Online Learning for Indoor Asset Detection

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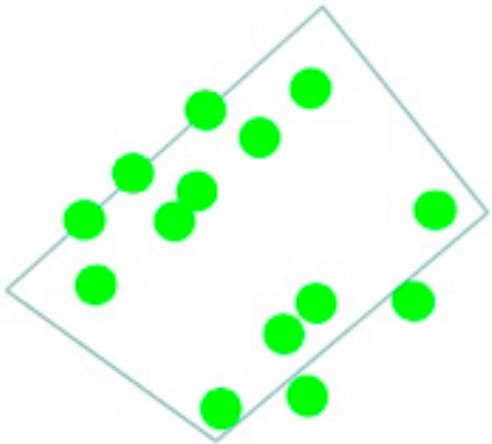
Motivation

- **Problem:**
    - Goal: record asset type and location within building
    - Uses: Climate control, safety, security, maintenance, etc…
    - Example assets: Router, fire sprinkler, fire alarm, fire alarm handle, EXIT sign, cardkey reader, light switch, emergency lights, fire extinguisher, outlet, etc.
- **Challenges:**
    - Existing methods manual, slow, & error prone
    - ML solutions have long far too long training time
    - Training on acquired imagery, not existing databases
- **Advantages:**
    - Semi-automated
    - Online learning learning on the fly with limited data
    - Exploit asset similarities within buildings
        - Instance rather than category recognition

(a) (b)

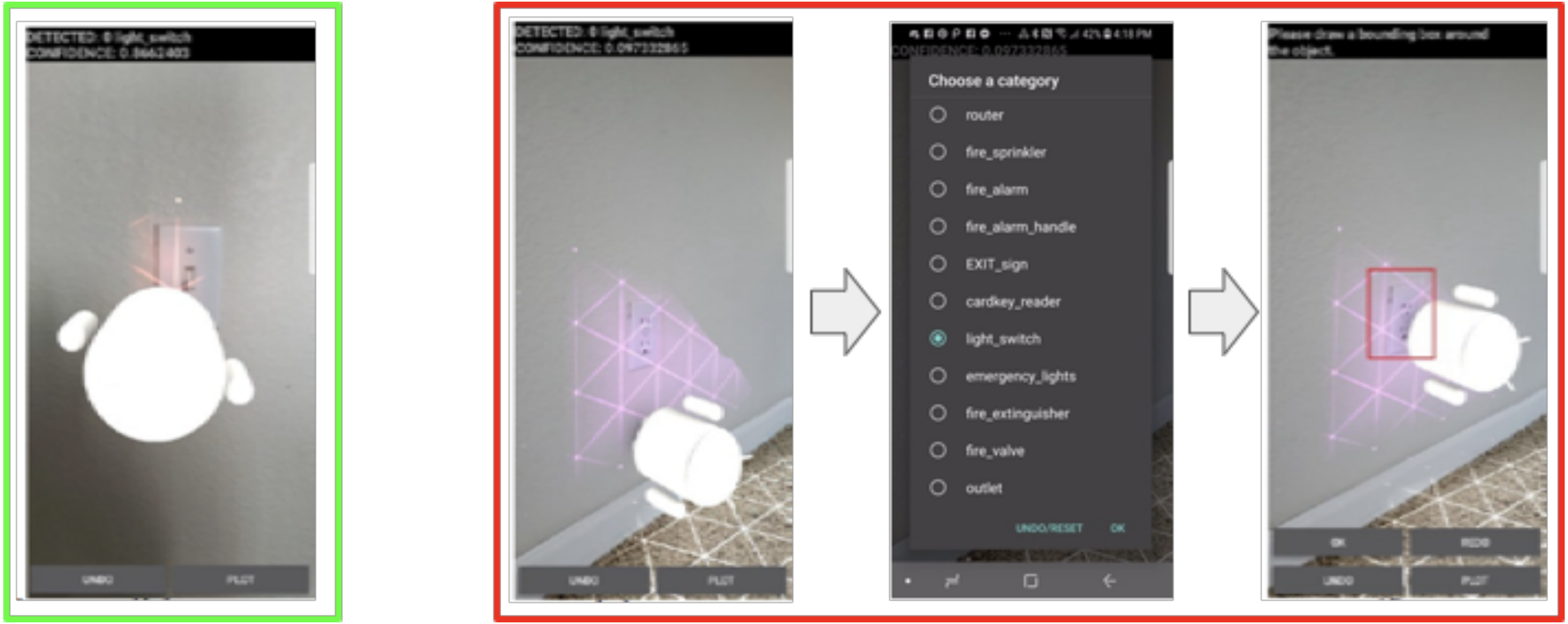
Smartphone App

- Human in the loop
- Detect/Identify assets
- Localize assets



[1] Kostoeva et. al. "Indoor 3D Interactive Asset Detection Using a Smartphone", SPIE Electronic Imaging 2018

Operation of the App



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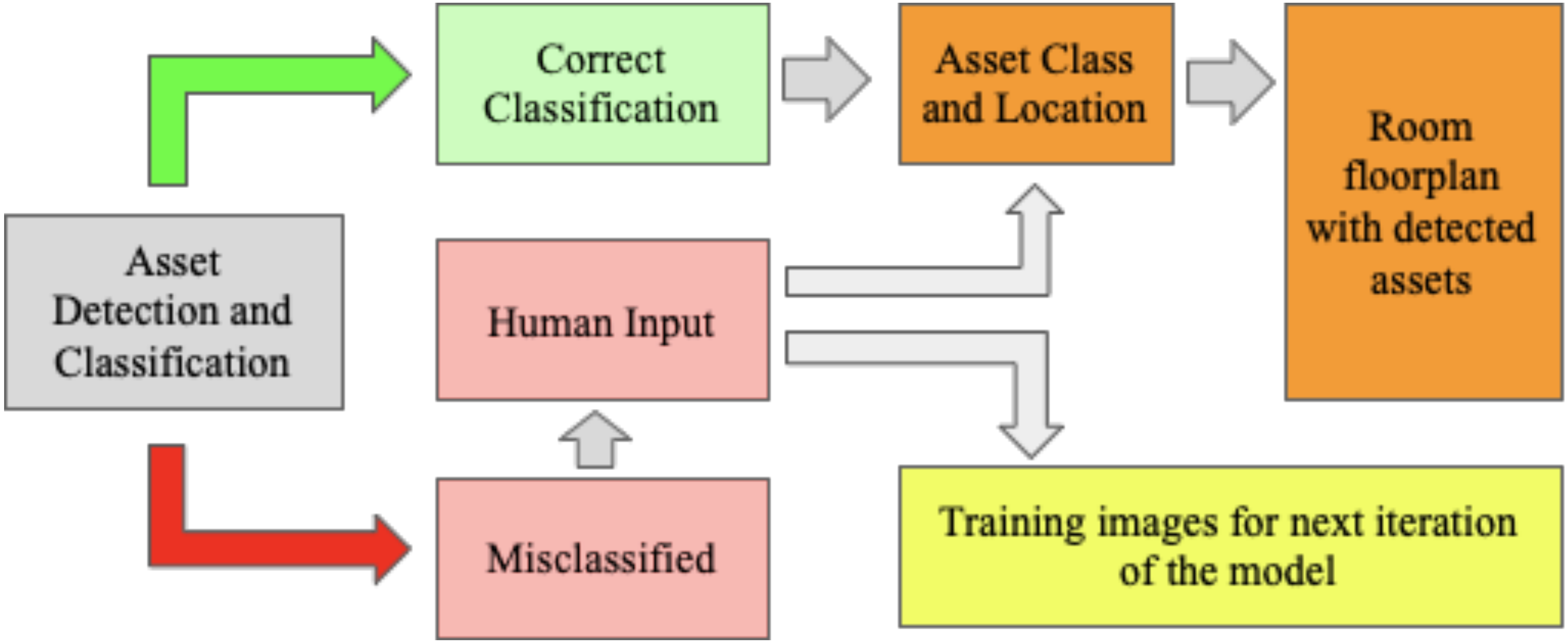
Workflow Within a Session



