Scaling deep RL on landmark localization

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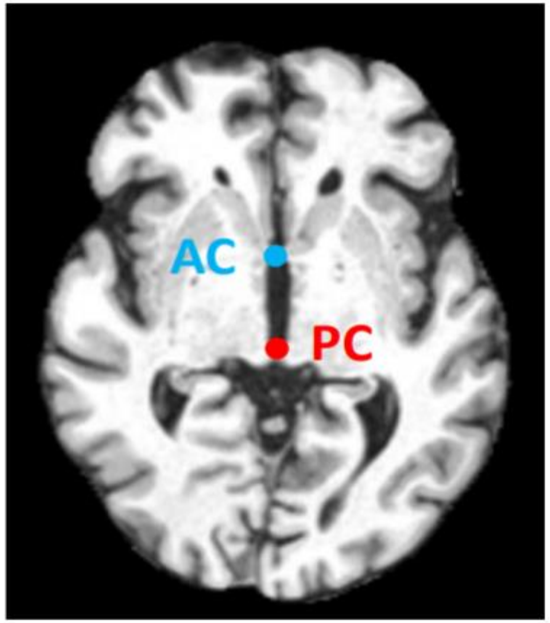
Background

- The field of radiology is moving towards a collaborative space between human experts and AI
- Automatic anatomical localization is an integral part of an AI radiology framework
- Anatomical localization has diverse application cross multiple task such as image segmentation, registration, and classification
- Deep reinforcement learning (RL) has emerged as one of the best techniques for landmark localization.

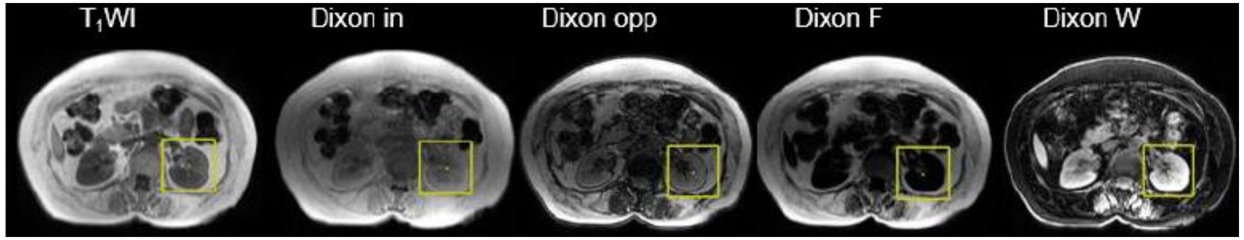


The anterior commissure (AC) and posterior commissure (PC) points in brain MRI.

the single 2D agent locating different landmarks in 2D slices

Deep RL setup

Source: https://github.com/bocchs/MIDRL-2D

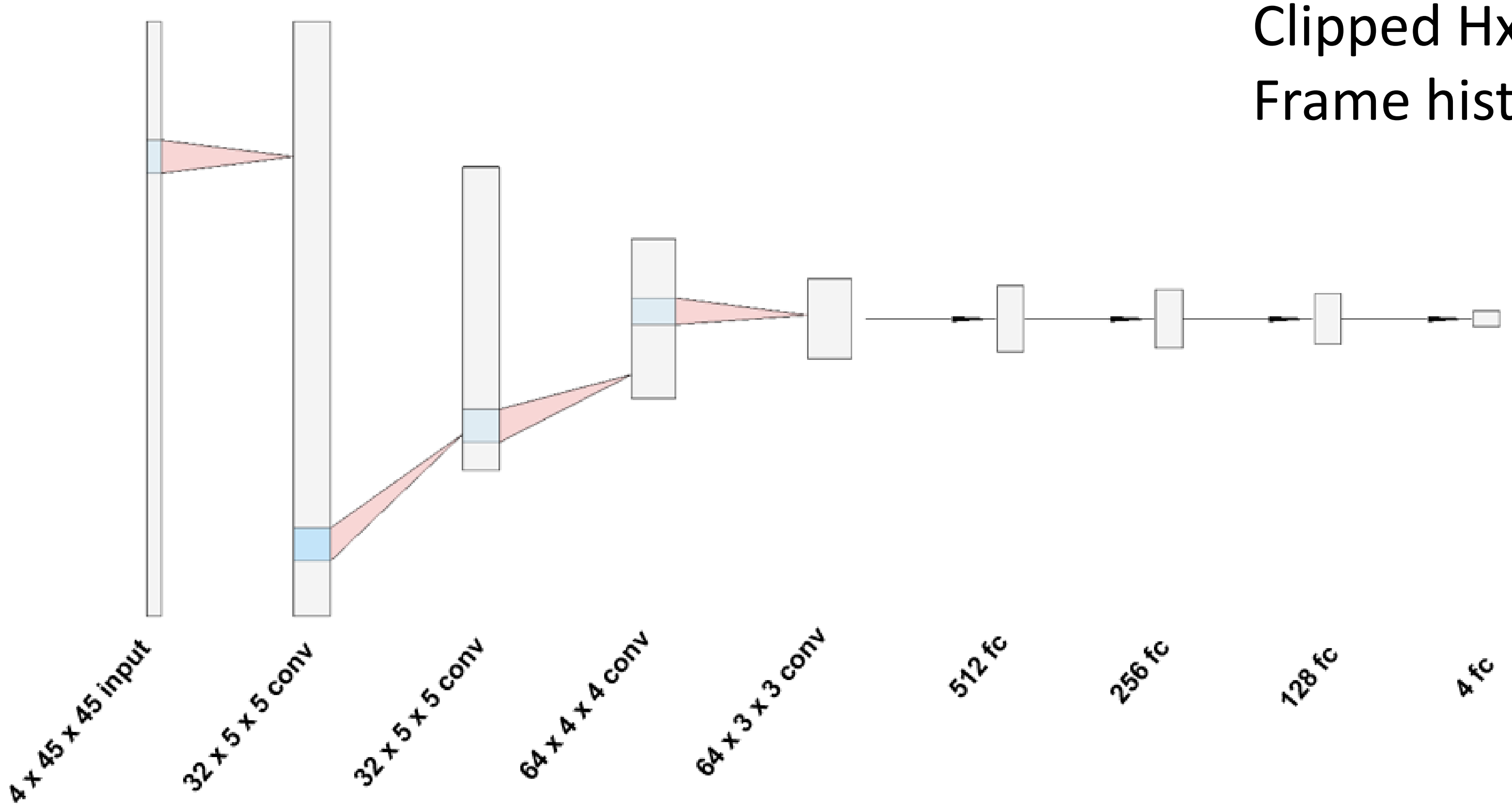


- Environment: Radiological image
- State: Sequence of areas within the image (bounding box)
- Actions: move bounding box in one direction (+/-)
- Reward: change in Euclidean distance to landmark
  - + if moved closer to landmark
  - - if moved away
  - Clipped between 1 and 1
- Method: Q learning with experience replay

