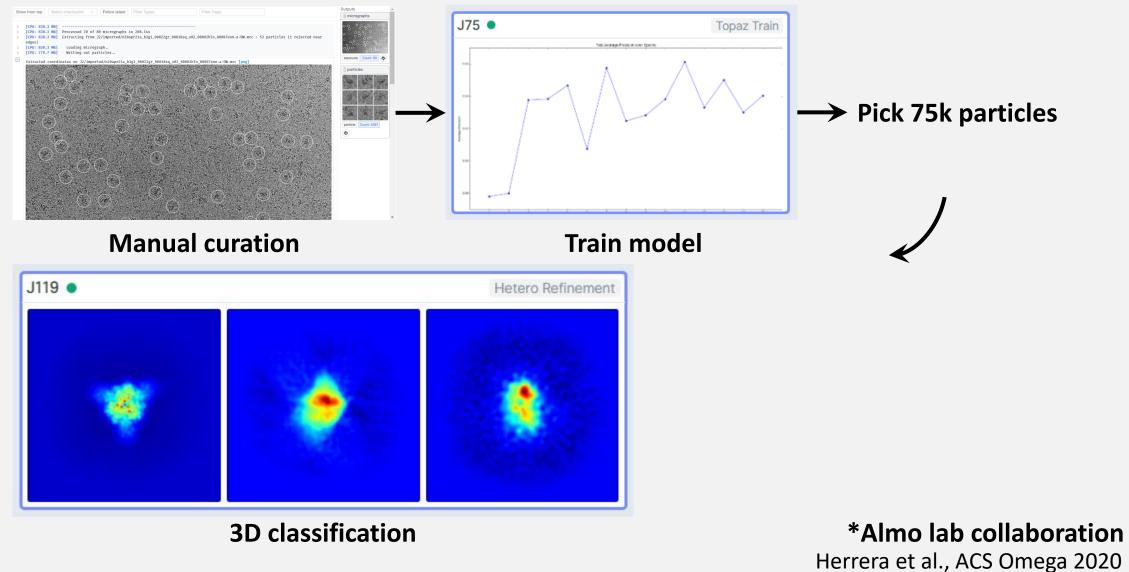




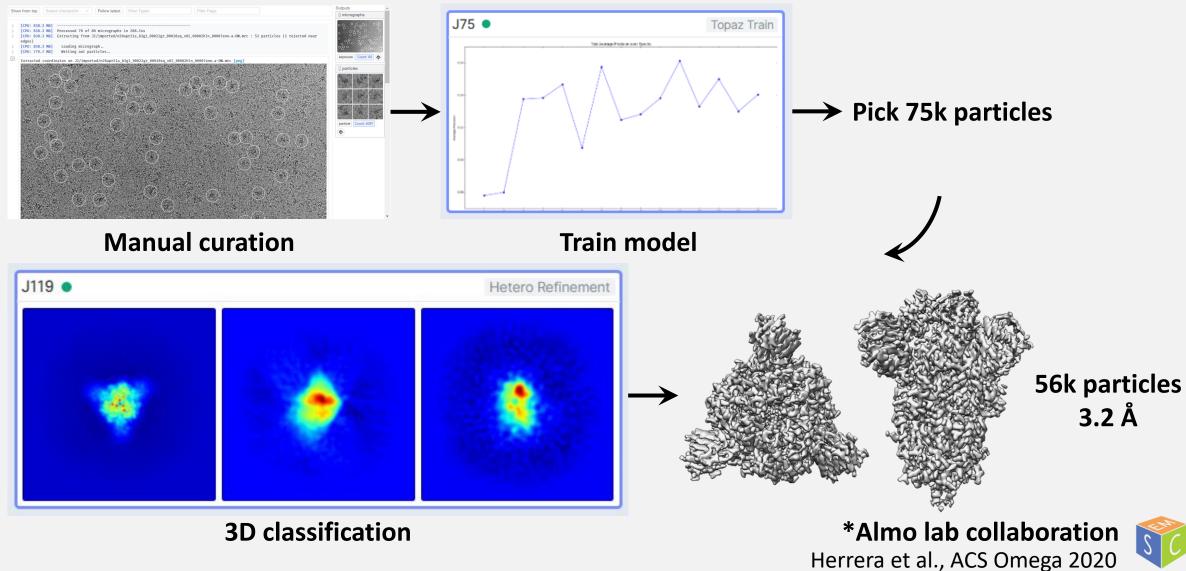


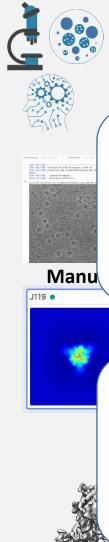






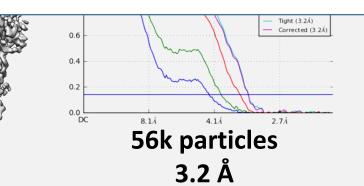




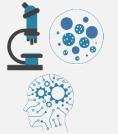


75% of particles used (manual curation) versus 60% (no manual curation)

Whole workflow completed within ~48 hours of data collection







It all depends on training particles

First workflow

Blob/template pick >> classify >> train Topaz

Better workflow \checkmark

Manually curate picks >> classify >> train Topaz









Some Topaz use examples in the literature

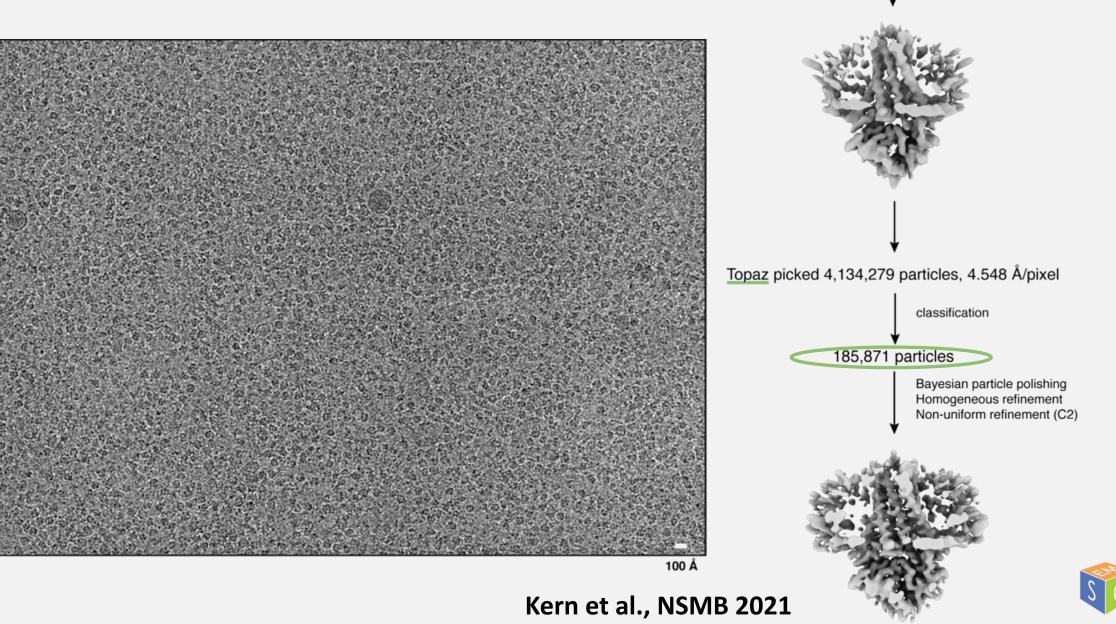






C

SARS-CoV-2 in nanodisc



Template picked 1,750,730 initial particles, 86,479 final particles



SARS-CoV-2 in nanodisc

For Topaz input round #1: For Topaz input round #2: 44,944 training particles from 61,531 training particles from partial dataset processing using topaz pick processing round #1 manual template picking Topaz round #1 (1,707,274), Box 256 px, 2.908 Å/px Topaz round #2 (2,245,142), Box 256 px, 1.454 Å/px 61,531 particles 68,008 particles Non-uniform refinement Initial lowpass resolution 6 Å Mask near 6 Å , Far 14 Å C2 symmetry Reference from previous NU 2.26 Å 2.33 Å Merged particles from round 1 and 2 Removed Duplicates at 100 Å distance 91,799 particles, 300 px box 0.727 Å/px (Re-Extracted) 2.08 Å

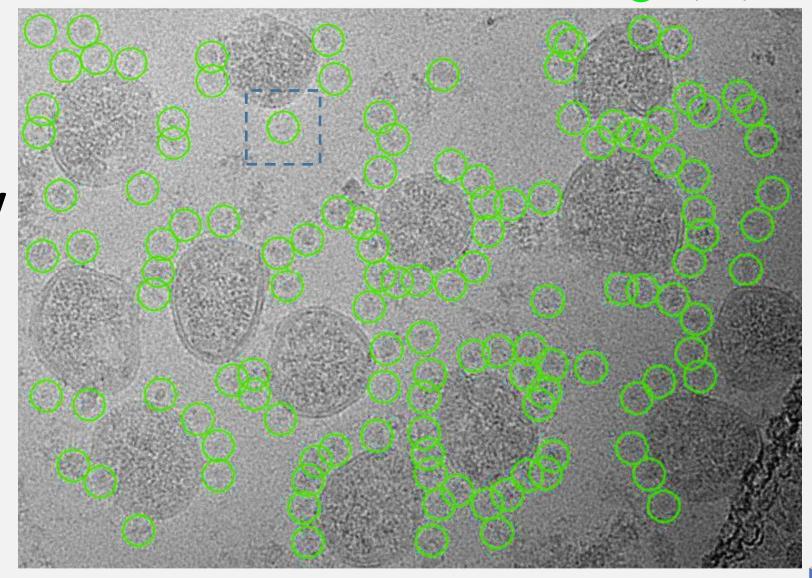






SARS-CoV-2 on virions

After manually curating 100 micrographs:





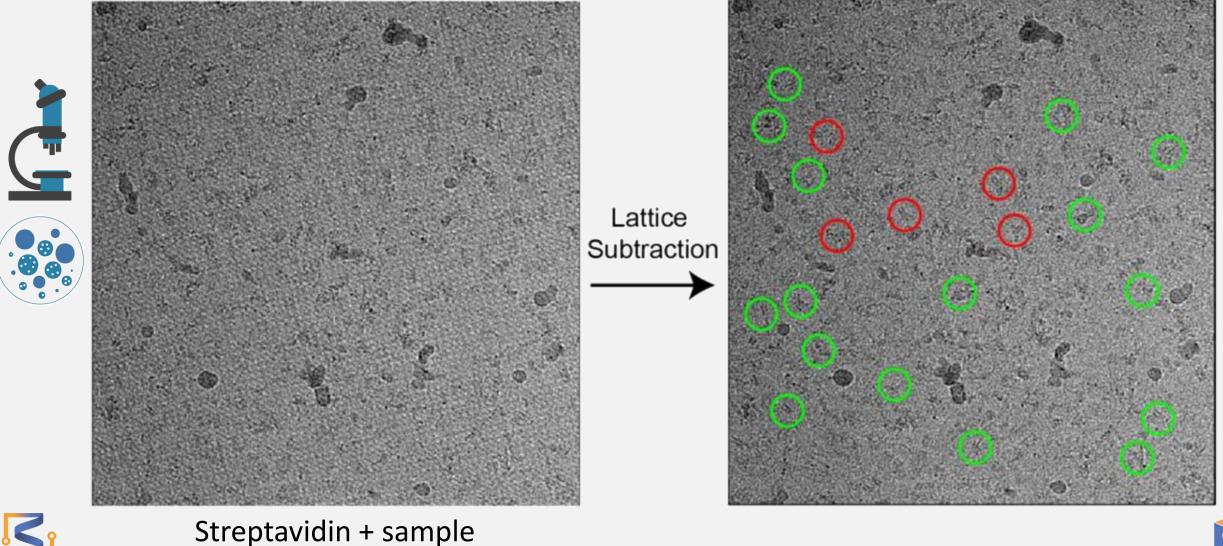


Topaz picks



Polycomb complex

Manual picks Additional Topaz picks





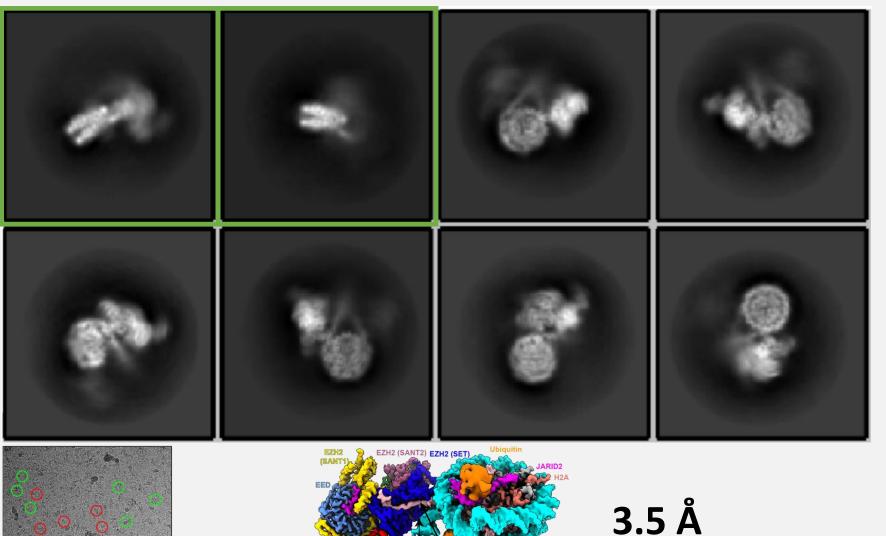
Kasinath et al., Science 2021





Polycomb complex

After trying Relion picking, **EMAN** neural picking, and Topaz, only **Topaz picked** these views well