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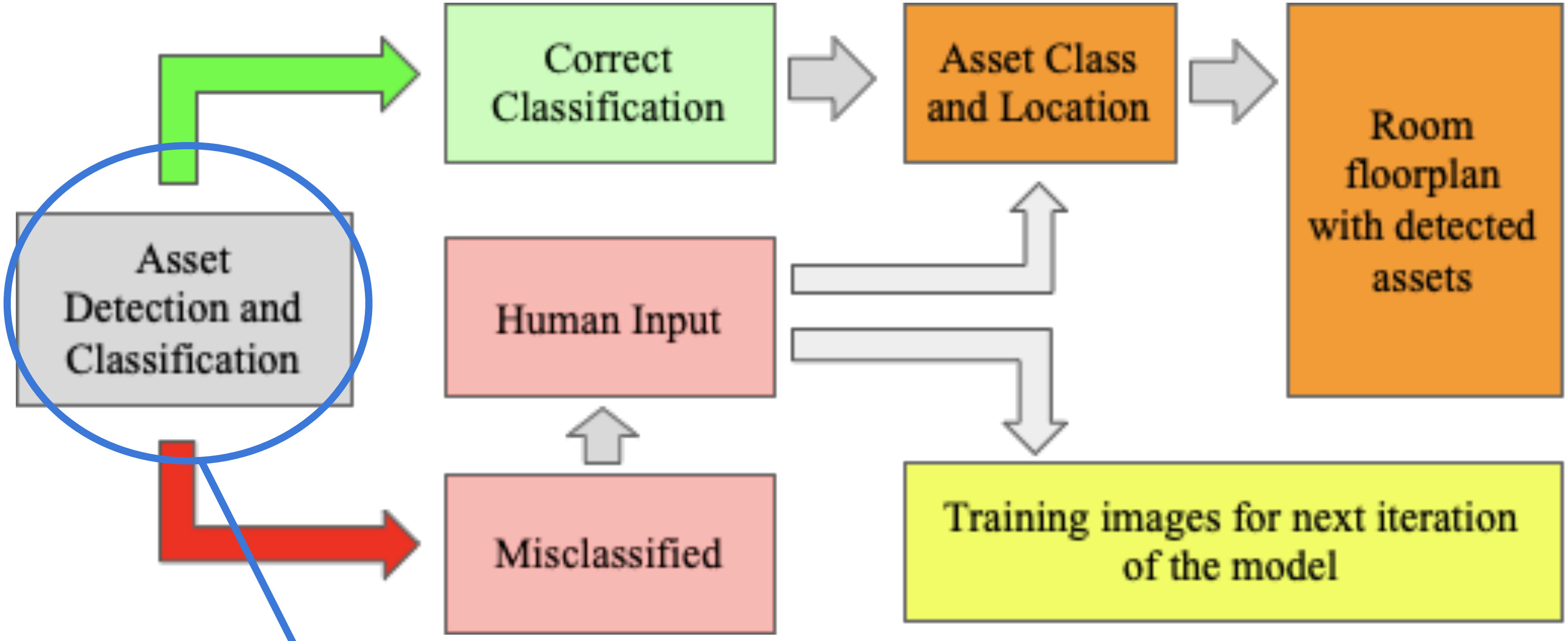


How do we accomplish this?

Previous Approach: Transfer Learning

- Single Shot Detector (SSD) model [1]:
    - Mobile net V1 pre-trained on the MSCOCO dataset [2]
    - Data Augmentations
- Convert trained model to TFLite Model to reside on smartphone

[1] Kostoeva et. al. “Indoor 3D Interactive Asset Detection Using a Smartphone”, SPIE Electronic Imaging 2018
[2] Lin et. al. “Miscrosoft COCO: Common Objects in Context“ , 2015

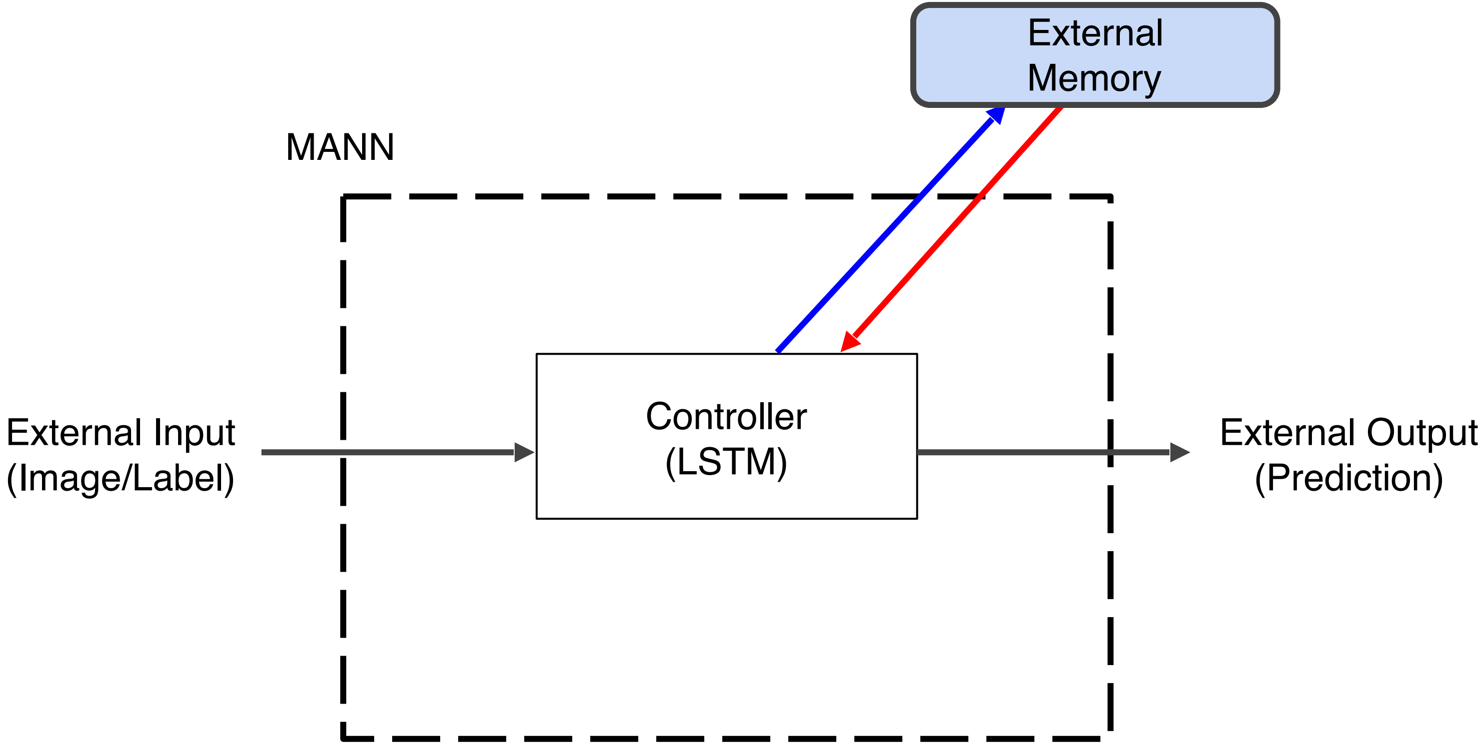
Shortcomings of previous approach:

- No real-time adaptation to seen examples
  - Model frozen during each session; updated only in between sessions
  - Lower accuracy for new buildings
- Retrain on all previous examples
  - Training times of more than 18 hours!