the single 2D agent locating different landmarks in 2D slices

2D DQN single agent

Clipped HxW = 45 x 45
Frame history Length C = 4



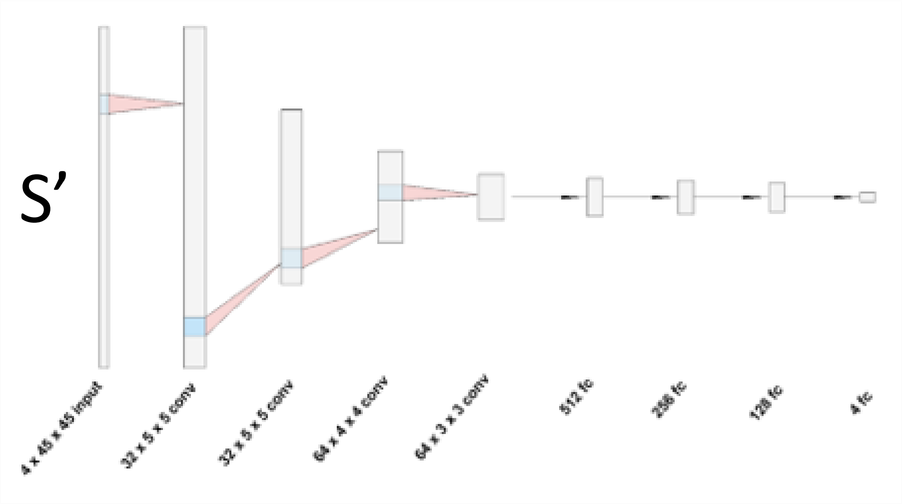
- Input: bounding box regions from last 4 time steps
- Output: Q-value for each action (x++, x--, y++, y--)

Training

Gamma = 0.9, batch =48,
lr = 0.001, Optimizer: Adam
Gradient Clipping, lr scheduler
e-greedy policy with decreasing e

Target Network DQN_T

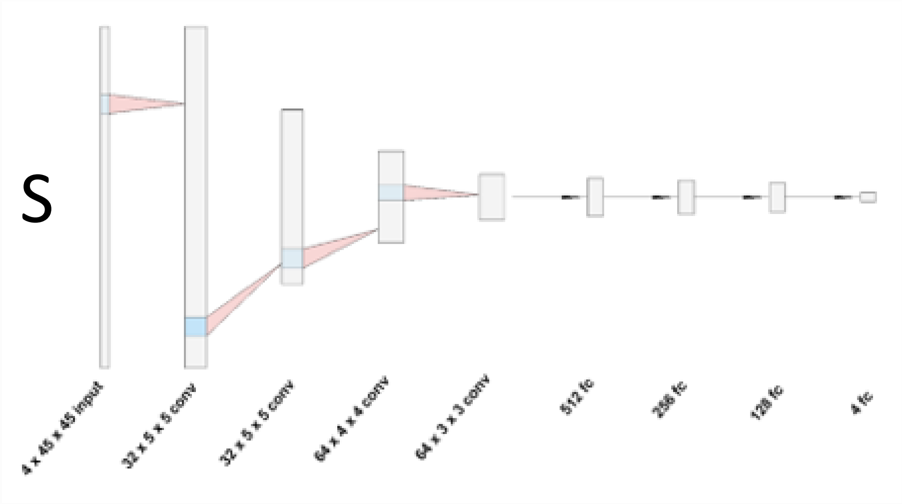
S’



Q(s’,a’)

Policy Network DQN_P

S

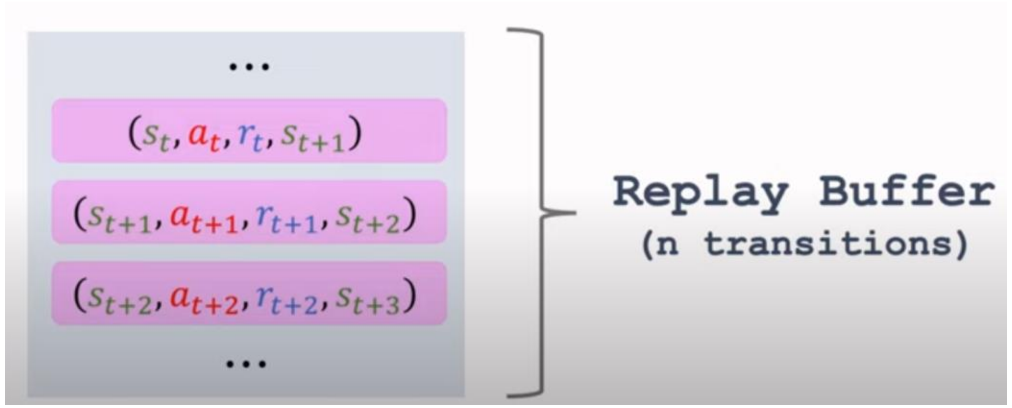


Q(s,a)

Target = r + gamma * Q(s’,a’)
Loss = Huber loss (Target, Q(S,a))

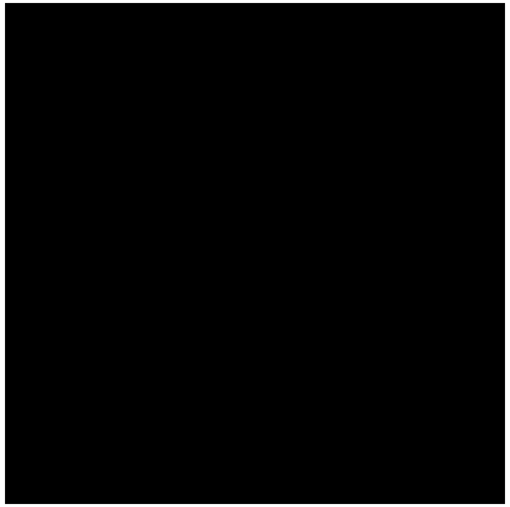
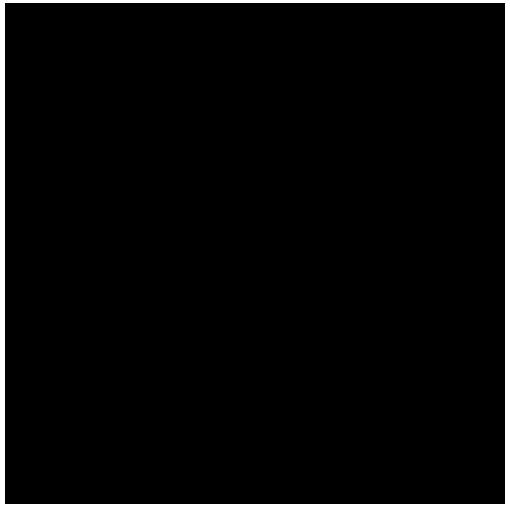
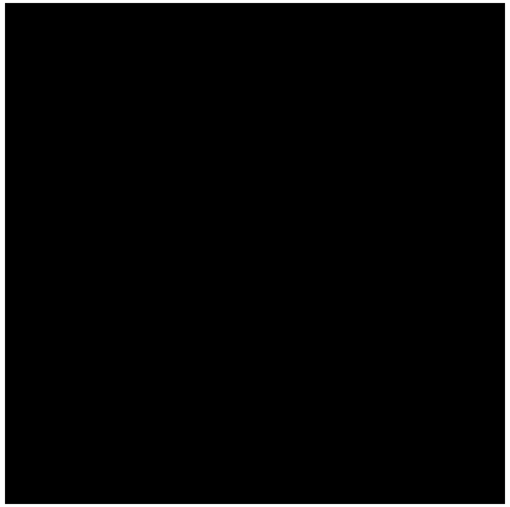
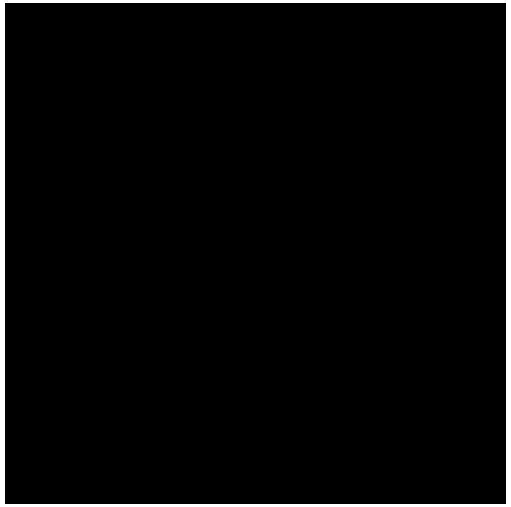
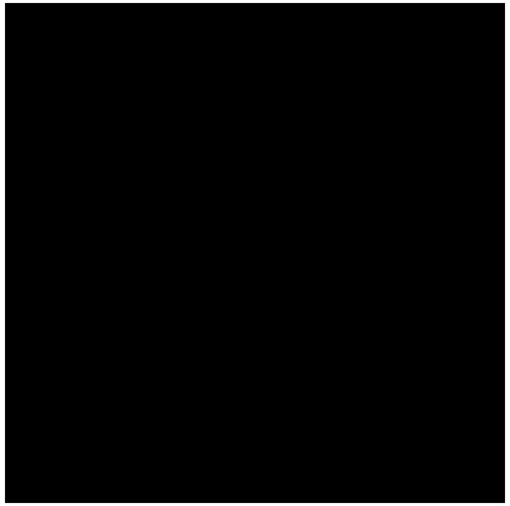
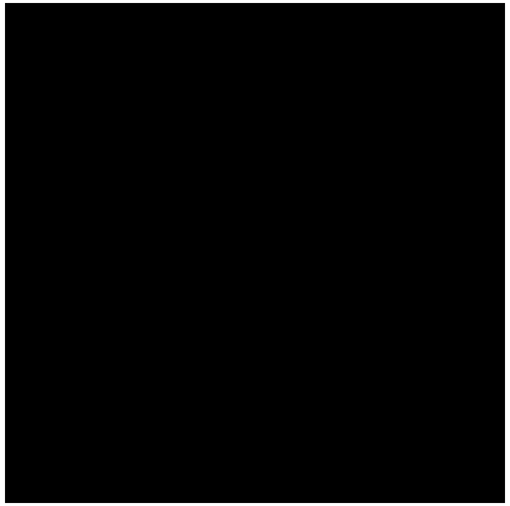
Experience replay