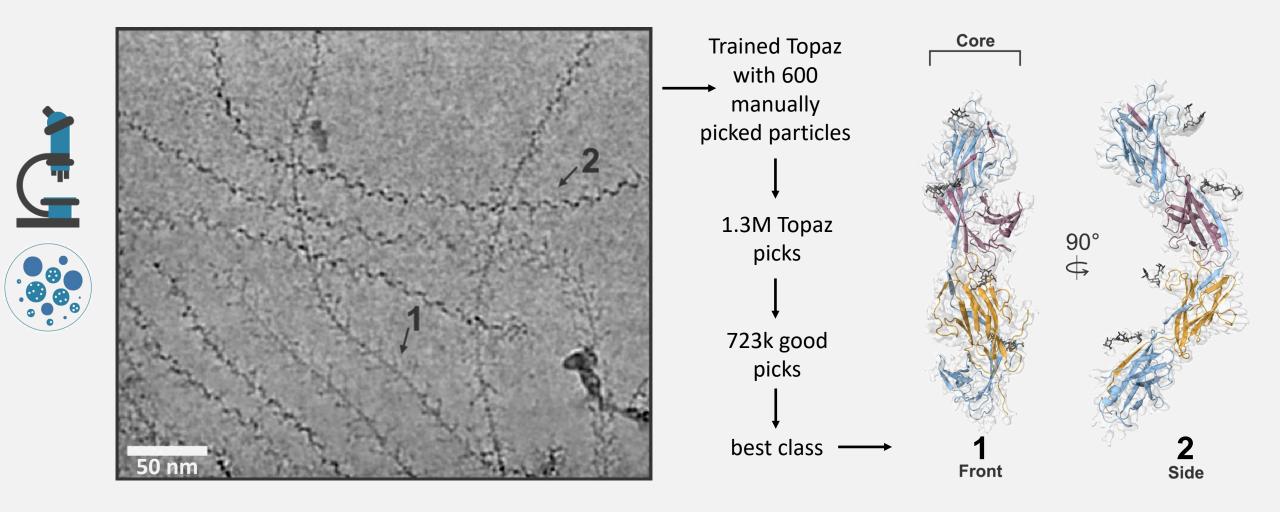








Uromodulin filament core







Interphotoreceptor retinoid-binding protein

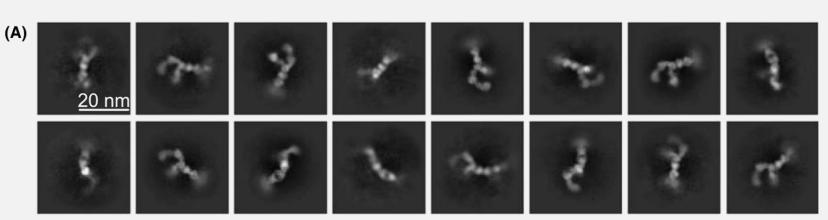


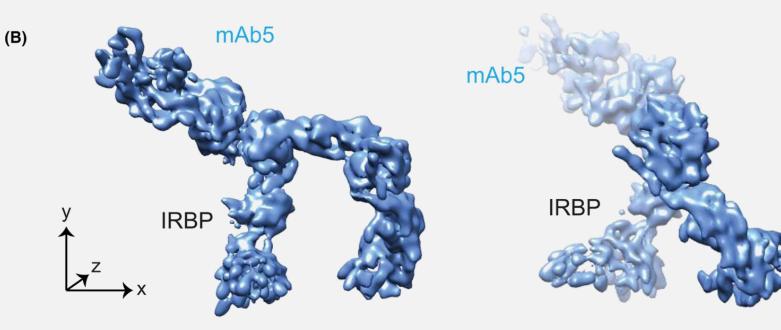
particles using templates

Picked 109k

2D/3D curation down to 17k particles

Trained Topaz to pick the best —— 13k particles







Sears et al., FASEB 2020

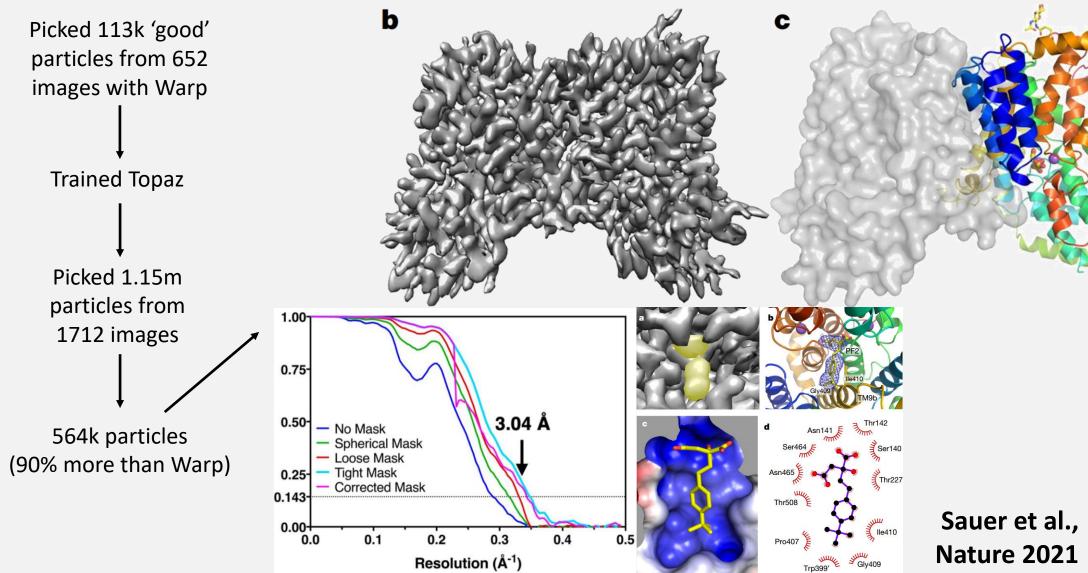


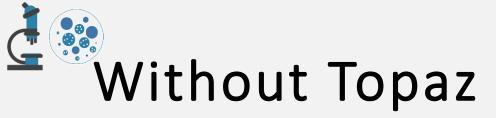


Human citrate transporter from 20° tilted images









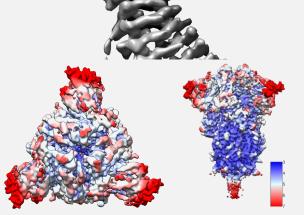
More particles

Higher resolution

Better angular distribution

Better classification

With Topaz









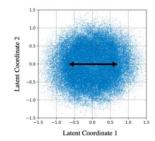


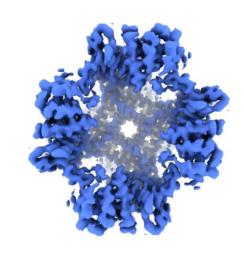
More particles = better flexibility analysis

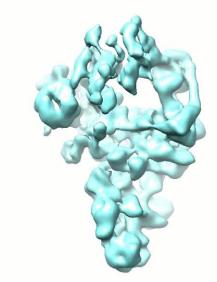
3D Flexible Refinement

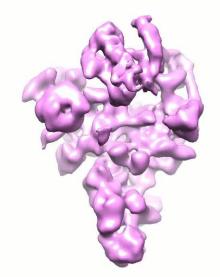
TRPV1 Ion Channel EMPIAR-10059

Latent coordinate 1











CryoSPARC 3DFlex

EMAN2













Next: Neural network Denoising







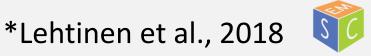
Topaz-Denoise



Noise2Noise* models trained on dozens of cryoEM datasets

- Train your own denoising model
- **Directly visualize difficult proteins** with confidence

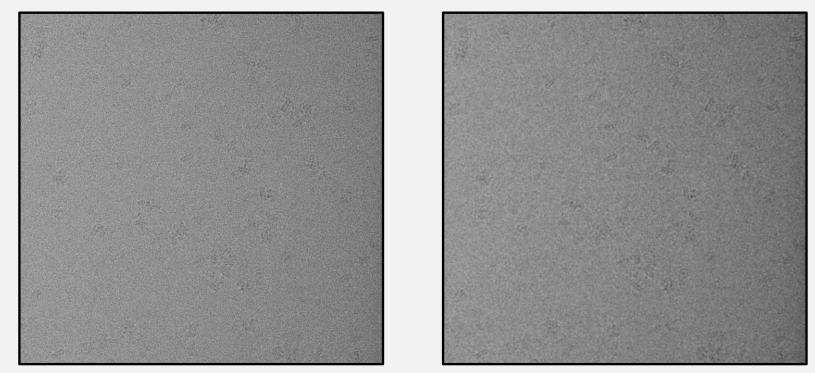






How does Noise2Noise work?





*same field of view



Noisy image 1

Noisy image 2

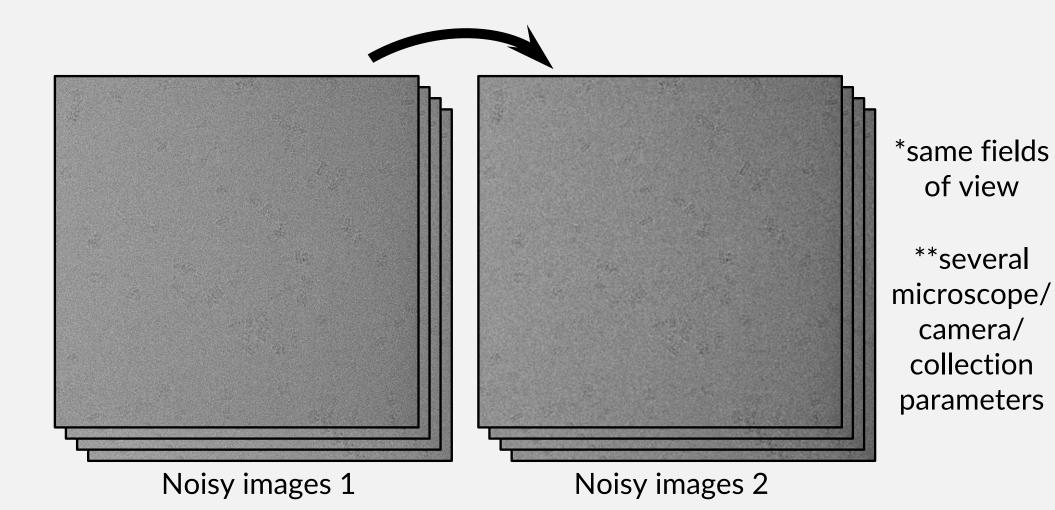








How does Noise2Noise work?



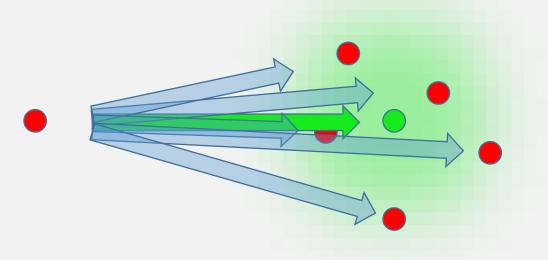








How does Noise2Noise work?