[1] Kostoeva et. al. "Indoor 3D Interactive Asset Detection Using a Smartphone", SPIE Electronic Imaging 2018

Proposed Approach: Online Learning

MANN (Memory Augmented NN)



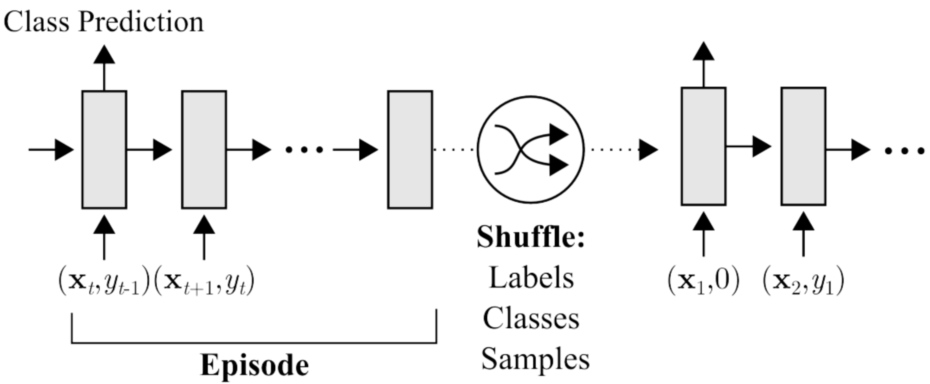
[3] Graves et. al. "Neural Turing Machines", 2014
[4] Santoro et. al. "One-Shot Learning with Memory-Augmented Neural Networks", 2016

Why Use a MANN?

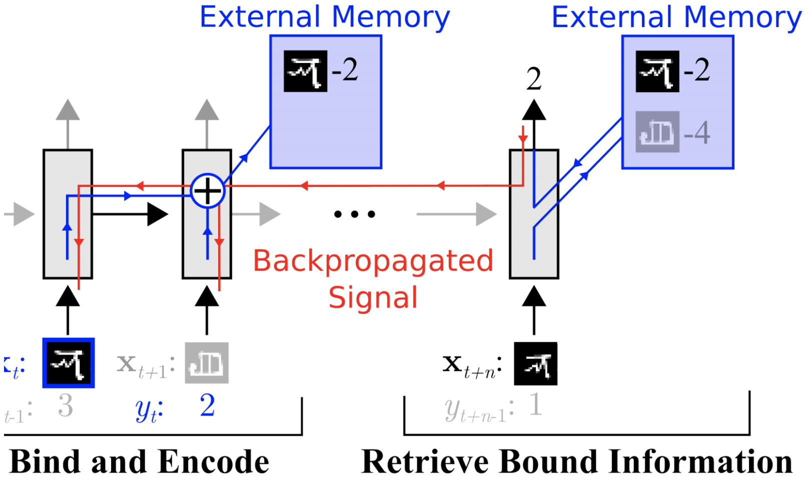
- Meta-learning in tasks that carry significant short- and long-term memory demands.
- Allows successful classification of never-before-seen instances
- **Long Term Memory - Update Weights of the Model:**
  - Used to maintain high level class differentiation
- **Short Term Memory - Utilization of External Memory:**
  - Adapt quickly to the new instances

[4] Santoro et. al. "One-Shot Learning with Memory-Augmented Neural Networks", 2016

Data Preparation



Training



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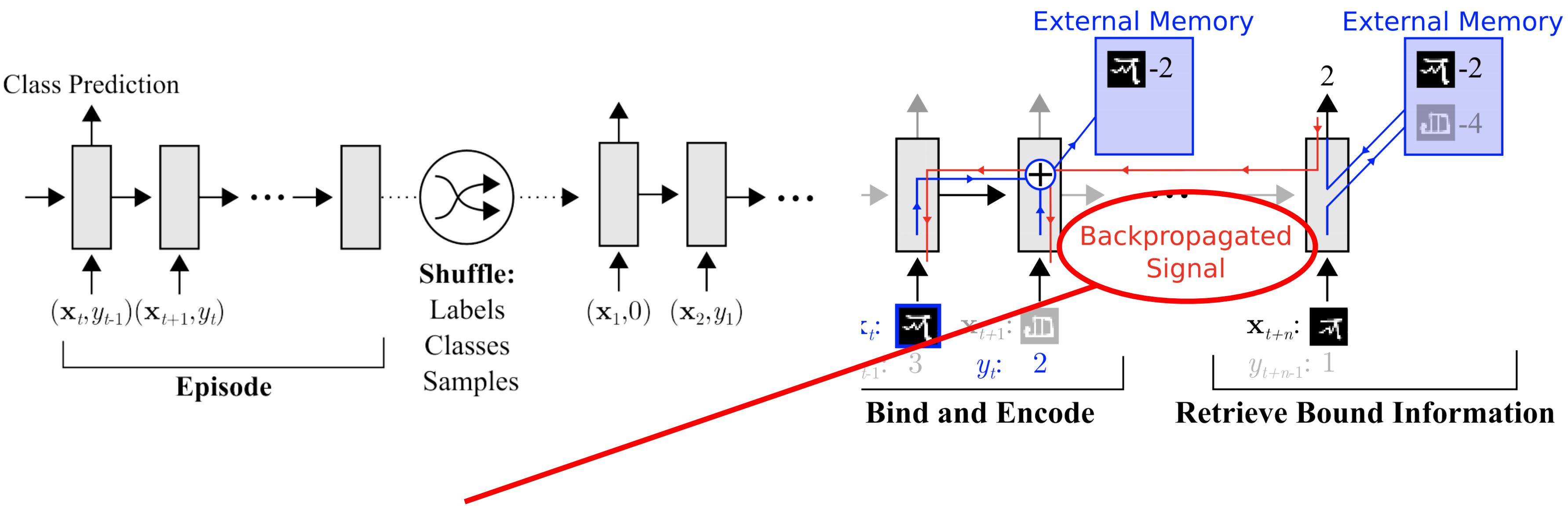
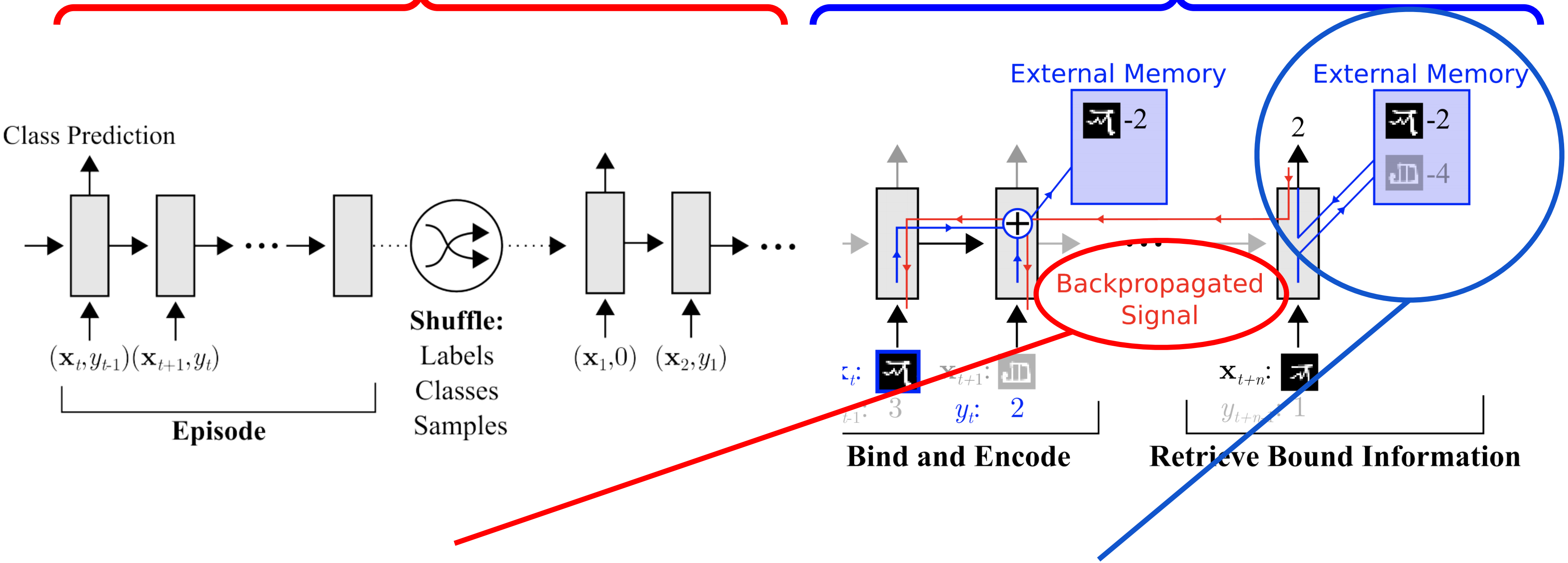
Training