- Experience: (S, A, R, S')
- TD or Q-learning problems:
  - Waste of Experience
  - Correlated Updates
- Replay Buffer



Uniform Sampling

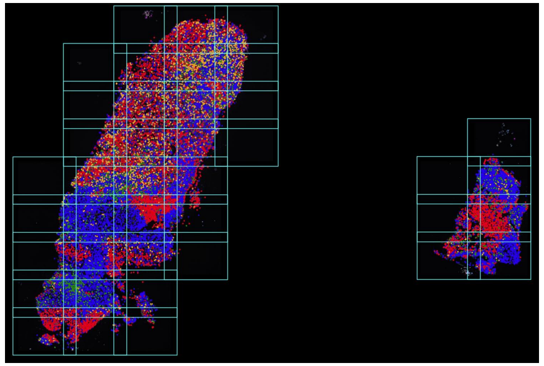
Examples of single 2D agent locating different landmarks in 2D slices.
Red is the target bounding box, yellow is the agent bounding box.

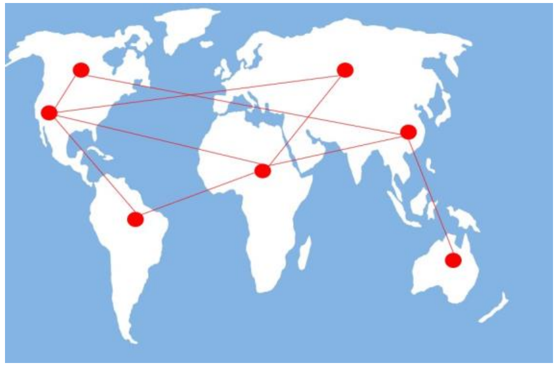
Vishwa S. Parekh, Alex E. Bocchieri, Vladimir Braverman, Michael A. Jacobs
Multitask radiological modality invariant landmark localization using deep reinforcement learning
https://github.com/bocchs/MIDRL-2D

Challenges in Medical Decision Support System

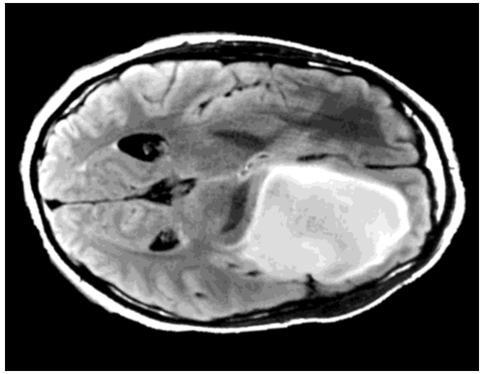
1. Data sets with very large cardinalities and high dimensionalities are emerging (100M+ to few B, 10~35 dim)
2. Memory problem with replay buffer
3. Existing dimensional reduction tools have suboptimal scaling
4. Data geo-distributed. direct aggregation impossible
5. Free movement of clinic data restricted