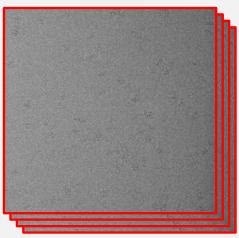






Unseen

Noisy image



Noisy images



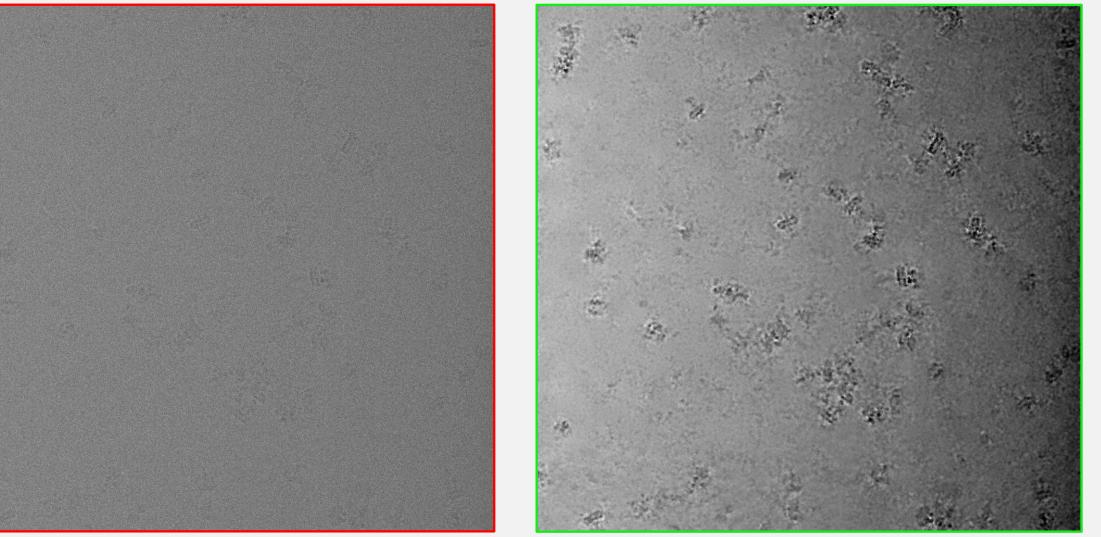








How well does the Topaz Denoise pre-trained model work?





Raw, noisy image

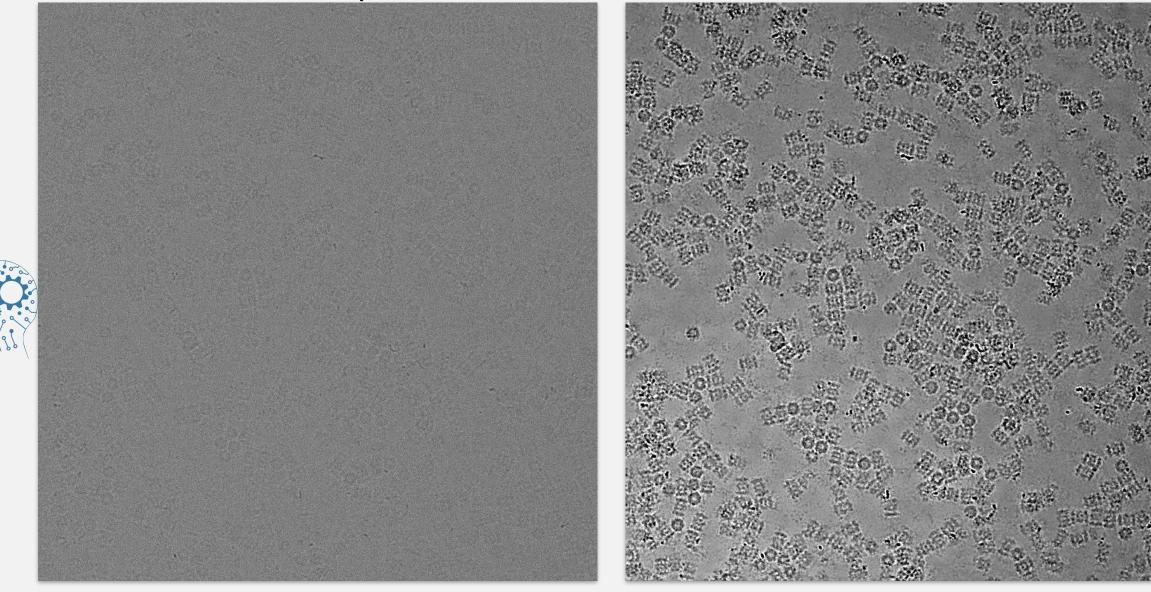
Protein in nanodisc



Denoised



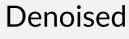
How well does the Topaz Denoise pre-trained model work?







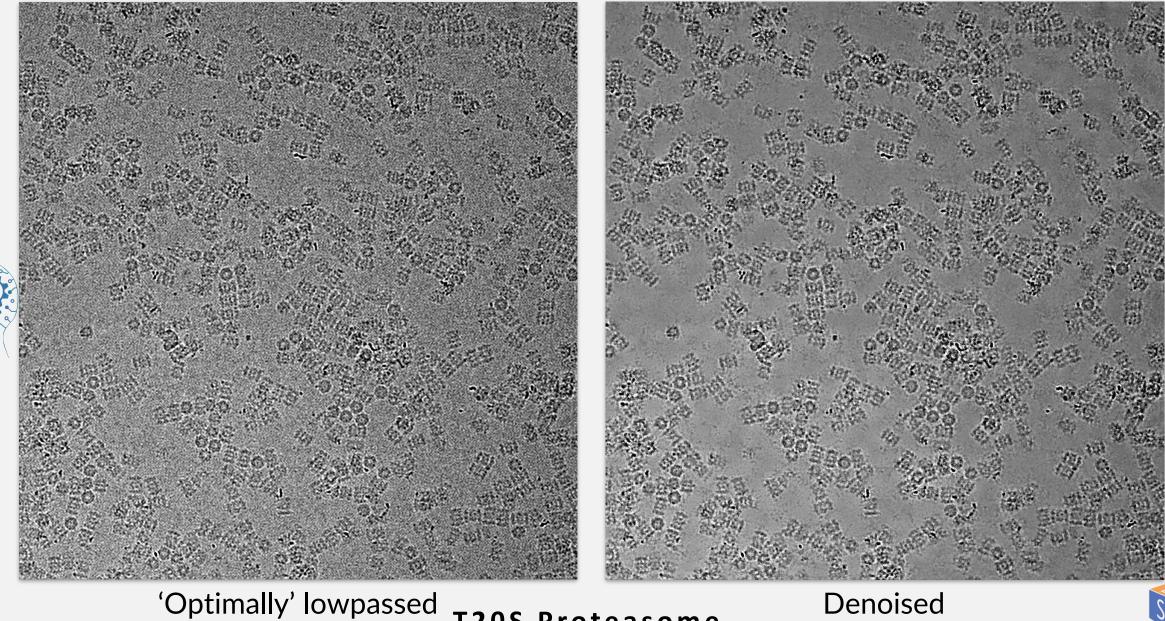
T20S Proteasome







How well does the Topaz Denoise pre-trained model work?

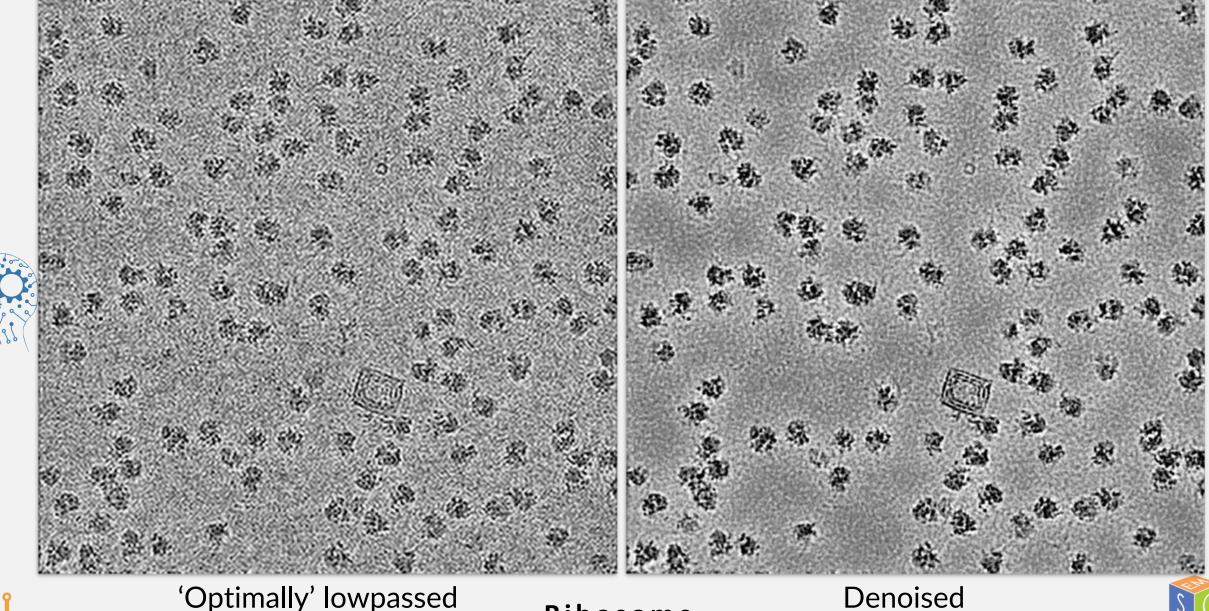


T20S Proteasome





How well does the Topaz Denoise pre-trained model work?



'Optimally' lowpassed

Ribosome



Ok, that's a nice Anti-Squinting Device

•••

But is it useful?

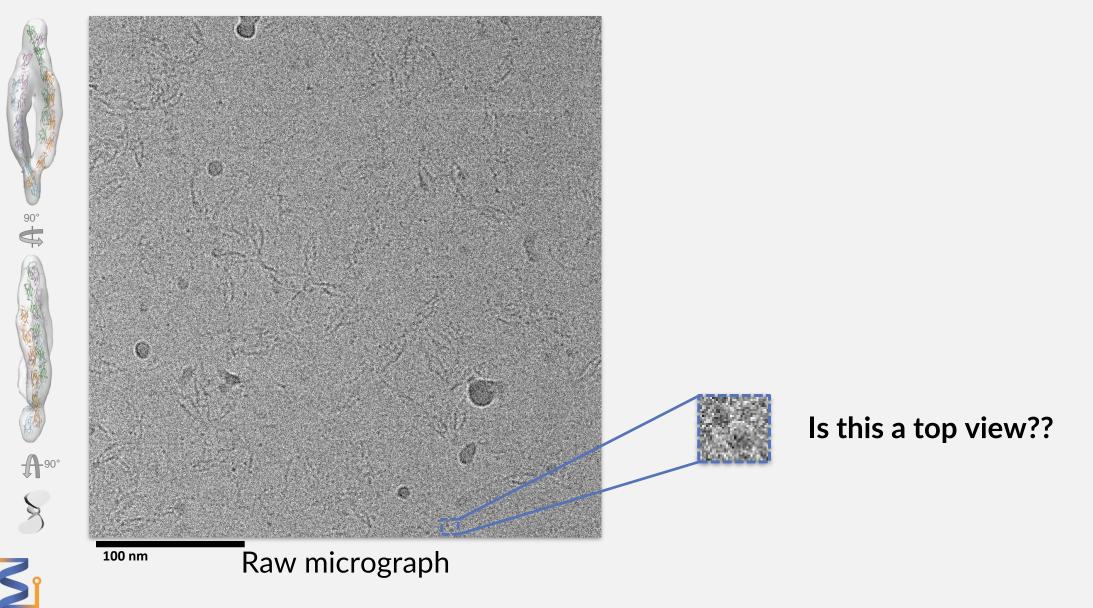






Can we identify small particle views?