Long Term Memory Updates

Data Preparation

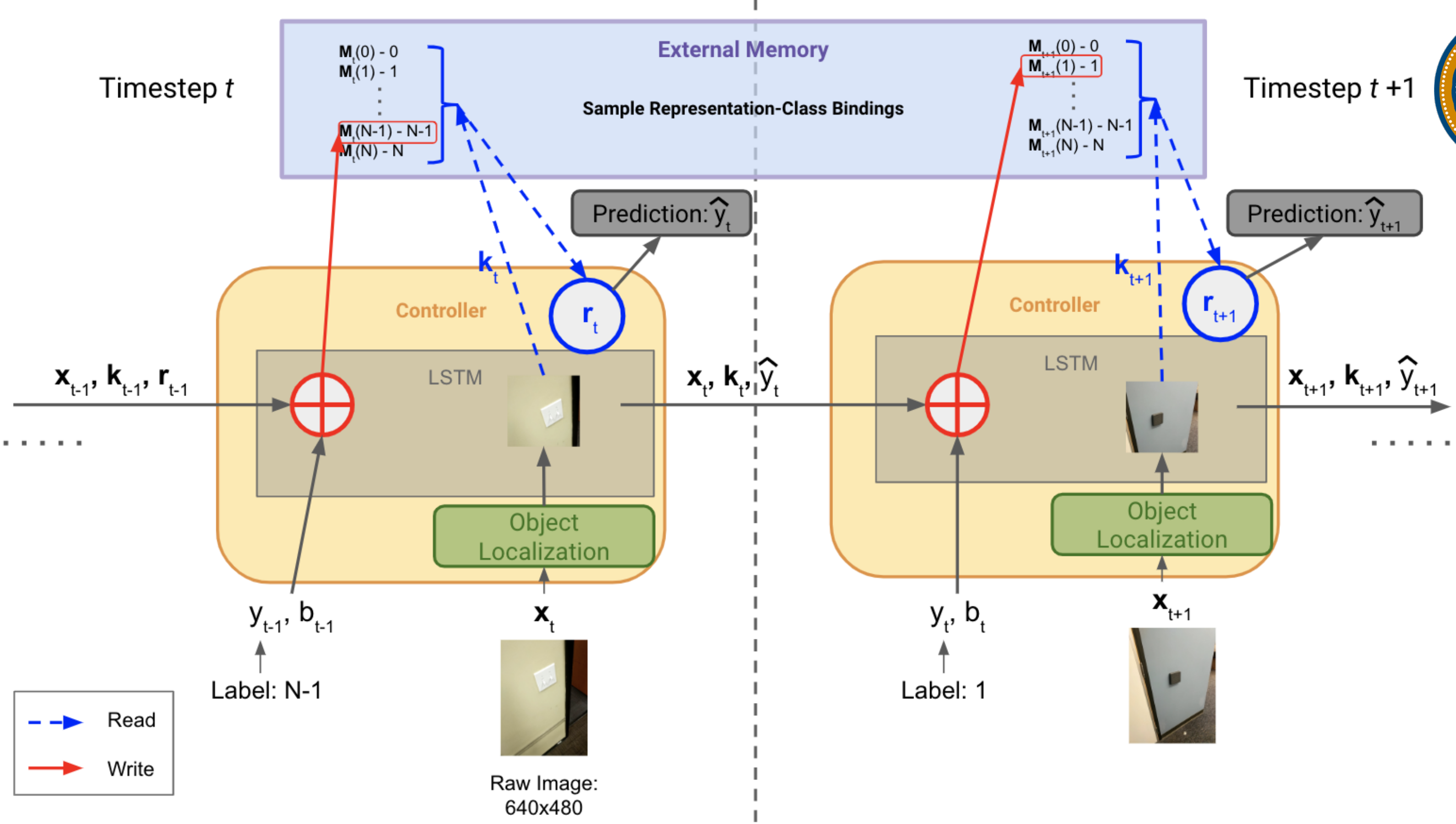
Training



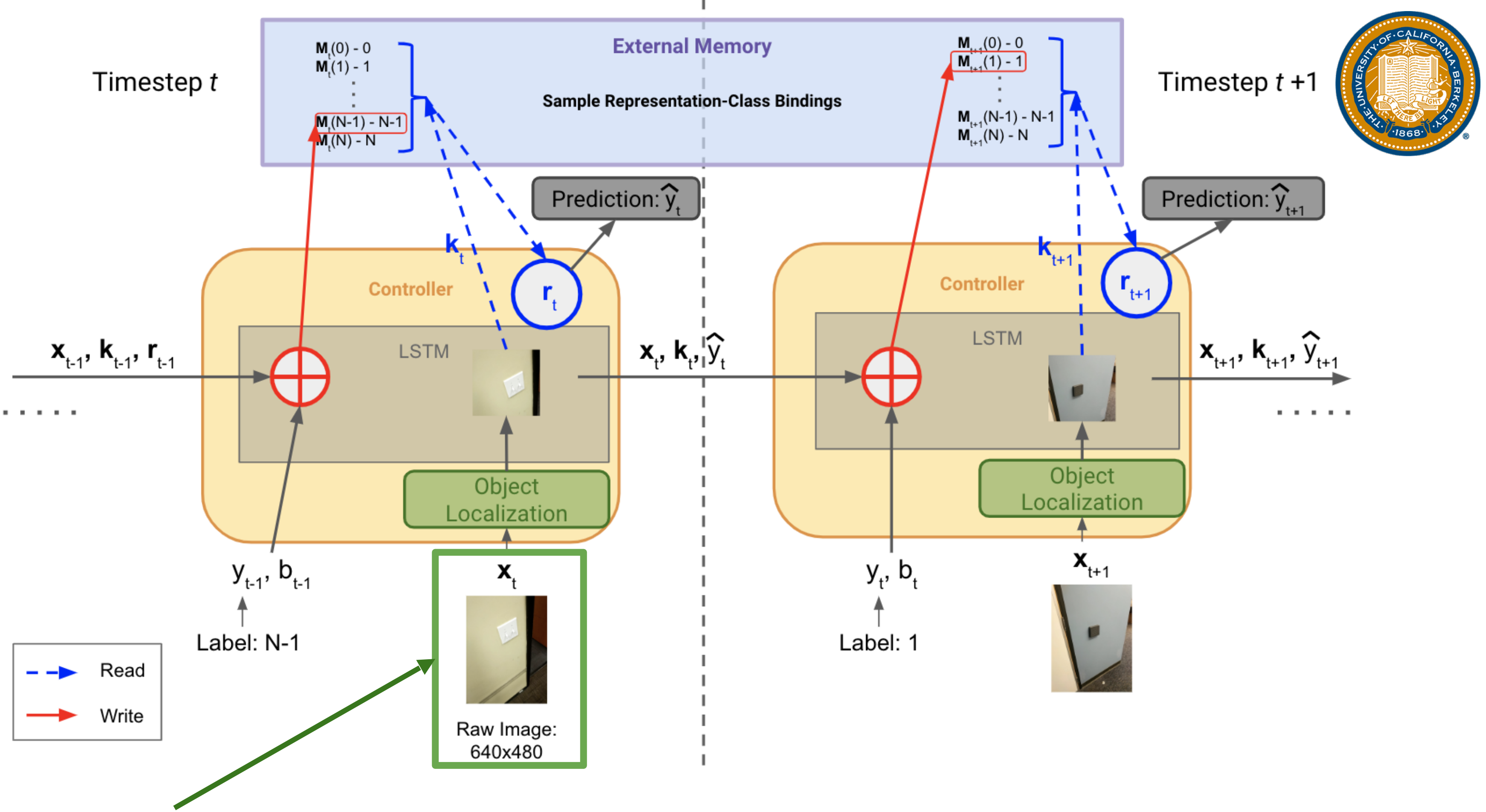
Long Term Memory Updates

Short Term Memory Updates

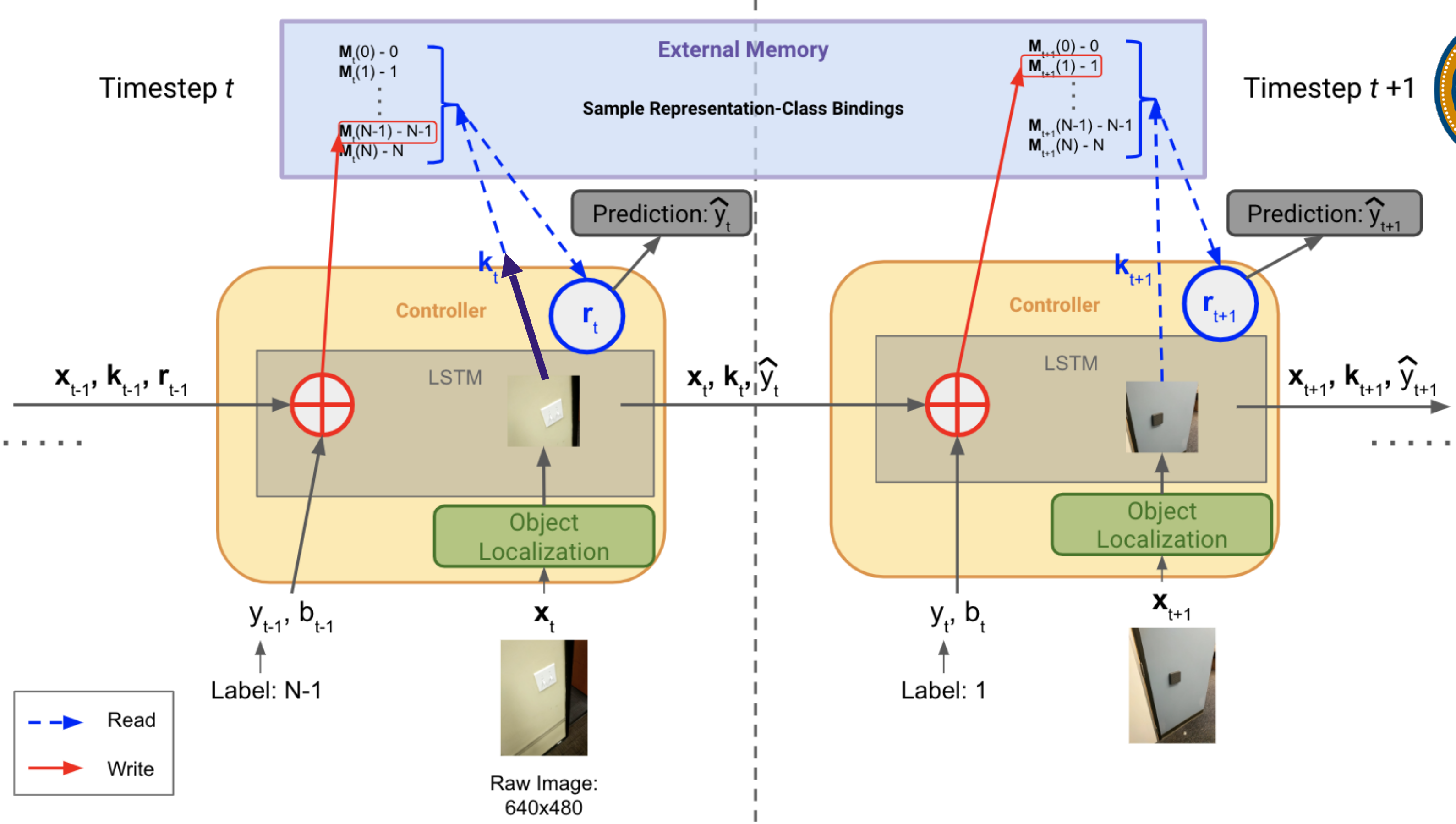
Define the moving parts of the system



Timestep t
External Memory
Sample Representation-Class Bindings
Timestep t +1
Prediction: ŷt
Prediction: ŷt+1
Controller
LSTM
Object Localization
Controller
LSTM
Object Localization
Label: N-1
Label: 1
Raw Image: 640x480
Read
Write