Billions of pixels from one set of tumor biopsies



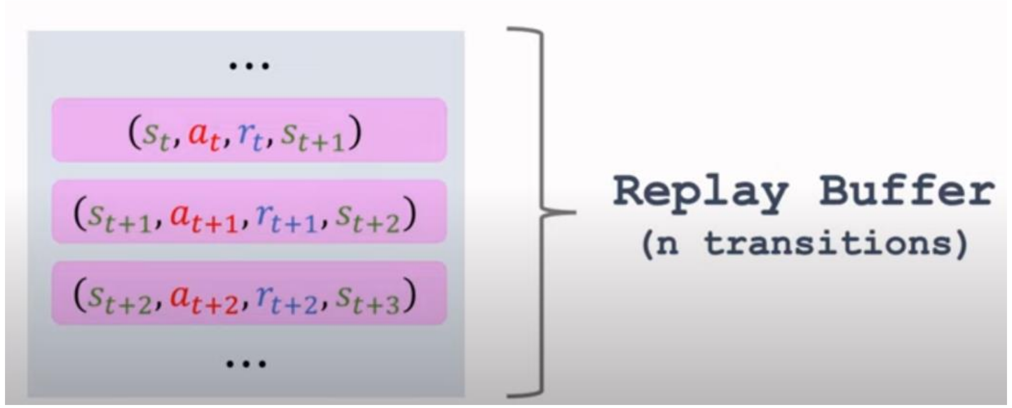
Geo-distributed

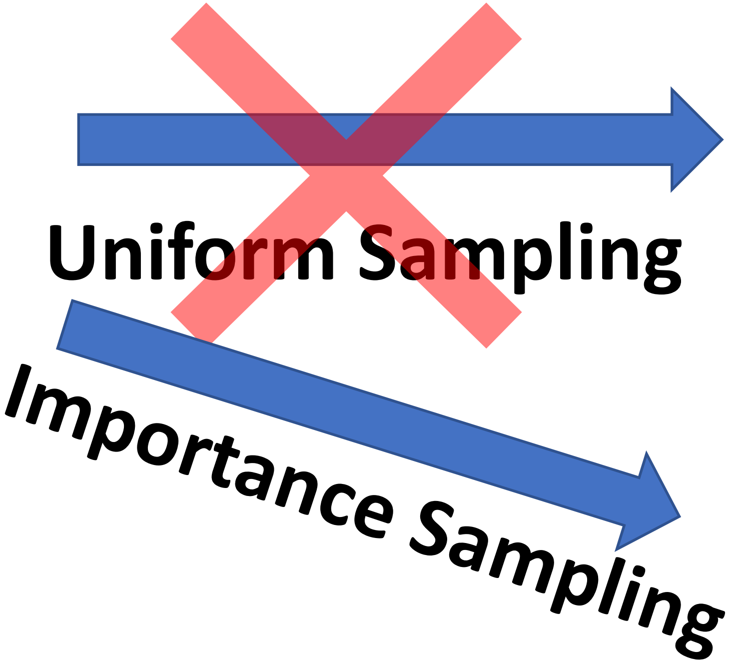


Private and sensitive healthcare data

Experience replay

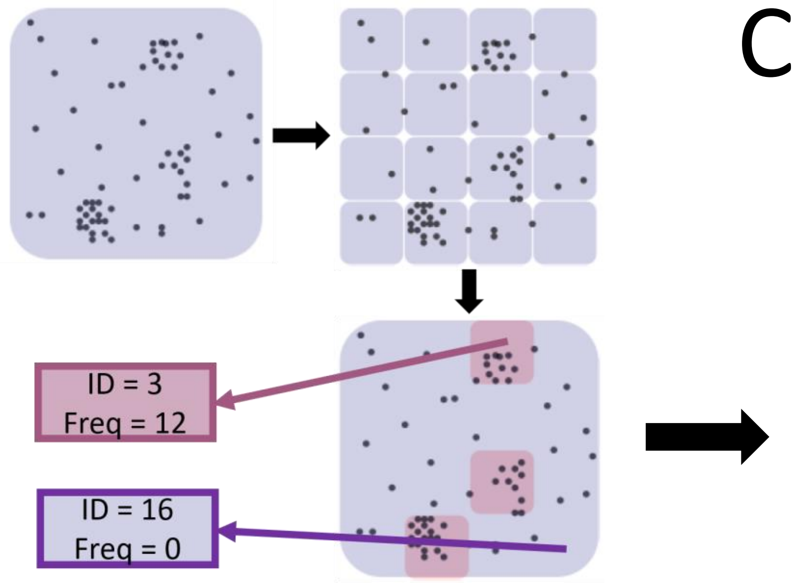
- Stream of Experience: (S0, A0, R0, S1) , (S1,A1,R1,R2)….
- Replay Buffer





1. Giving high priority to high TD error experiences
   - (S,A,R,S,delta) - tuple
2. Sketching the Experience

Count Sketch Algorithm



Stream:

Count Sketch Hash Table

	C1	C2	C3	C4	C5
R1 +1	+5	-1	3	+6	-7
-1 R2	-1	-1	5	-2	0
R3	-2	+1 +1	-9	+3	4

Not available!