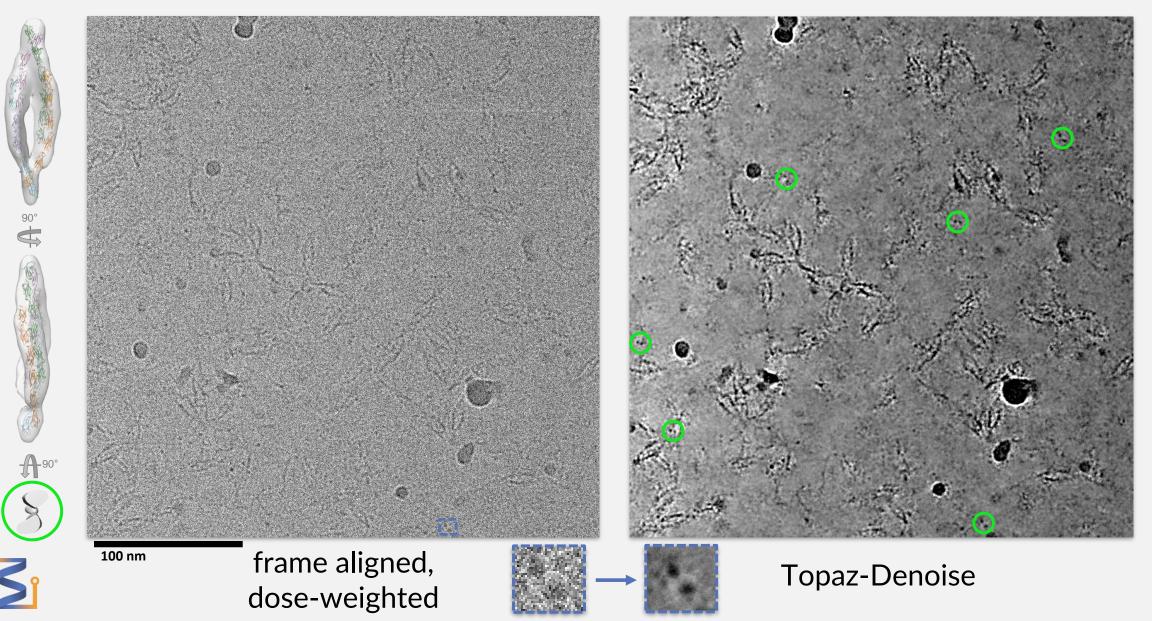


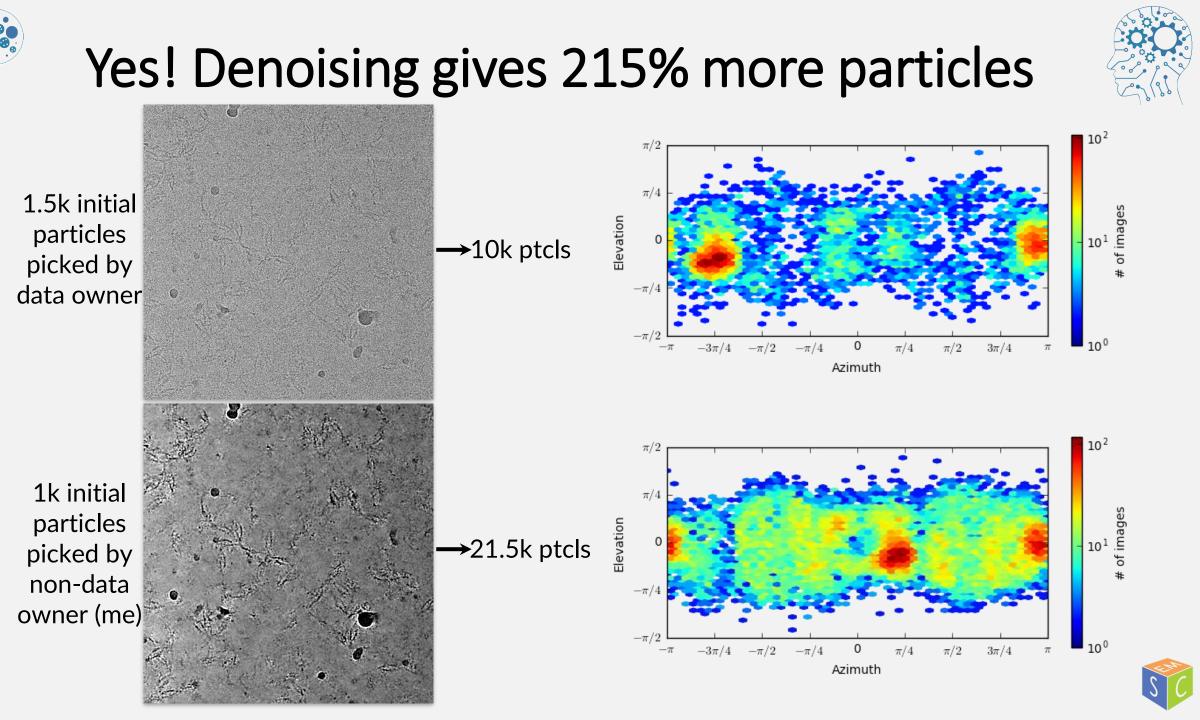


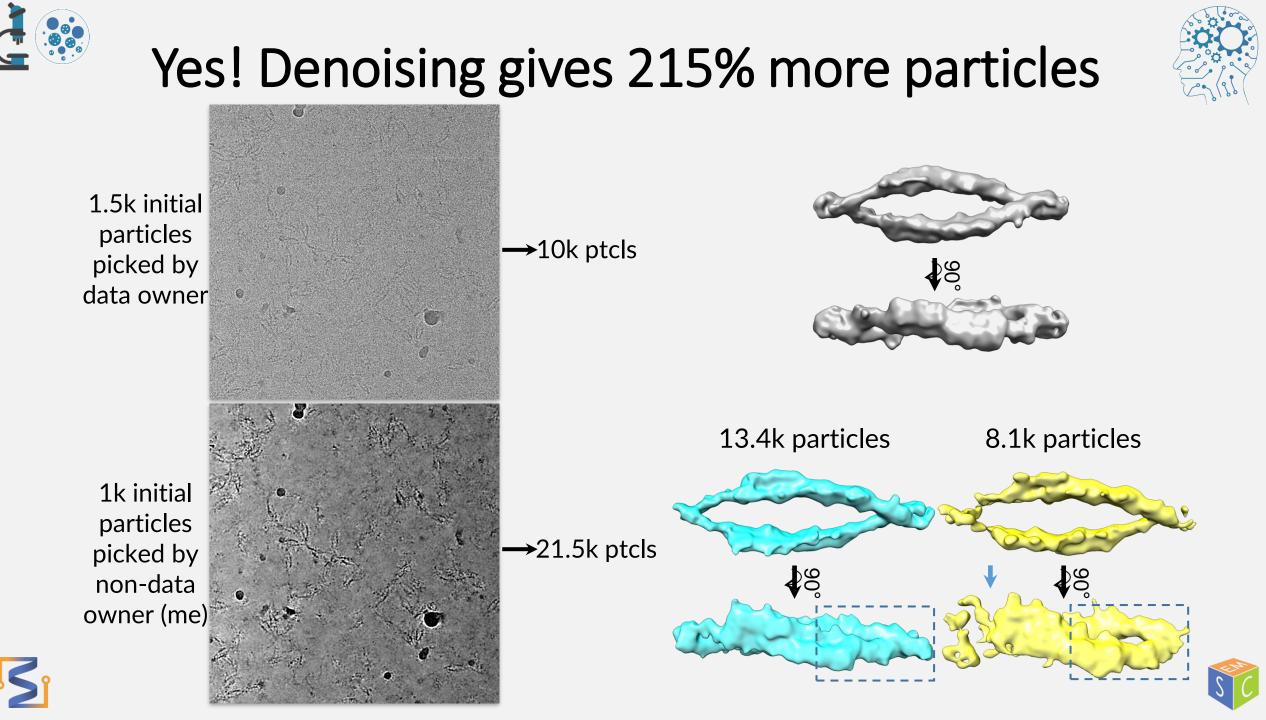


Can we identify small particle views?











Can we be more confident about what is in *image/sample backgrounds*?

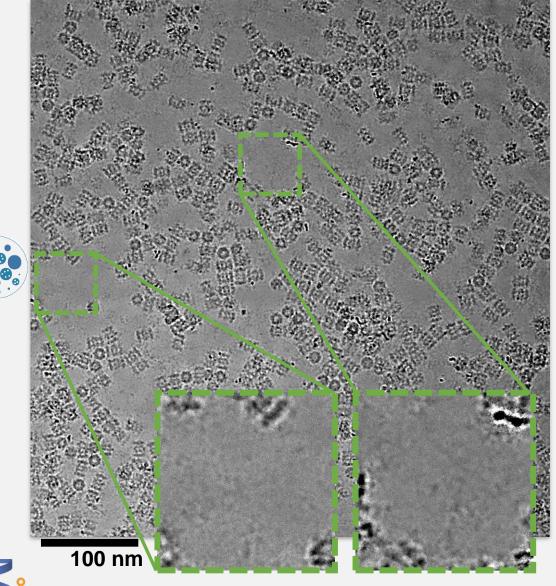


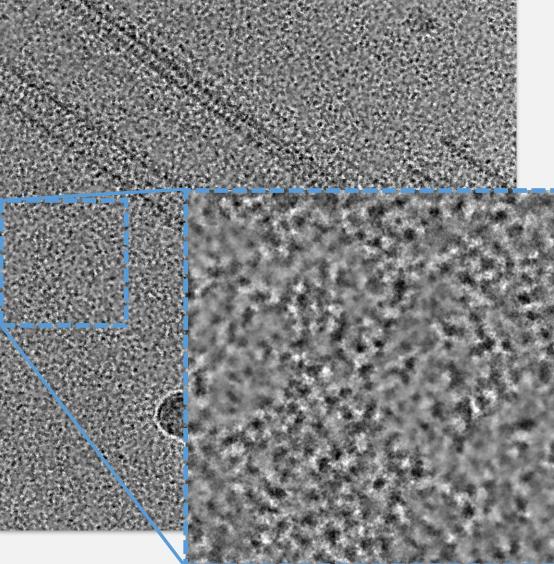






What is in your background?





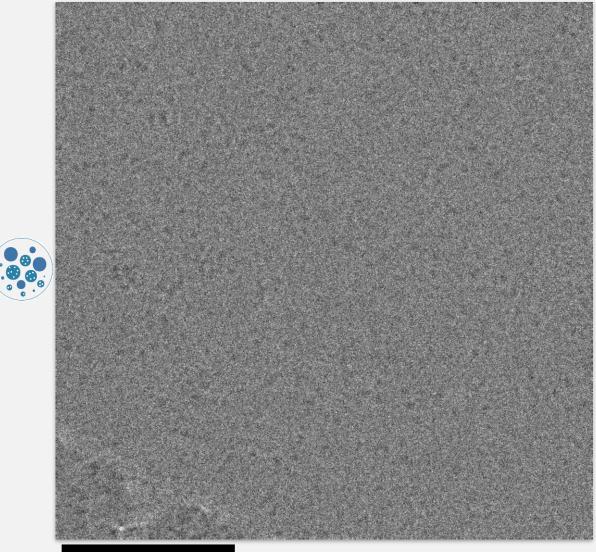
Positive control

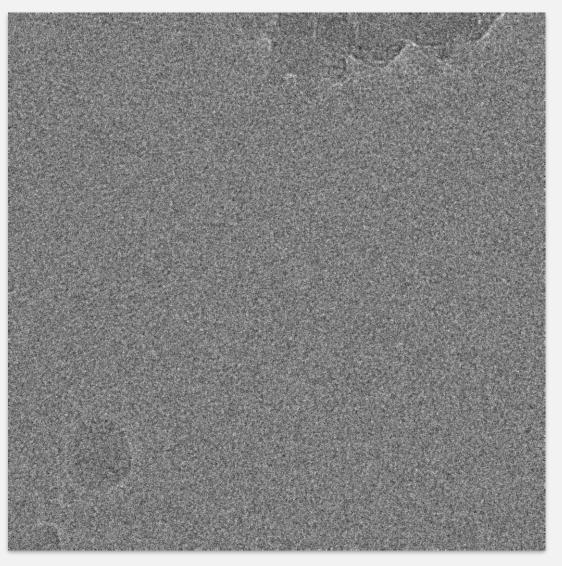


Negative control



What is in your background?