- $\mathbf{x}_t$ - vectorized raw image provided to model at time *t*



Timestep t
Timestep t +1
External Memory
Sample Representation-Class Bindings
M_t(0) - 0
M_t(1) - 1
M_t(N-1) - N-1
M_t(N) - N
M_t+1(0) - 0
M_t+1(1) - 1
M_t+1(N-1) - N-1
M_t+1(N) - N
Prediction: ŷ_t
Prediction: ŷ_t+1
k_t
r_t
k_t+1
r_t+1
Controller
LSTM
Controller
LSTM
x_t-1, k_t-1, r_t-1
x_t, k_t, ŷ_t
x_t+1, k_t+1, ŷ_t+1
Object Localization
Object Localization
y_t-1, b_t-1
Label: N-1
x_t
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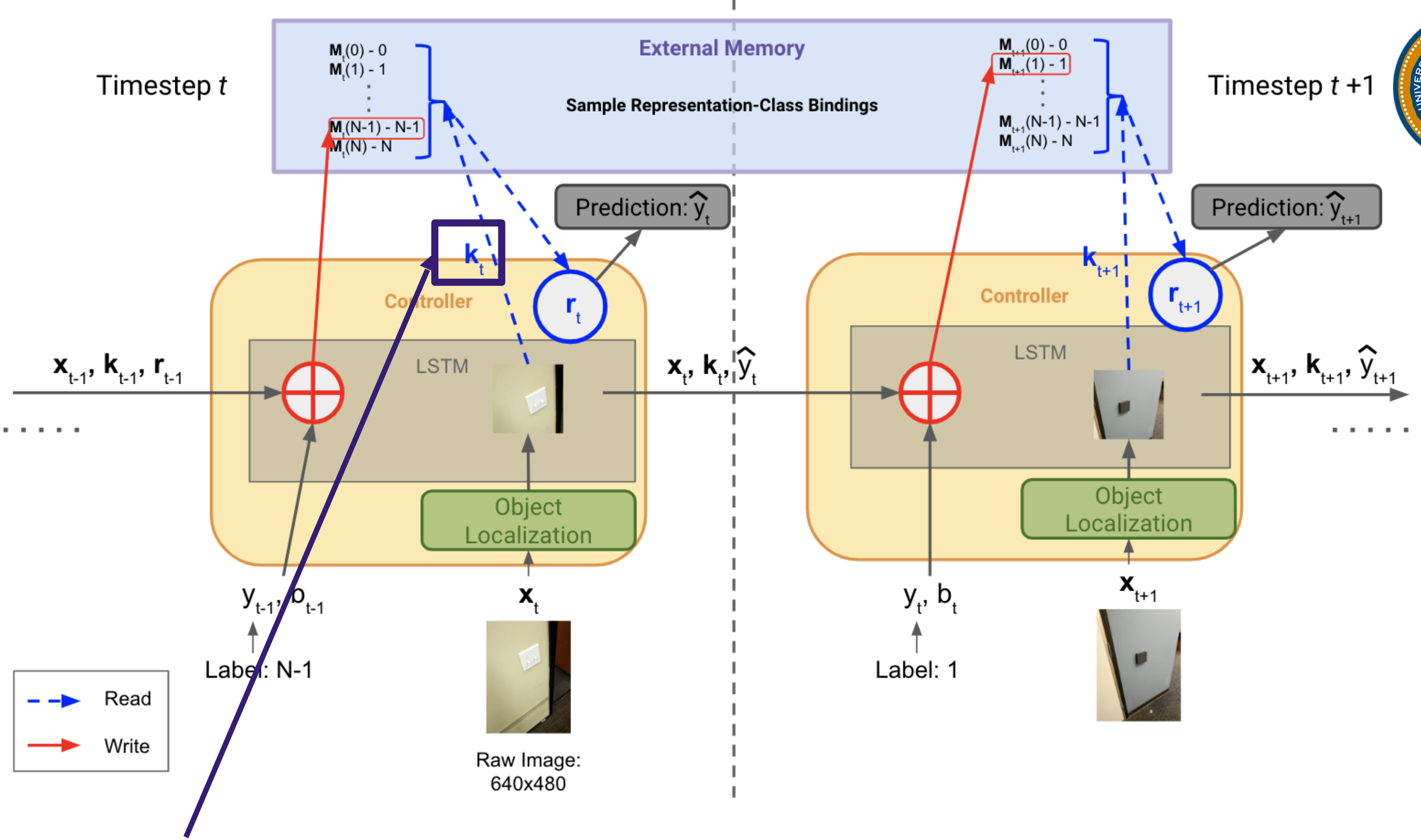
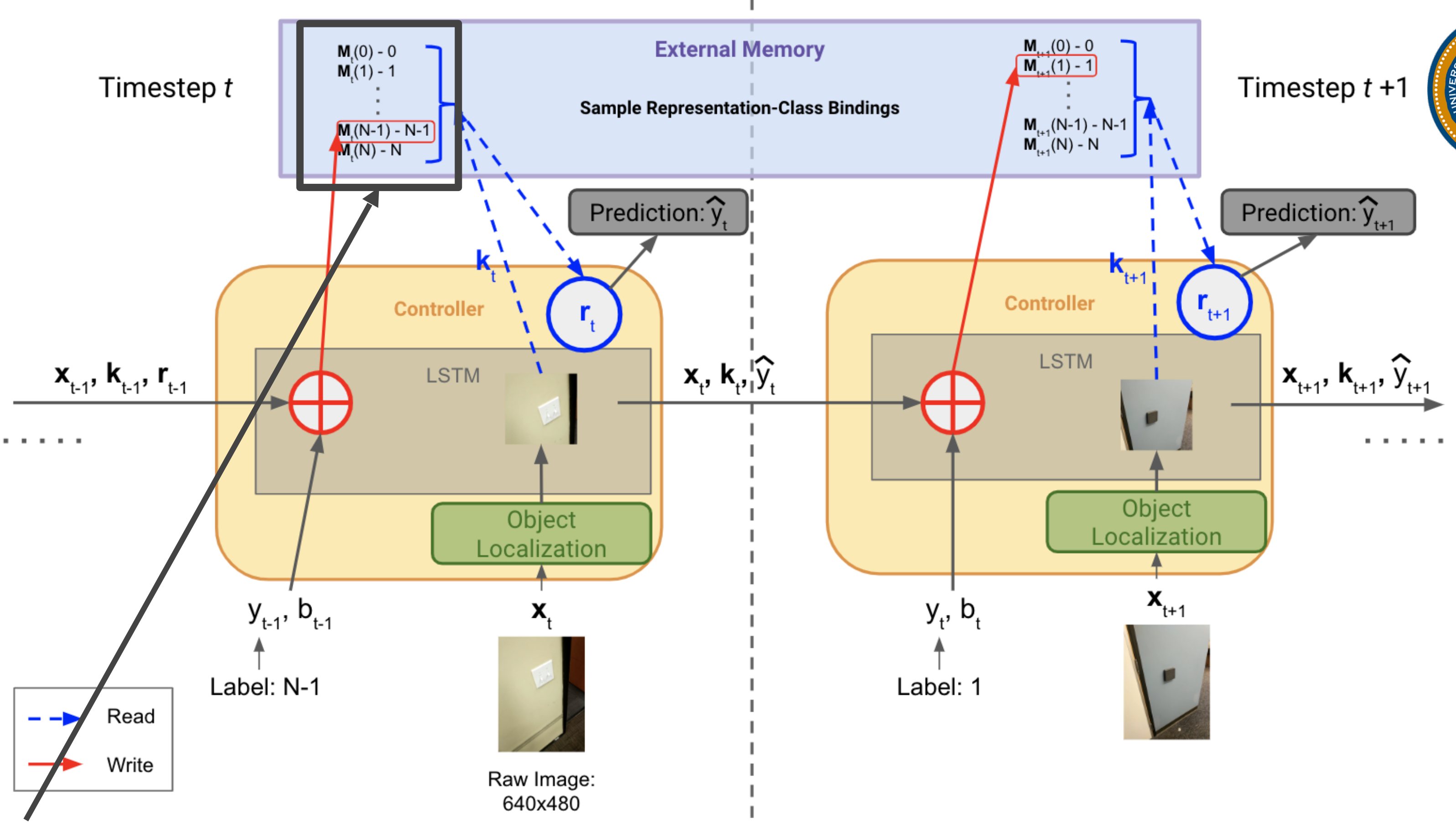
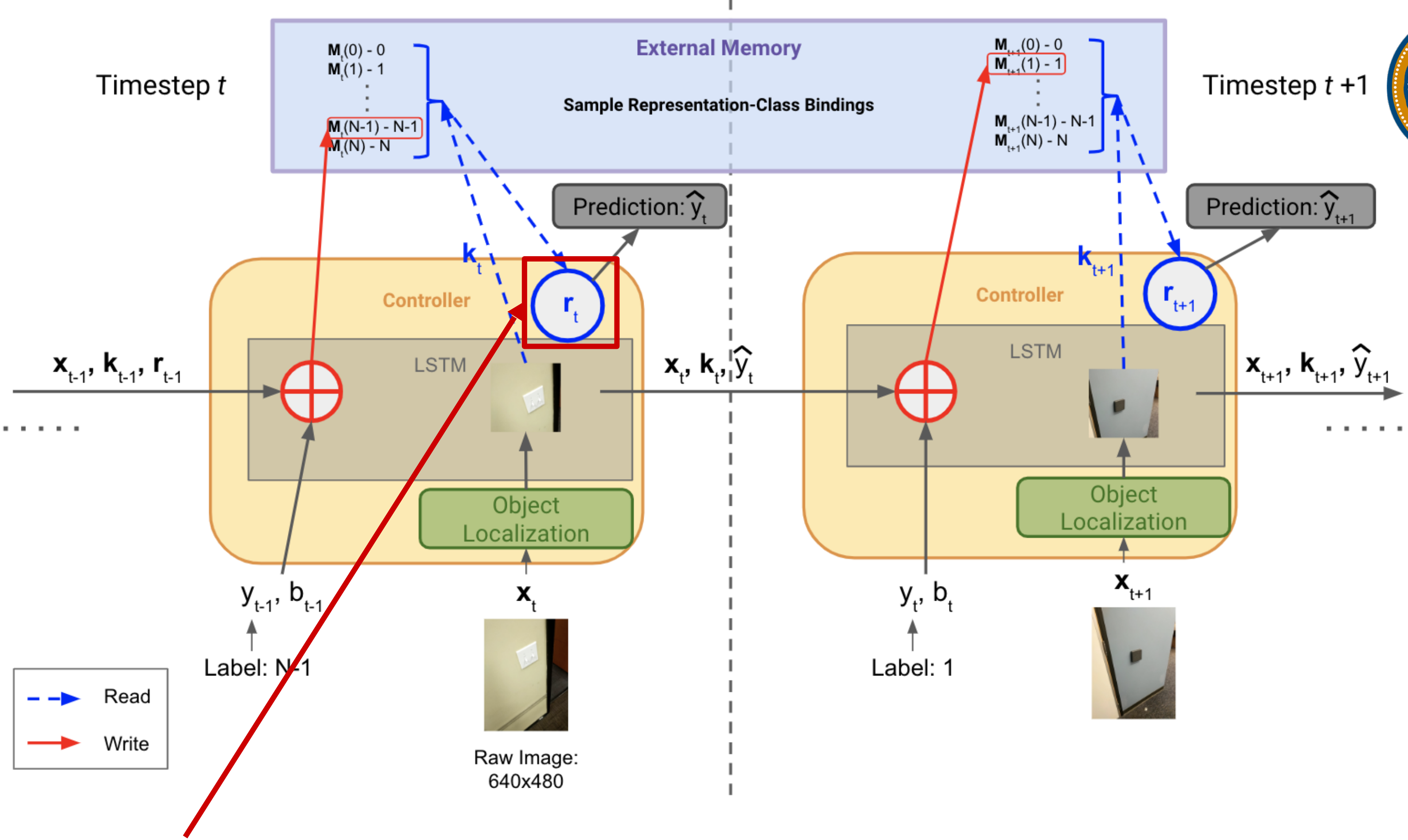