Item	Frequency
	2
	3
	14
	5
	4
	1

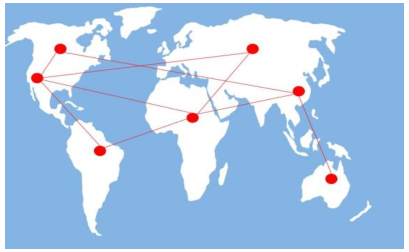
Heavy Hitters

R1	sign	bucket
	+1	3
	-1	2
	-1	4
	-1	5
	+1	4
	-1	1

R2	sign	Bucket
	-1	2
	+1	5
	-1	1
	+1	3
	+1	2
	-1	1

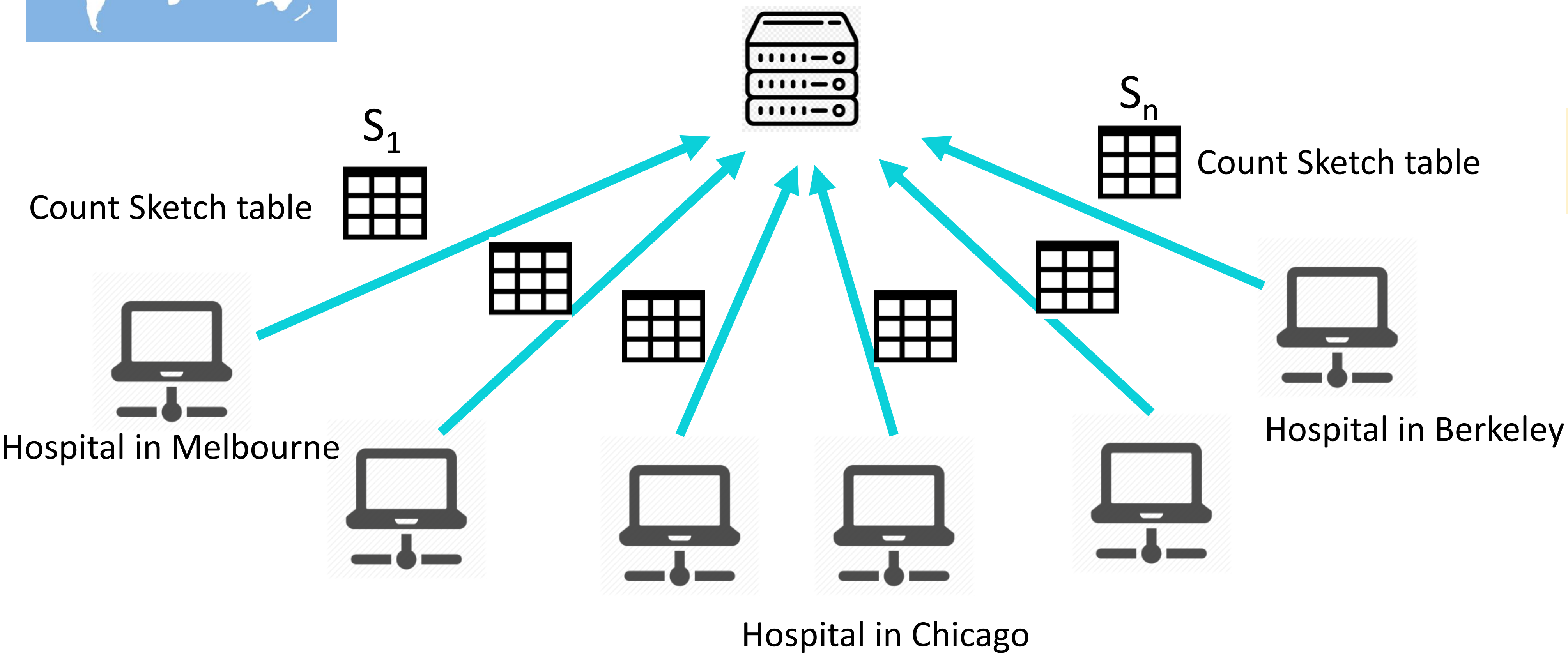
R3 ……

Count Sketch Algorithm



Count Sketch uses sublinear memory and can be aggregated

Server in Baltimore $S = S_1 + \ldots + S_n$

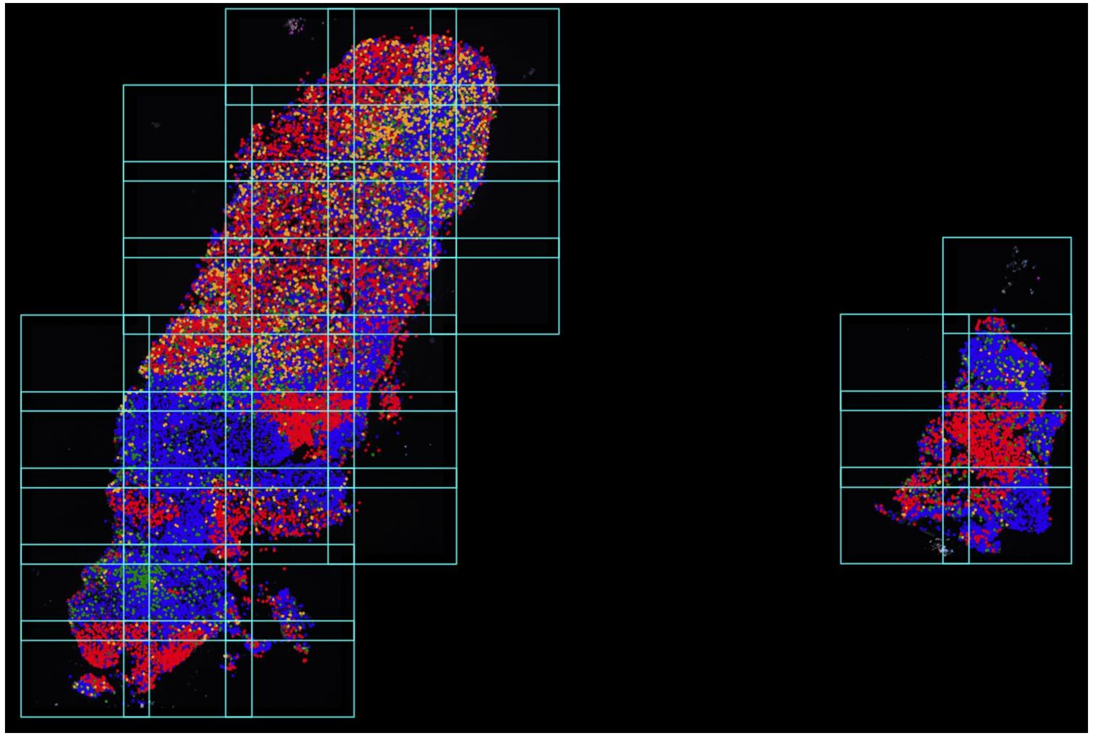


Hash not invertible:
Privacy protected!