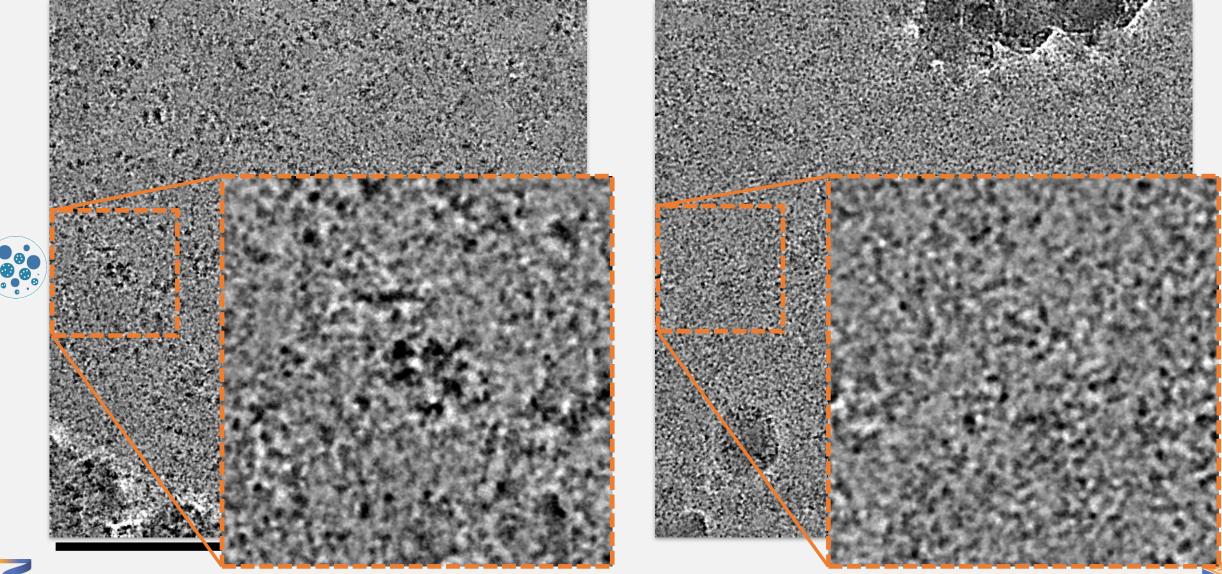
Raw images







What is in your background?



S

Topaz Denoise

Mao et al., PNAS, 2013



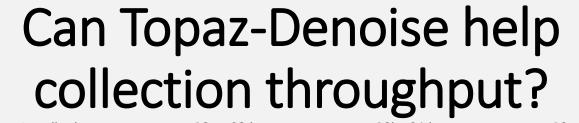


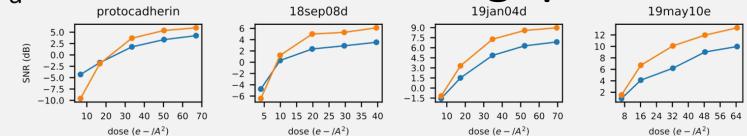
Can denoising help collection throughput?

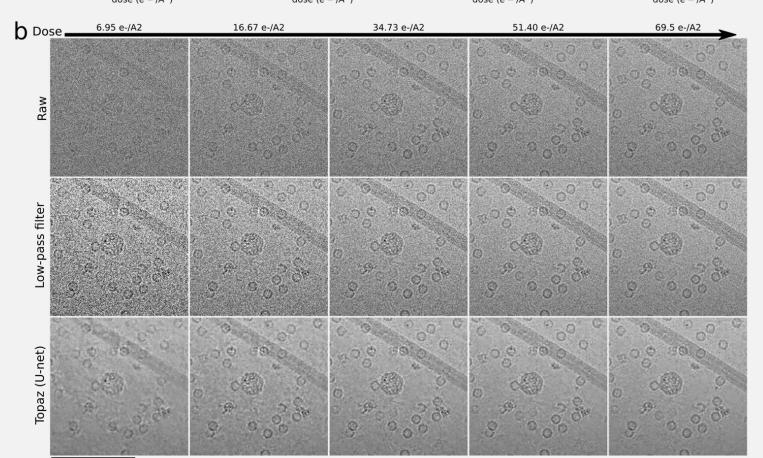














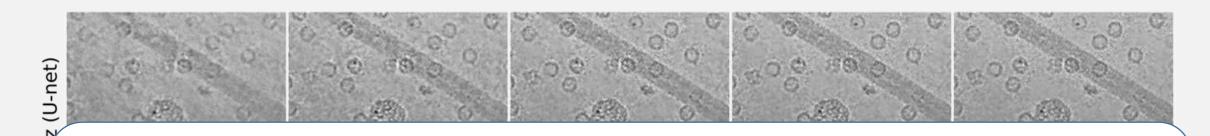




а



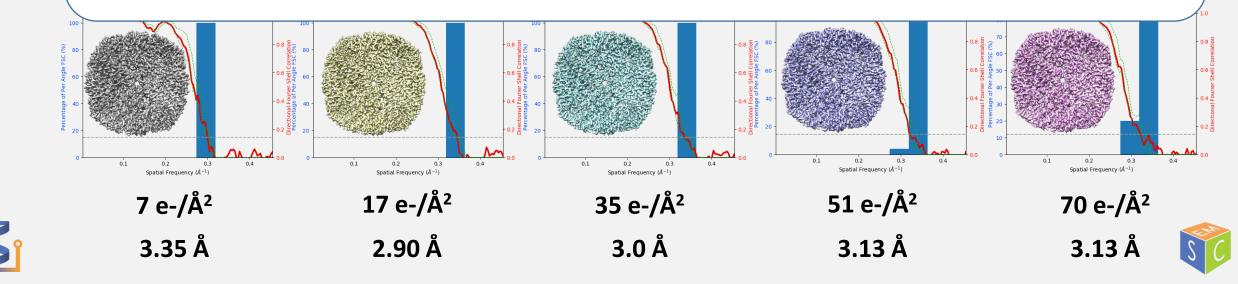
Can Topaz-Denoise help collection throughput?





Yes! You don't need more than ~20 e-/Å²

(for medium-large particles)





Ok, give me Topaz please!

github.com/tbepler/topaz

- Pre-trained picking and denoising models
- Full tutorial and explanations are included
- A universal HTML-based GUI is included
- Integrated into CryoSparc, Relion, Scipion, and Appion.







Summary

• Pick more and more accurately with Topaz

positive-unlabeled picking

Visualize and identify proteins more

confidently with Topaz Denoising

 Note: If you don't know what your particle looks like, do tomography first!

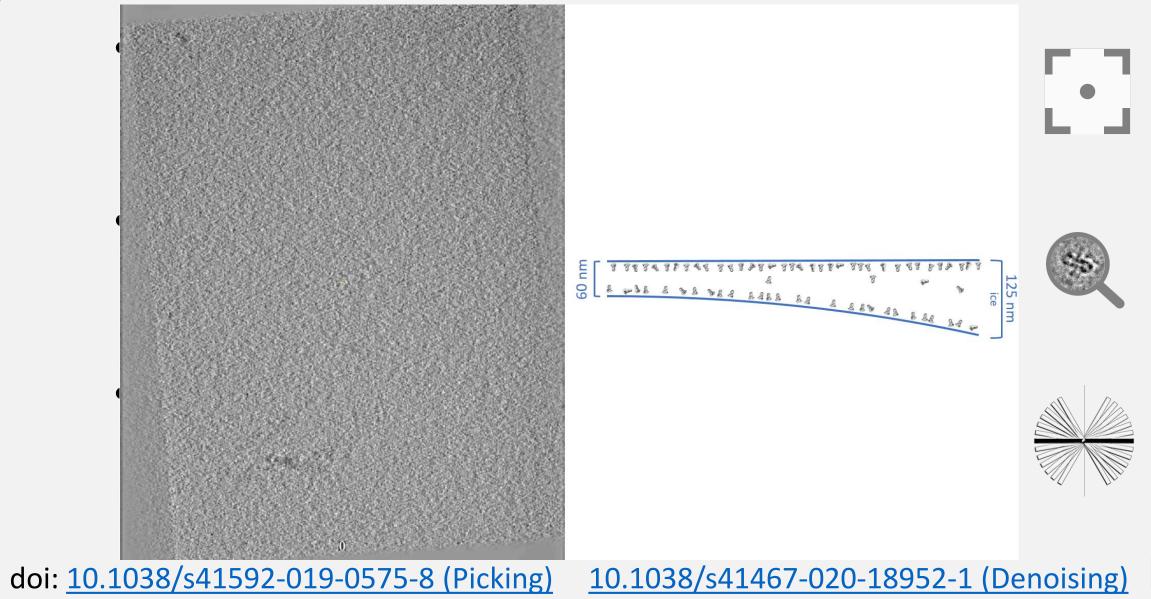


oi: <u>10.1038/s41592-019-0575-8 (Picking)</u> <u>10.1038/s41467-020-18952-1 (Denoising)</u>





Summary



SC



Summary

• In practice, people often publish with

multiple pickers – combine picks

• If you run Topaz iteratively, you must run 2D/3D

classification and manually check some

micrographs so you **don't get Einstein from noise**!



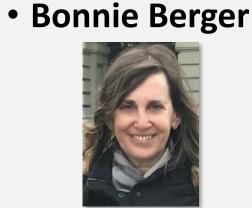
Acknowledgements

Massachusetts Institute of Technology Simons Electron Microscopy Center

• Tristan Bepler



- Andrew Morin
- Hoon Cho
- Tommi Jaakkola



CryoSparc Team

CSBi SNRAMN

• Jay Yoo



of Health

- Kotaro Kelley Misha Kopylov
- Ed Eng

- Bridget Carragher
- Daija Bobe
 Clint Potter

Columbia University

- Micah Rapp
- Julia Brasch
- Larry Shapiro

COLUMBIA University







Massachusetts Institute of Technology



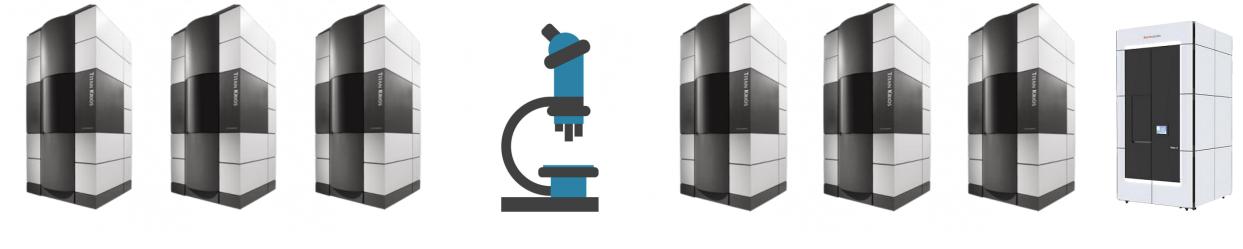
















Massachusetts Institute of Technology





C







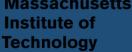
Apply for time & training (FREE!)

CryoEM: https://www.cryoemcenters.org

CryoET: https://www.cryoetportal.org















Massachusetts Institute of Technology



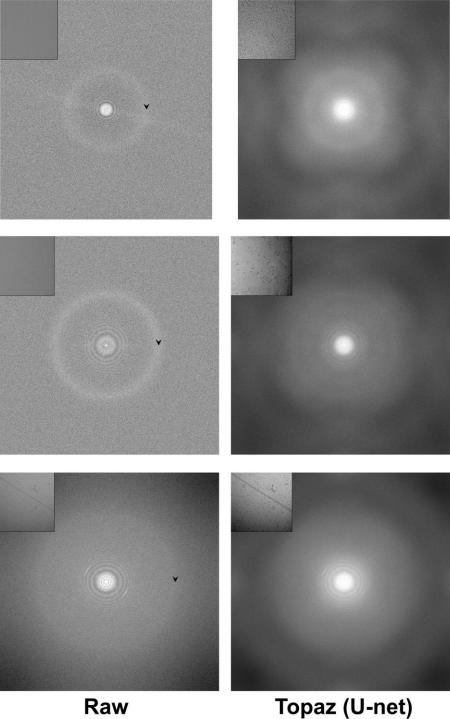
SIMONS ELECTRON MICROSCOPY CENTER







FFTs look cool!