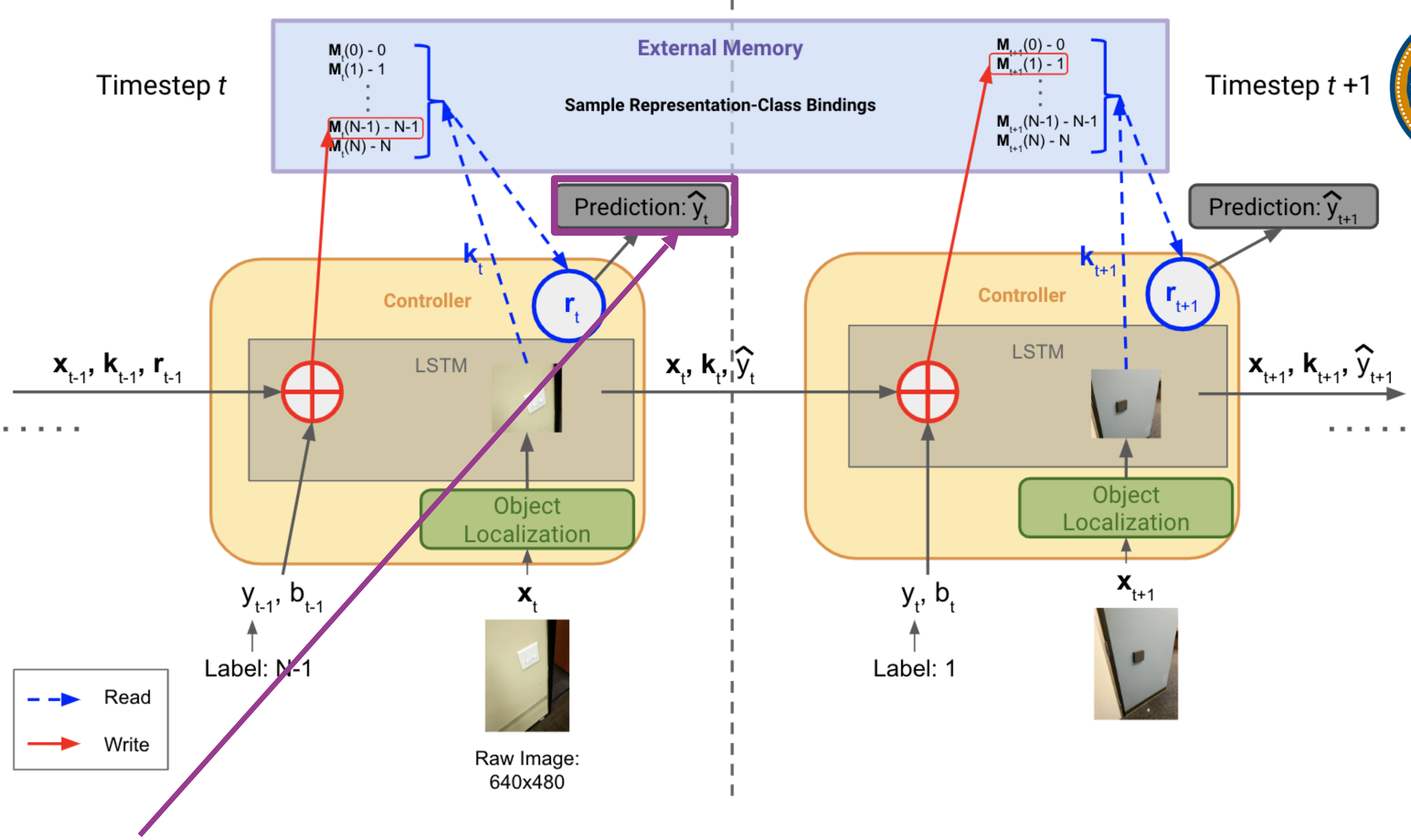
- $\mathbf{k}_t$ - *M*-dimensional vector “key” representation outputted by LSTM