Quick check on Count Sketch performance

Cancer Immunotherapy

54M pixels in 35 bands ~ 2B pix

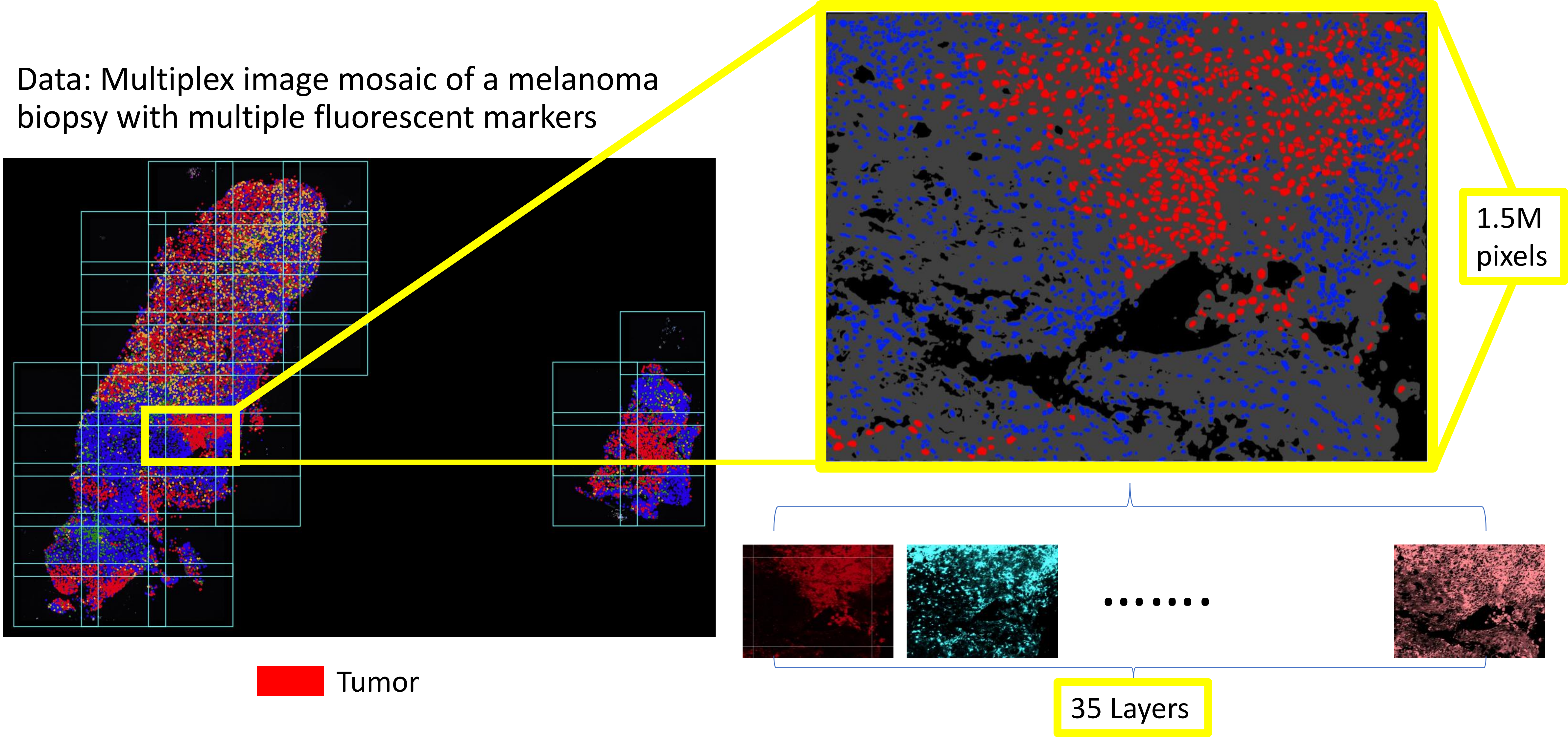


Cancer Imaging Data

40 Images, each is 35 Layers **x** 1.5M pix

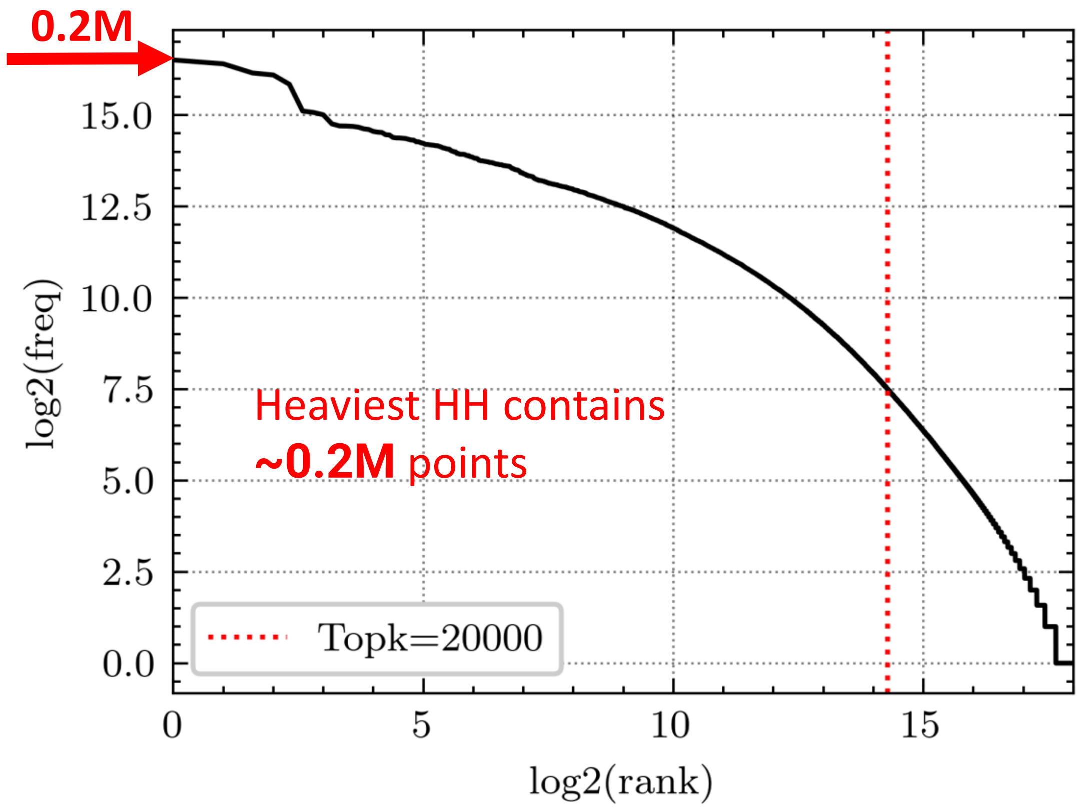
Total = 40 x 1.33M x 35 ≈ 2B pix

Data: Multiplex image mosaic of a melanoma biopsy with multiple fluorescent markers

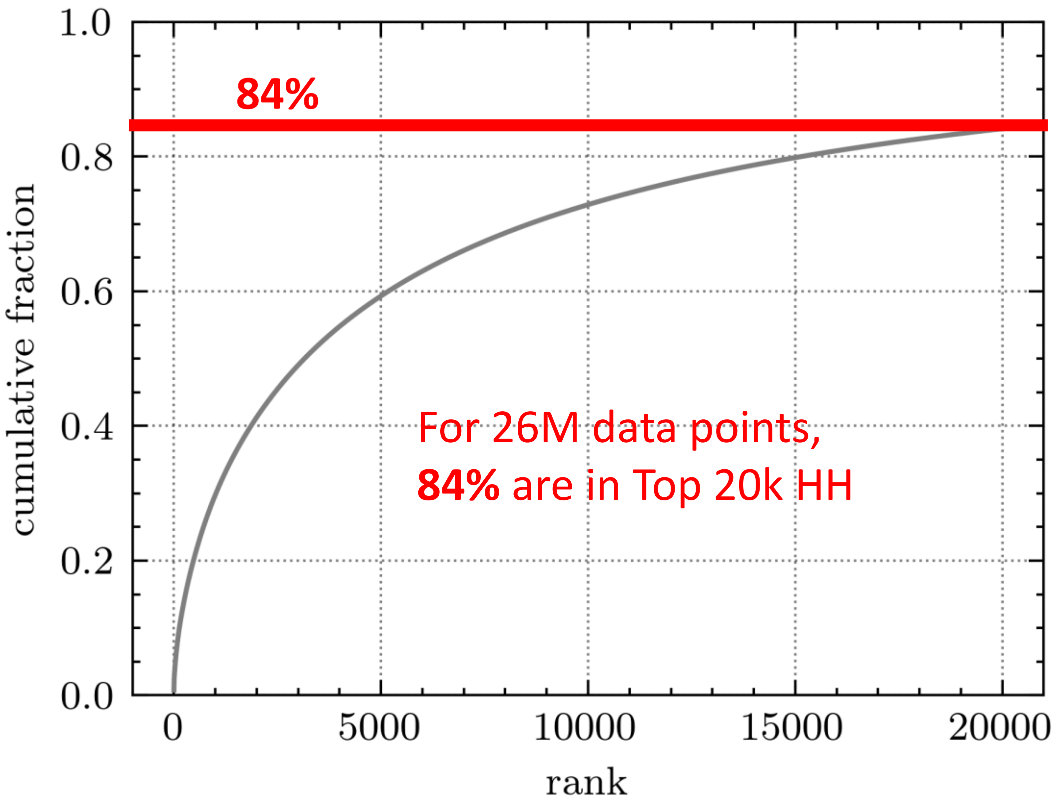


Quantization → (S,A,R,S')-tuple → Encoded Stream → Count Sketch → **Heavy Hitters** → tSNE/UMAP

HH cardinality vs Rank (first is top)