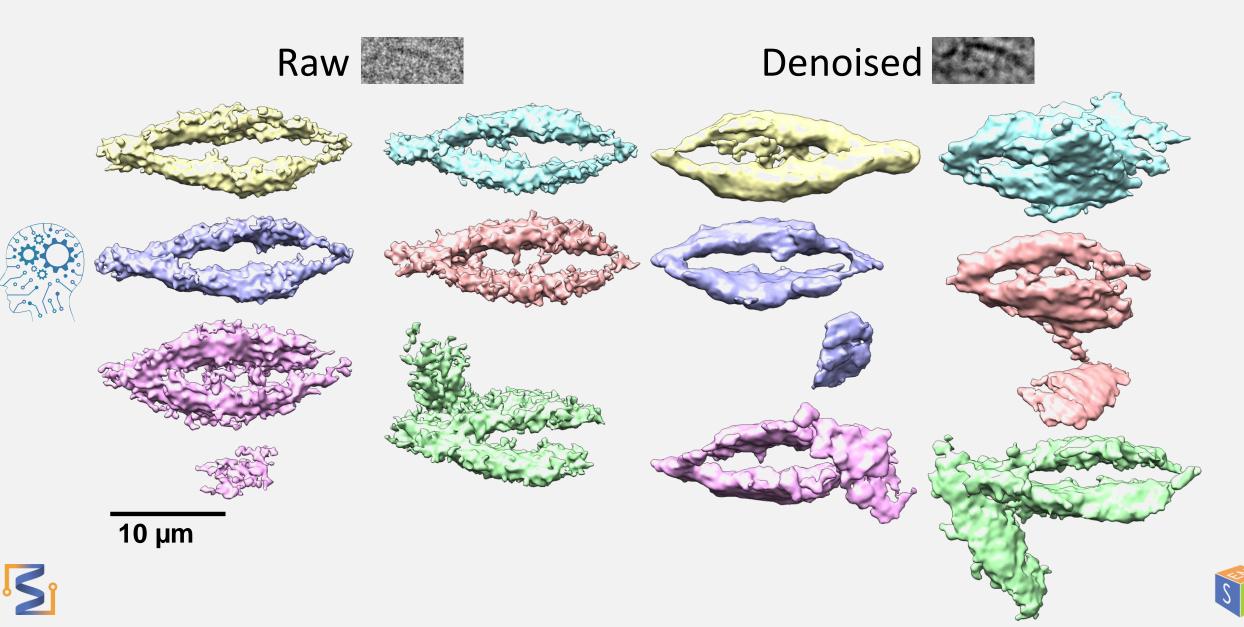
Topaz (U-net)







Denoised ab-initio models are less reliable







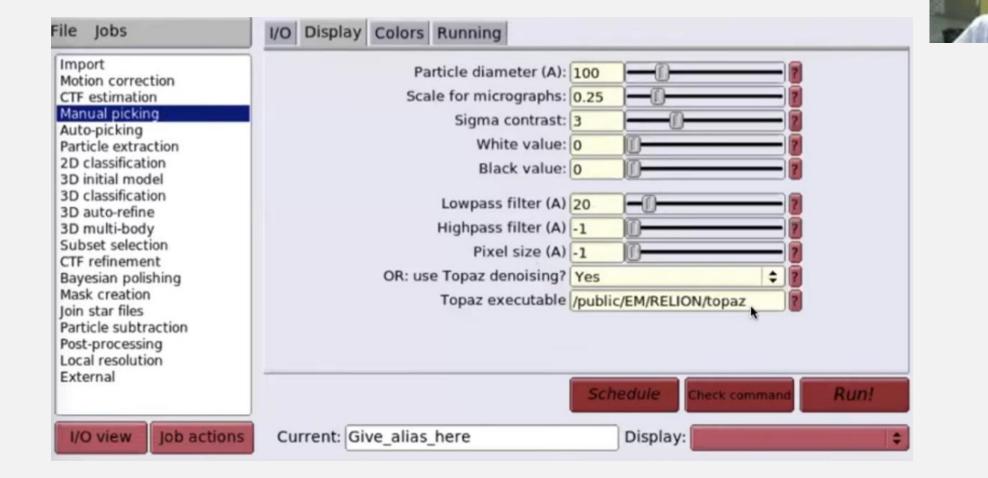
Quick look at Relion4 integration







Denoising in Relion4



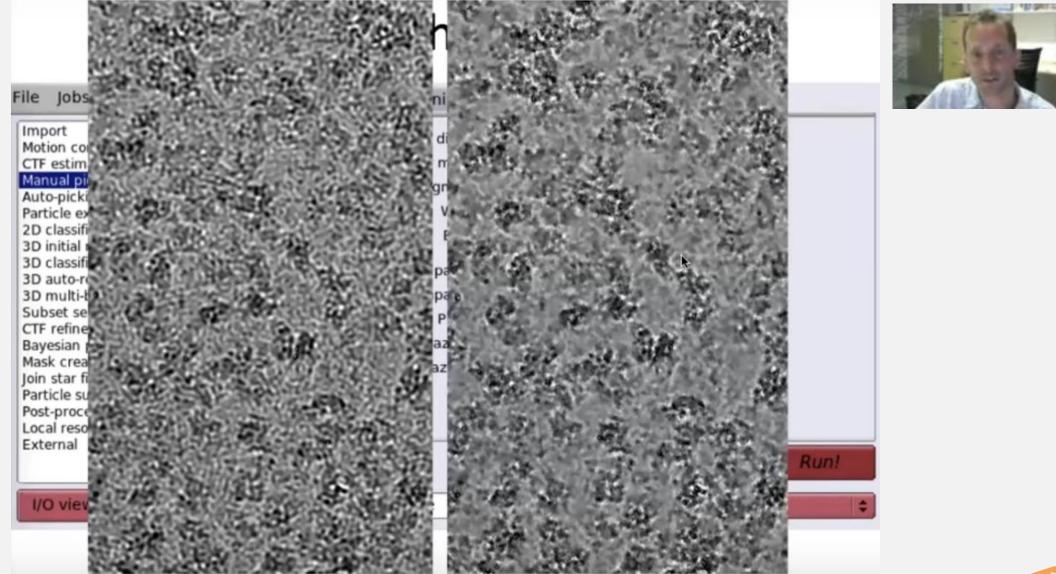








Denoising in Relion4



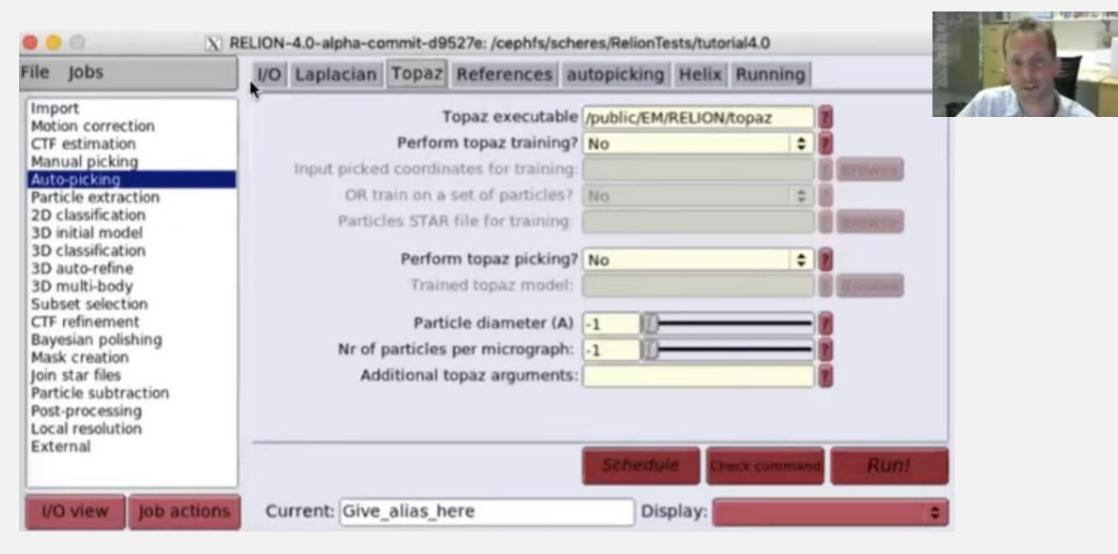








Topaz autopicking in Relion4

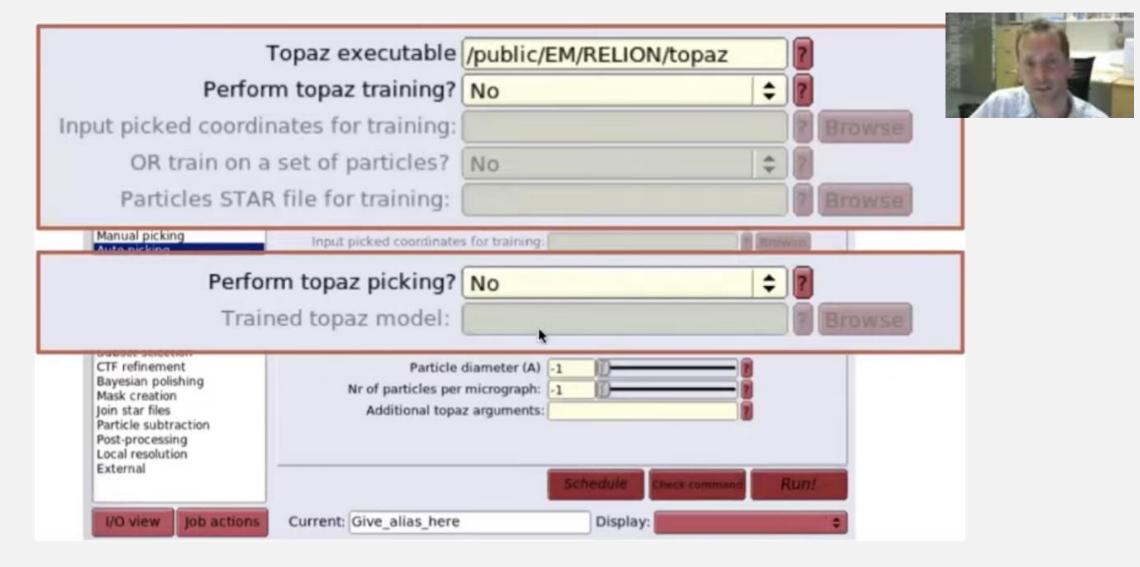








Topaz autopicking in Relion4

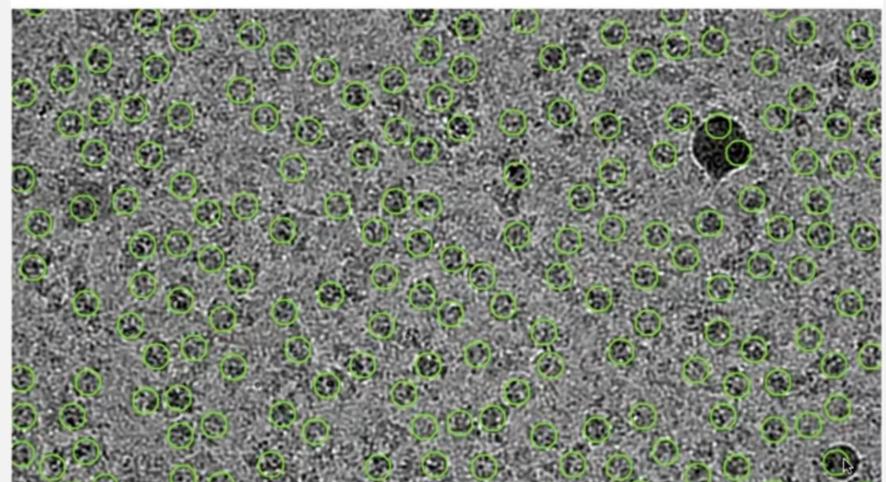






Topaz autopicking in Relion4 LoG-picking







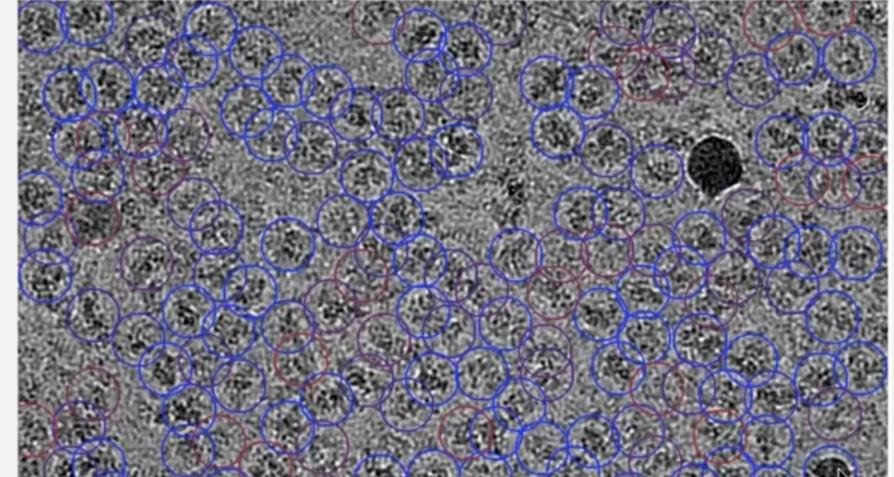






Topaz autopicking in Relion4 Re-trained Topaz picking















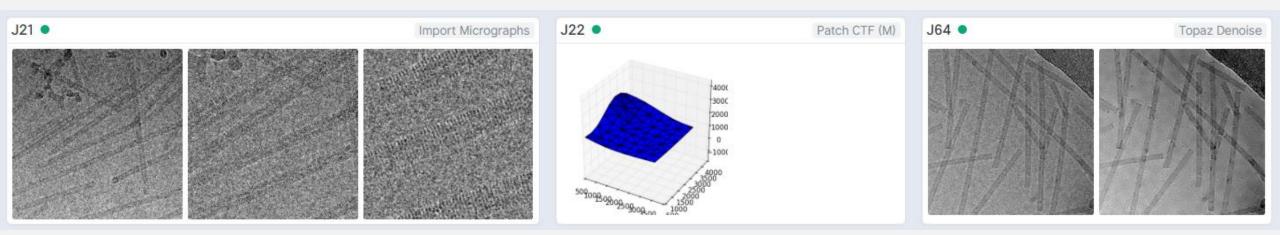
Best-practices Topaz Workflow (within CryoSparc)