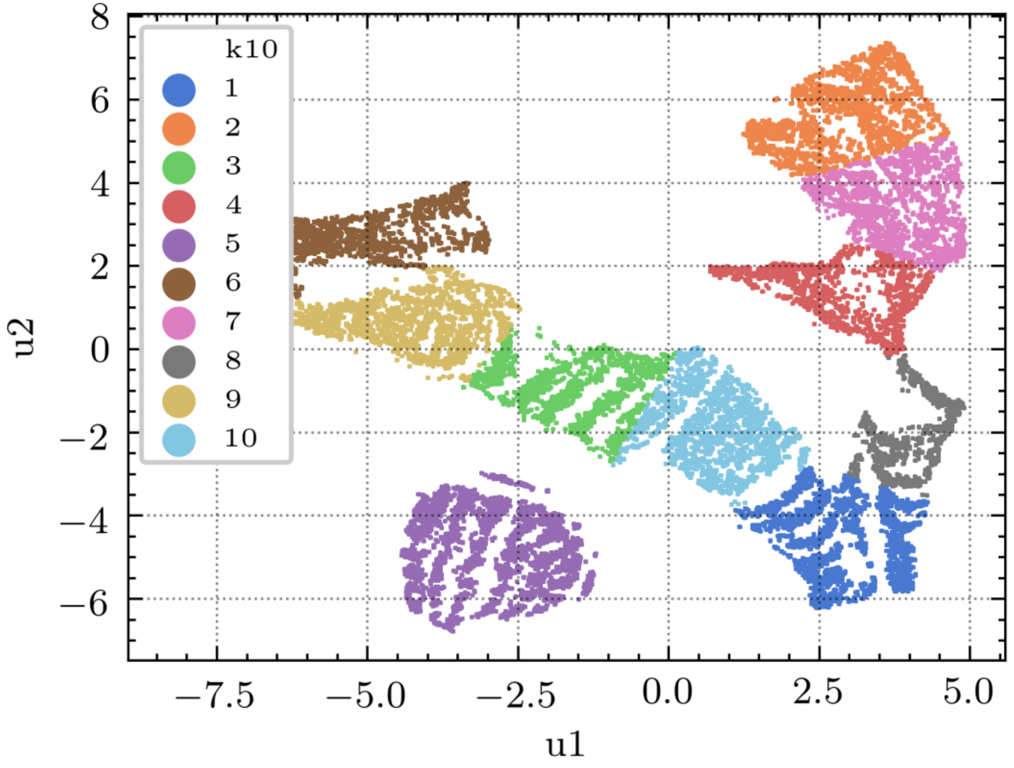
HH Cumulative Fraction vs Rank



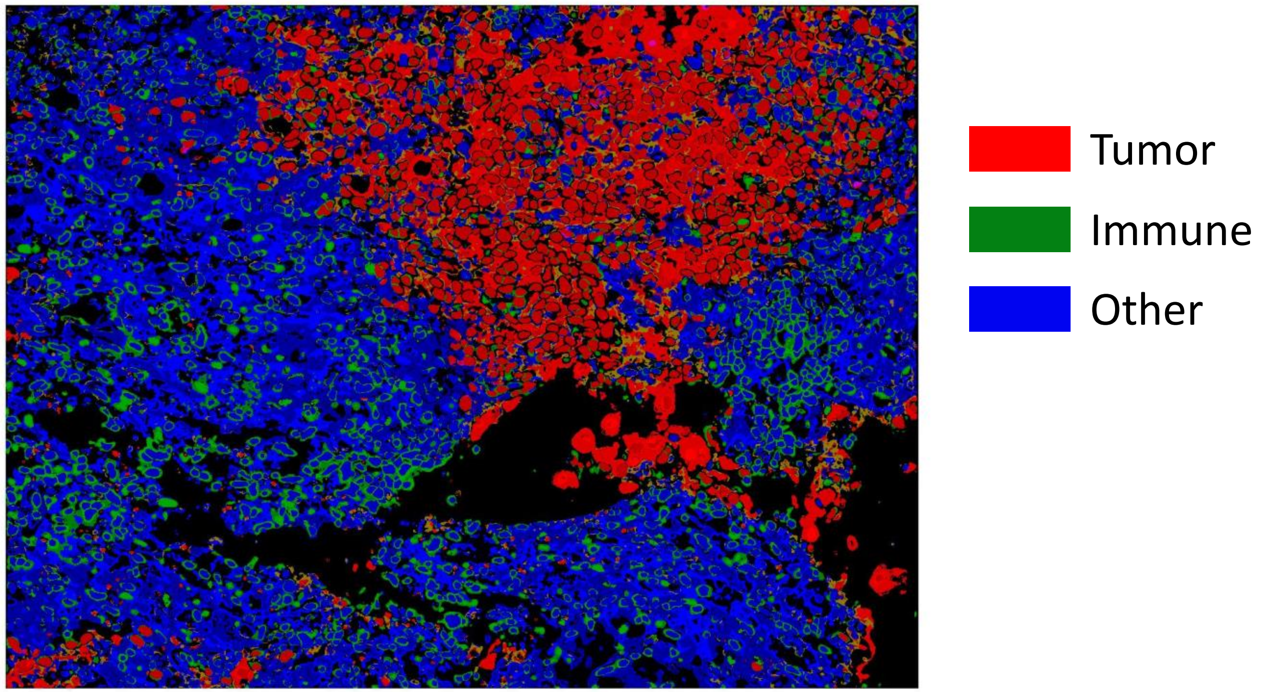
Clustering of the Heavy Hitters

Heavy Hitters → tSNE/UMAP

UMAP + KMEANS (20K HH)



Clusters shown on one image



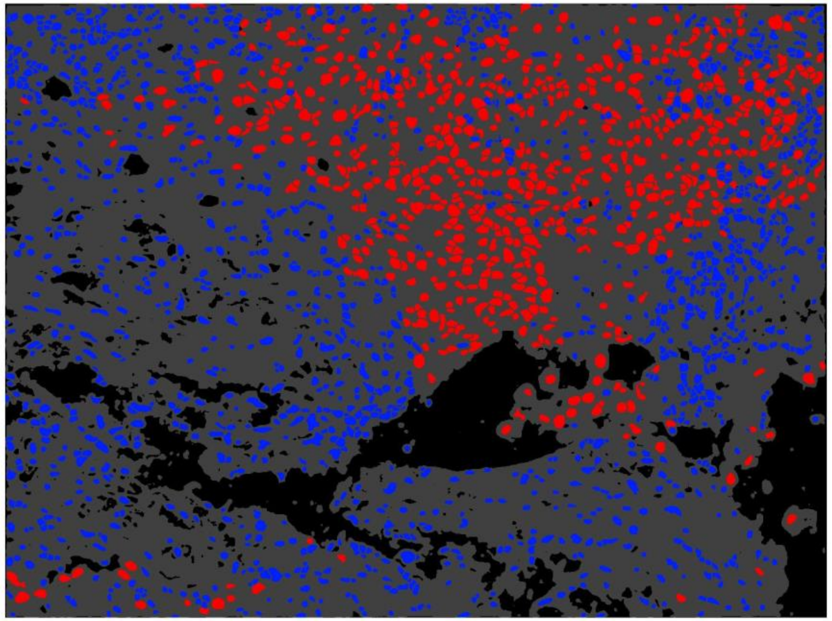
Results

Our pixel-based clustering is in excellent agreement with results derived from state-of-the-art cell segmentation using also shape information

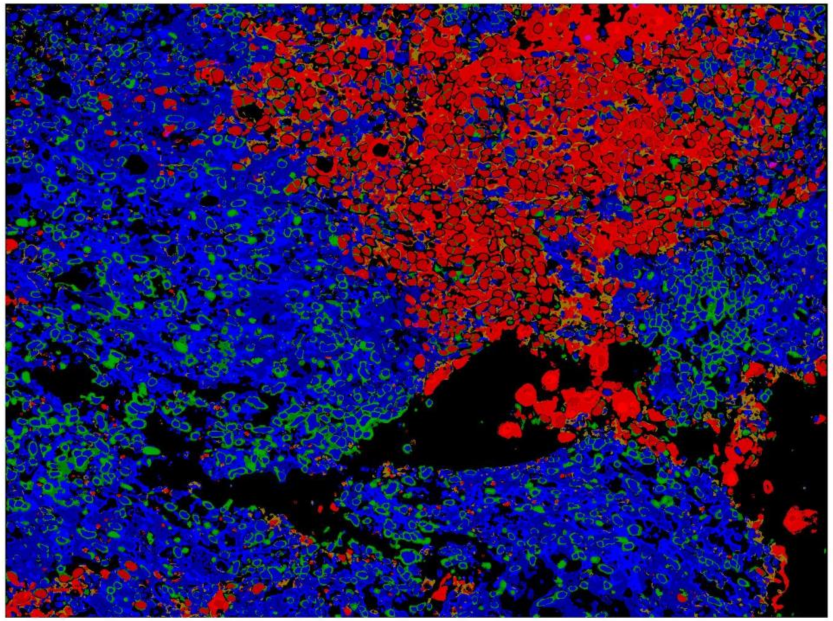
	Tumor (A)	Other (A)
Tumor (B)	95792	3675
Other (B)	6795	108630