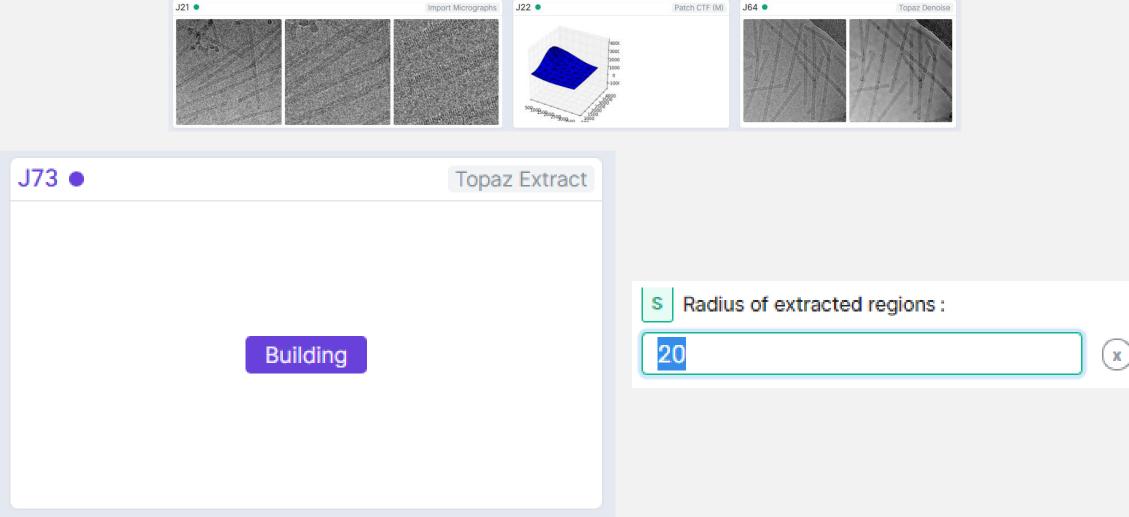
General Recommended Workflow shown in CryoSPARC EMPIAR-10022: TMV