Tumor Misclassification Rate: 3.5%

Label image from cell segmentation software (A)



Pixel classifications from our Sketch & Scale pipeline (B)



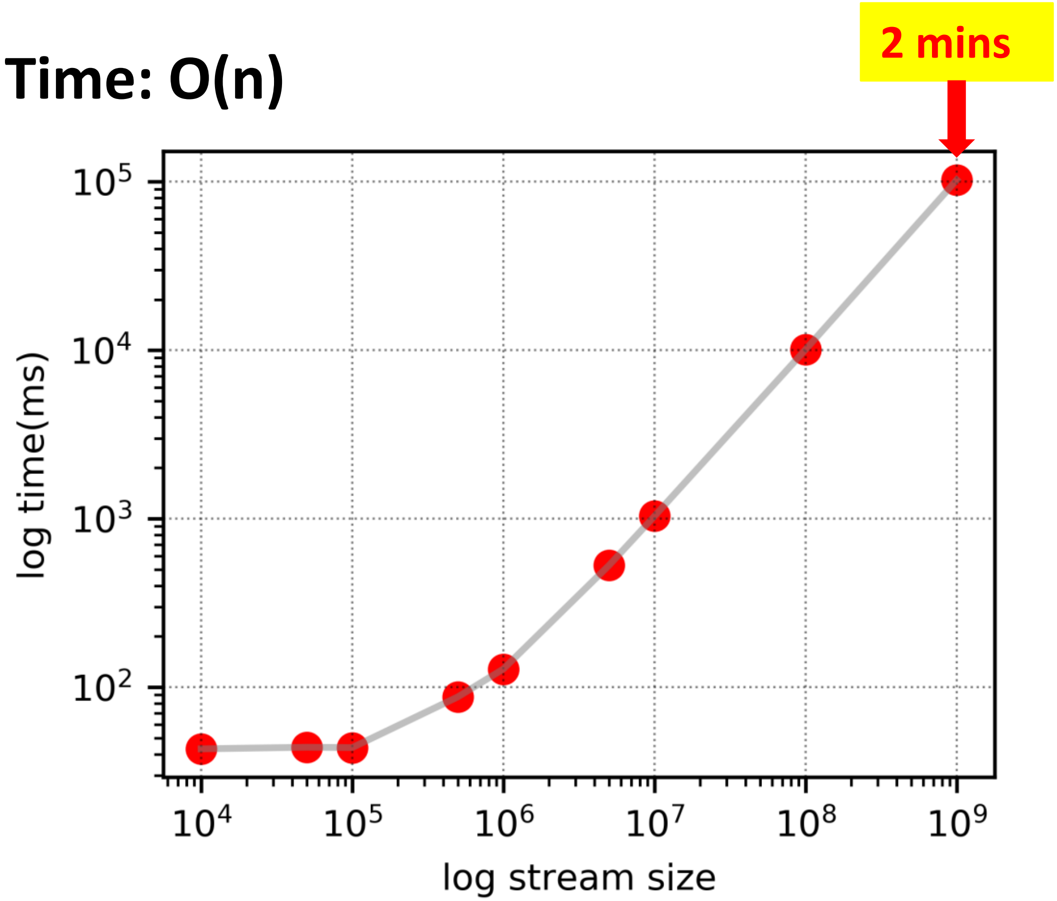
Tumor

Immune

Other

Scaling Performance

Time: O(n)



Memory: O(log(n))

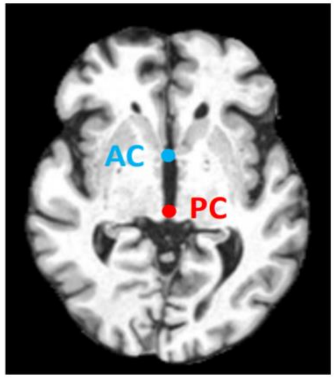
- Sketch Table Parameters:
  - R = 16
  - C = 100000
  - Top k = 20000

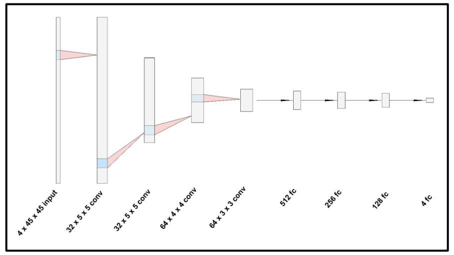
Count Sketch Preprocessor can find low-dimensional embedding of state-action space in a time and memory efficient way.

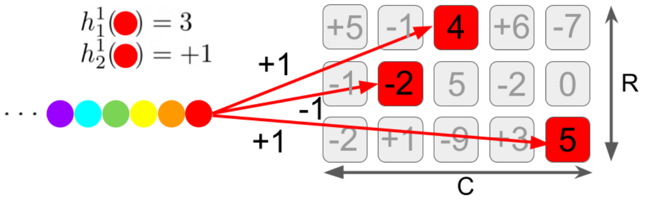
Conclusion: Count Sketch Preprocessor can scale up deep Q learning capacity

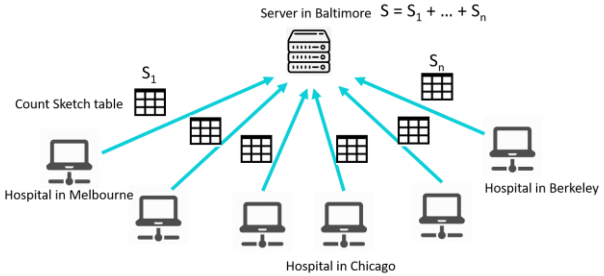
Quantization → (S,A,R,S')-tuple → Encoded Stream → Count Sketch → Coreset w/ Frequency List → DQN

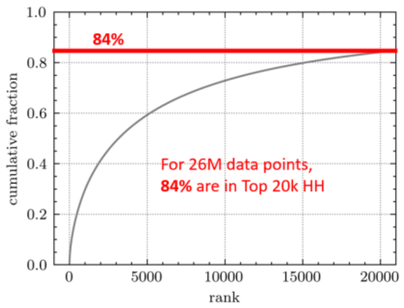
1. Deep RL for medical decision support system
2. Adding Count Sketch preprocessor can find real clustering in large data sets, using streaming
3. The sketches stored in logarithmic space can be easily moved, shared and aggregated.
4. Privacy preserved as re-indentification impossible

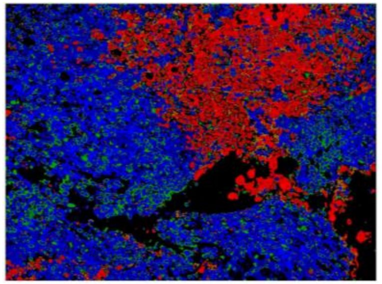












Reference

- Amir Alansary, …Daniel Rueckert. Evaluating Reinforcement Learning Agents for Anatomical Landmark Detection. Medical Image Analysis, 2019.
- https://github.com/bocchs/MIDRL-2D
- Wei, V., Ivkin, N., Braverman, V., and Szalay, A., “Sketch and Scale: Geo-distributed tSNE and UMAP”, IEEE BigData 2020.
- https://github.com/ViskaWei/sketch-scale