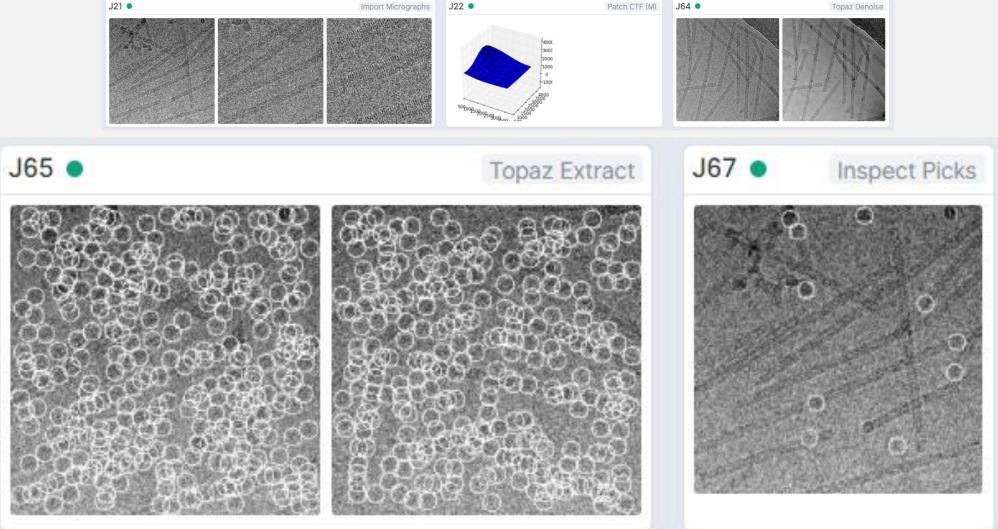












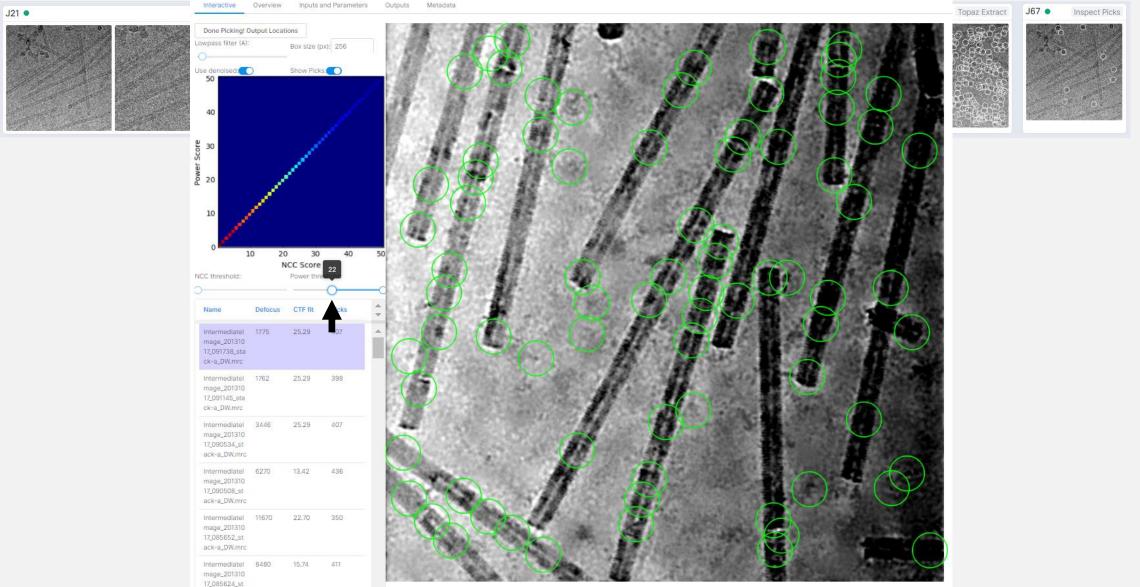




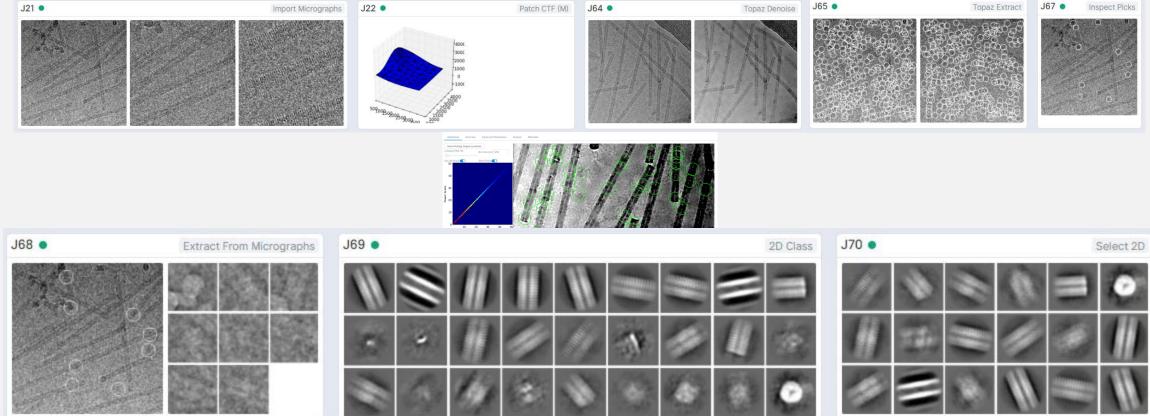




S

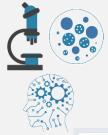


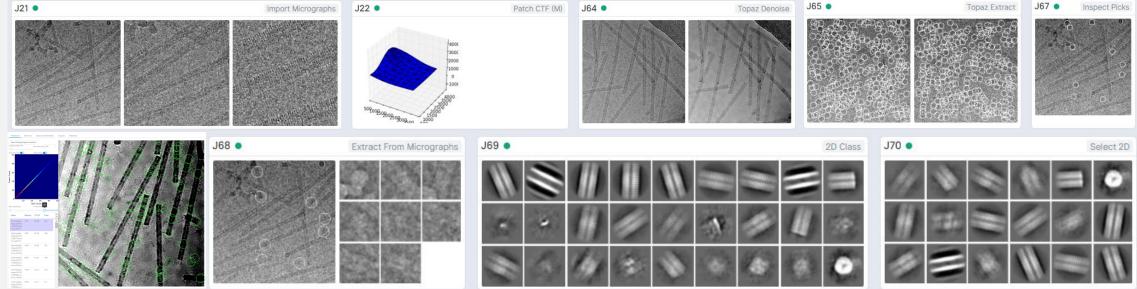








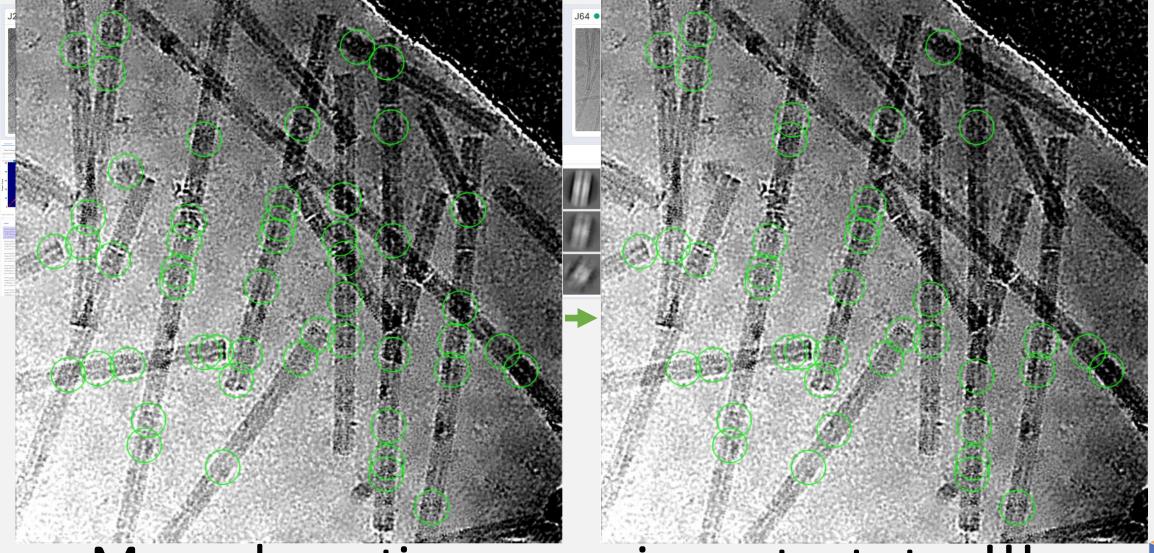


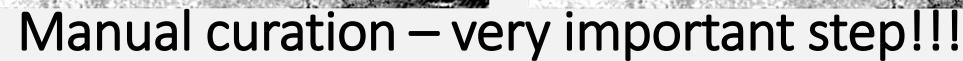




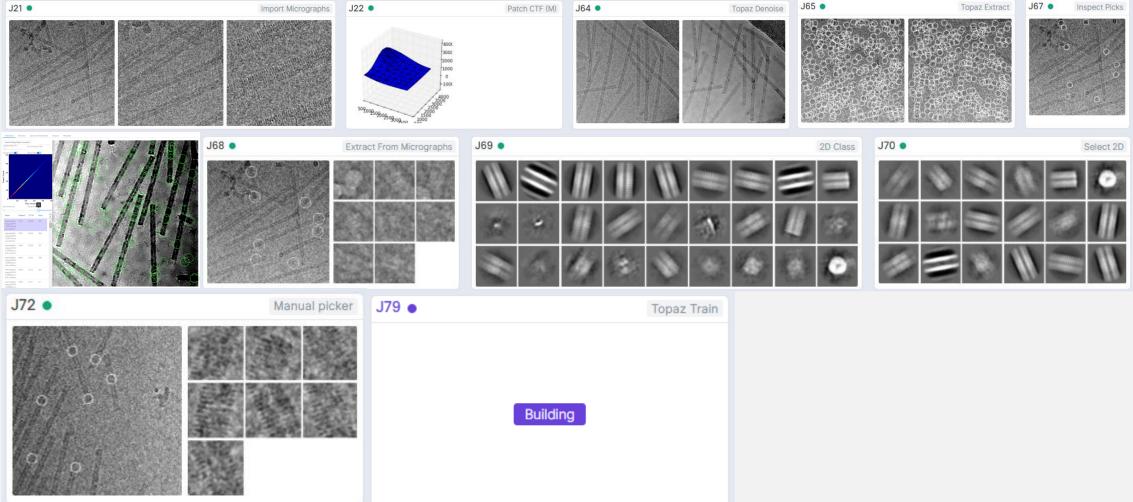








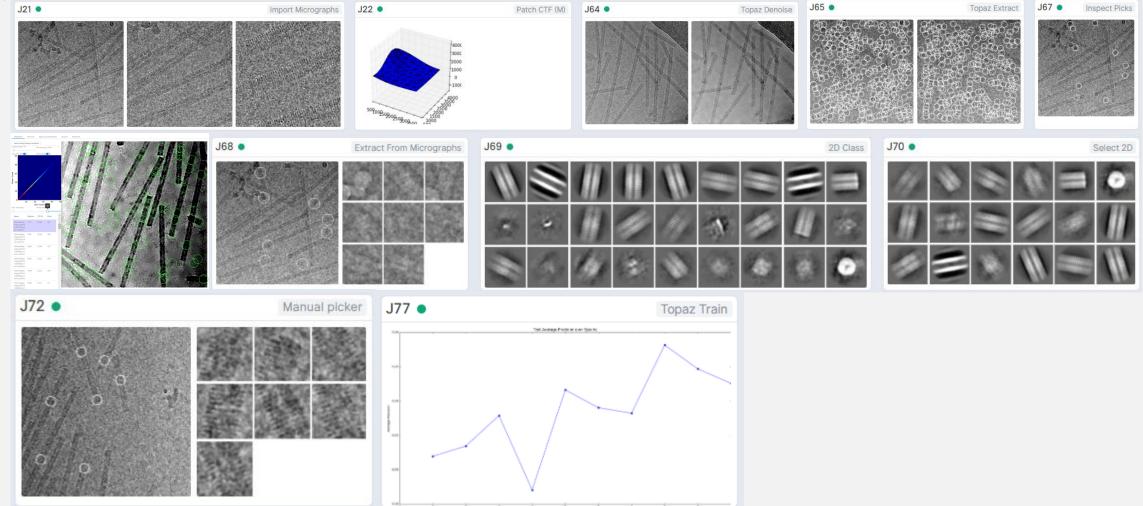




Trained with 3.3k manually curated particles





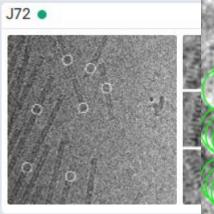


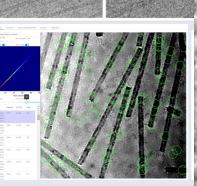
Trained with 3.3k manually curated particles

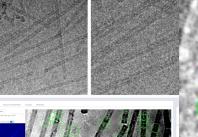


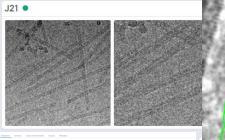


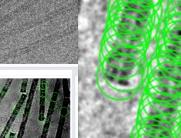
En las

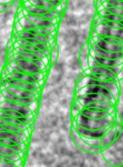


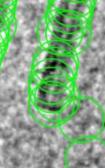


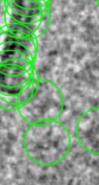


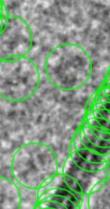


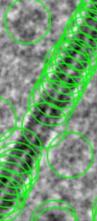




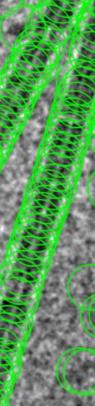


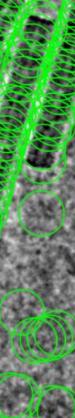


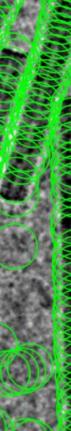




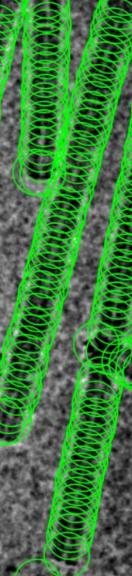


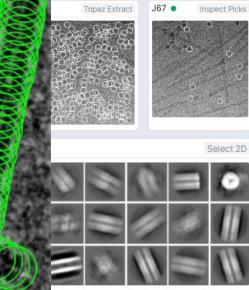






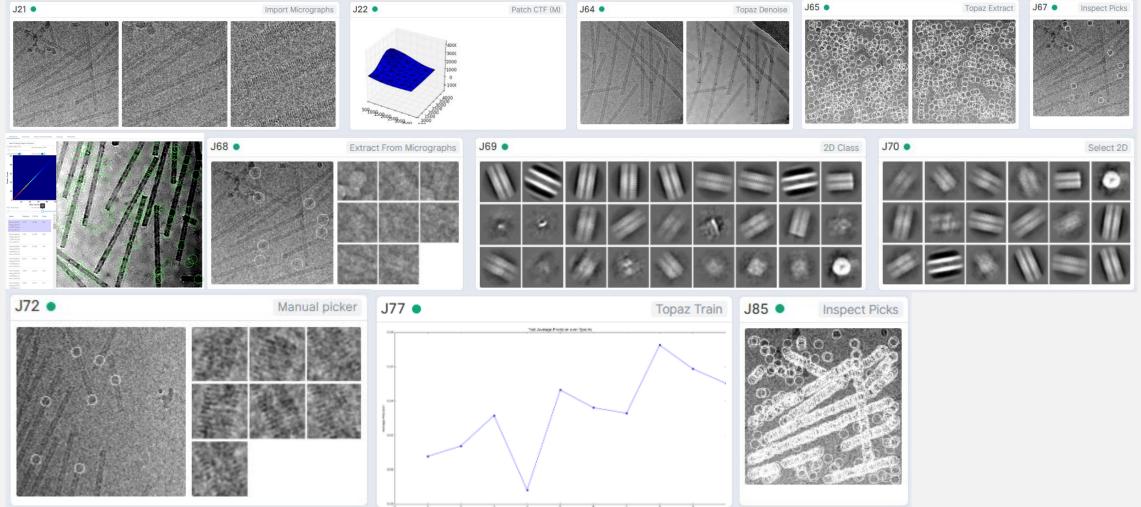








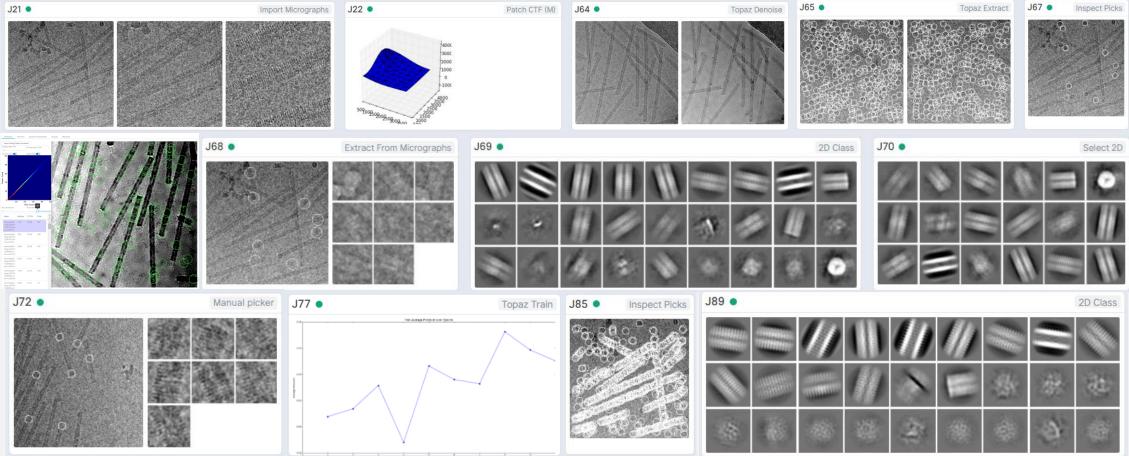








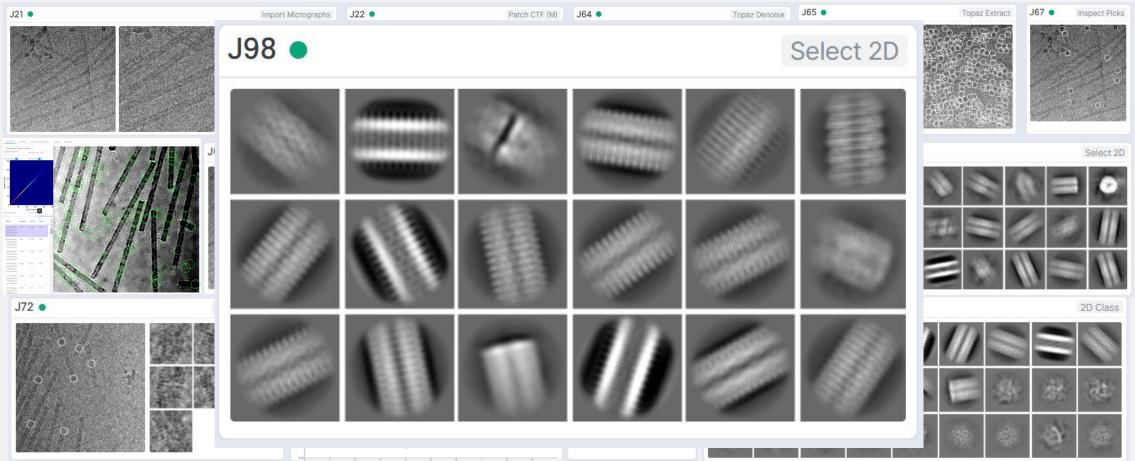








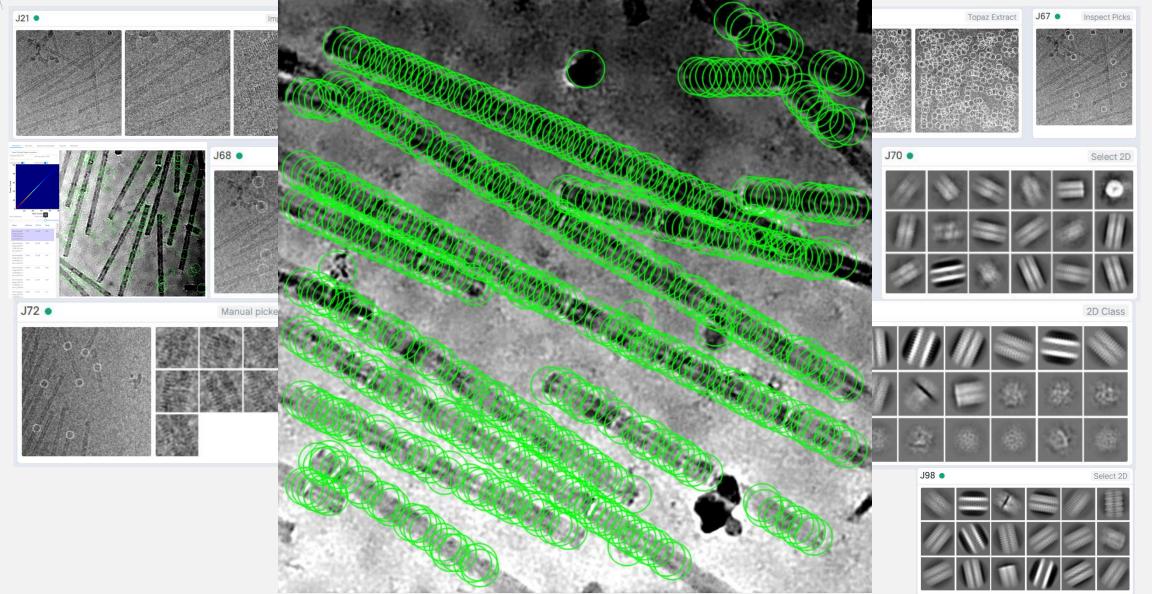




91% of particles picked were kept







SC