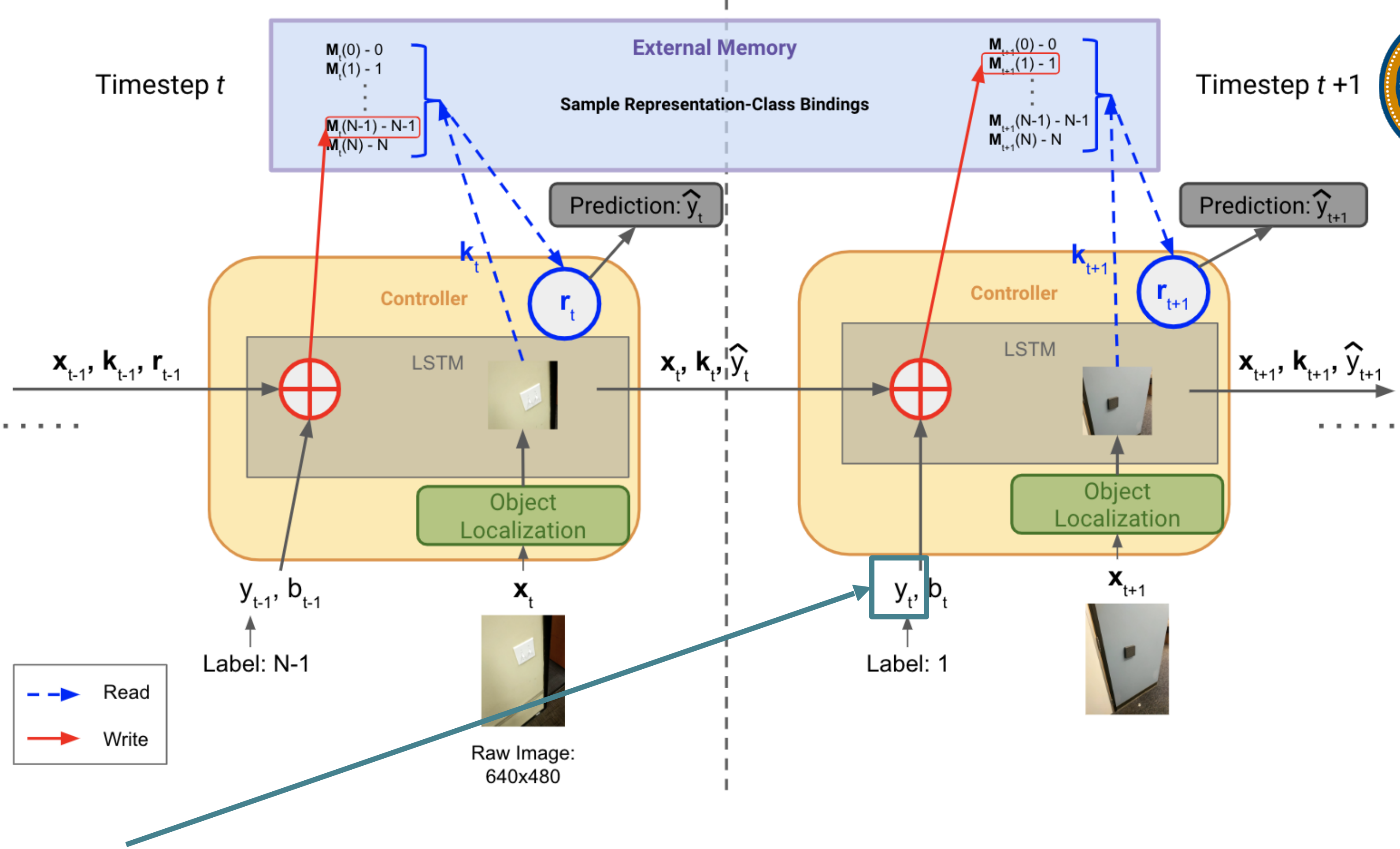
- $\mathbf{M_t}$ - the $N \times M$ memory matrix at time t
  - N - the number of classes in our system, 10, for the number of assets
  - M - dimension of the condensed representation, generated by the LSTM, for an input image



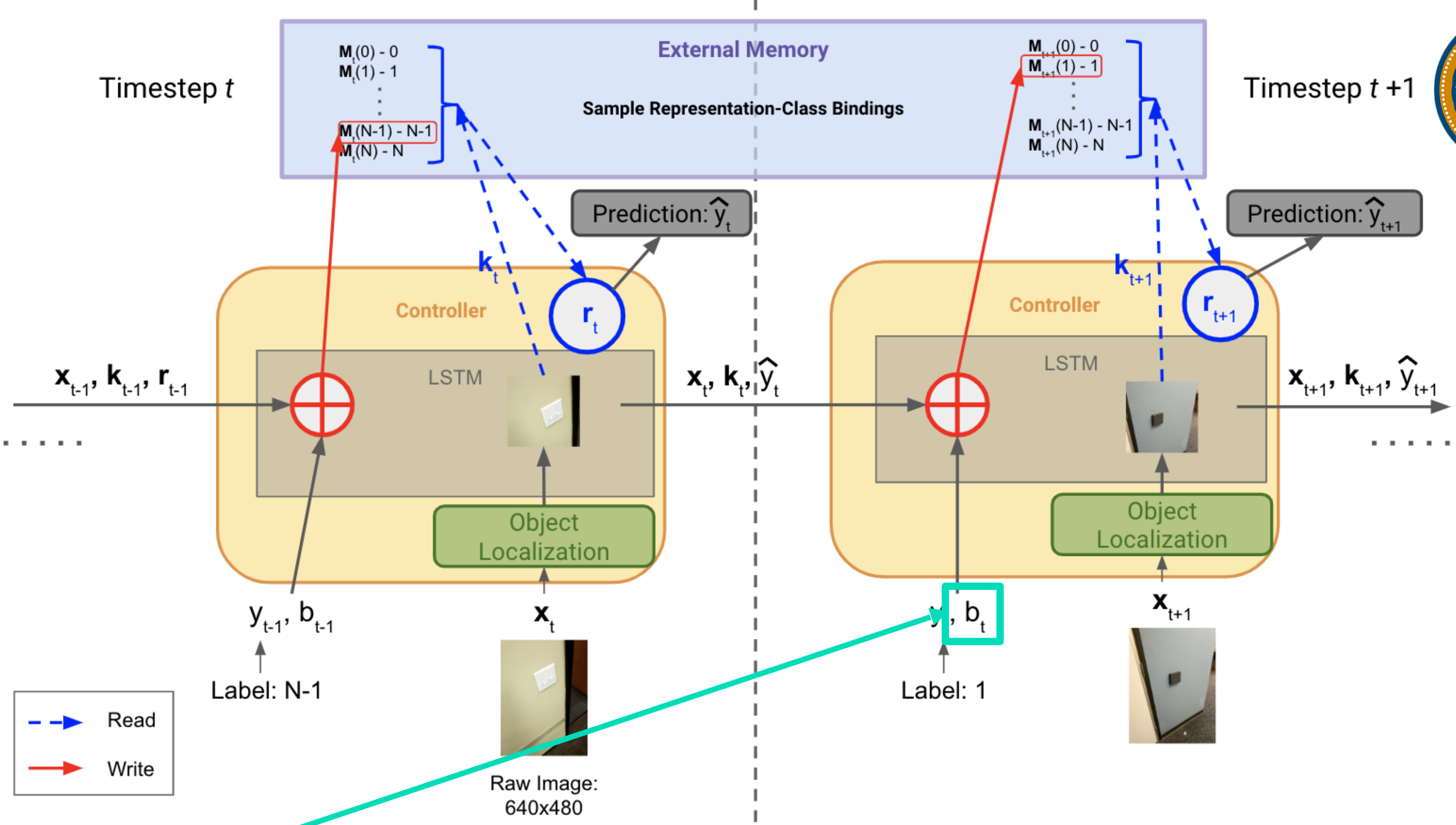
- $\mathbf{r_t}$ - “memory” read from the memory matrix read at time *t*



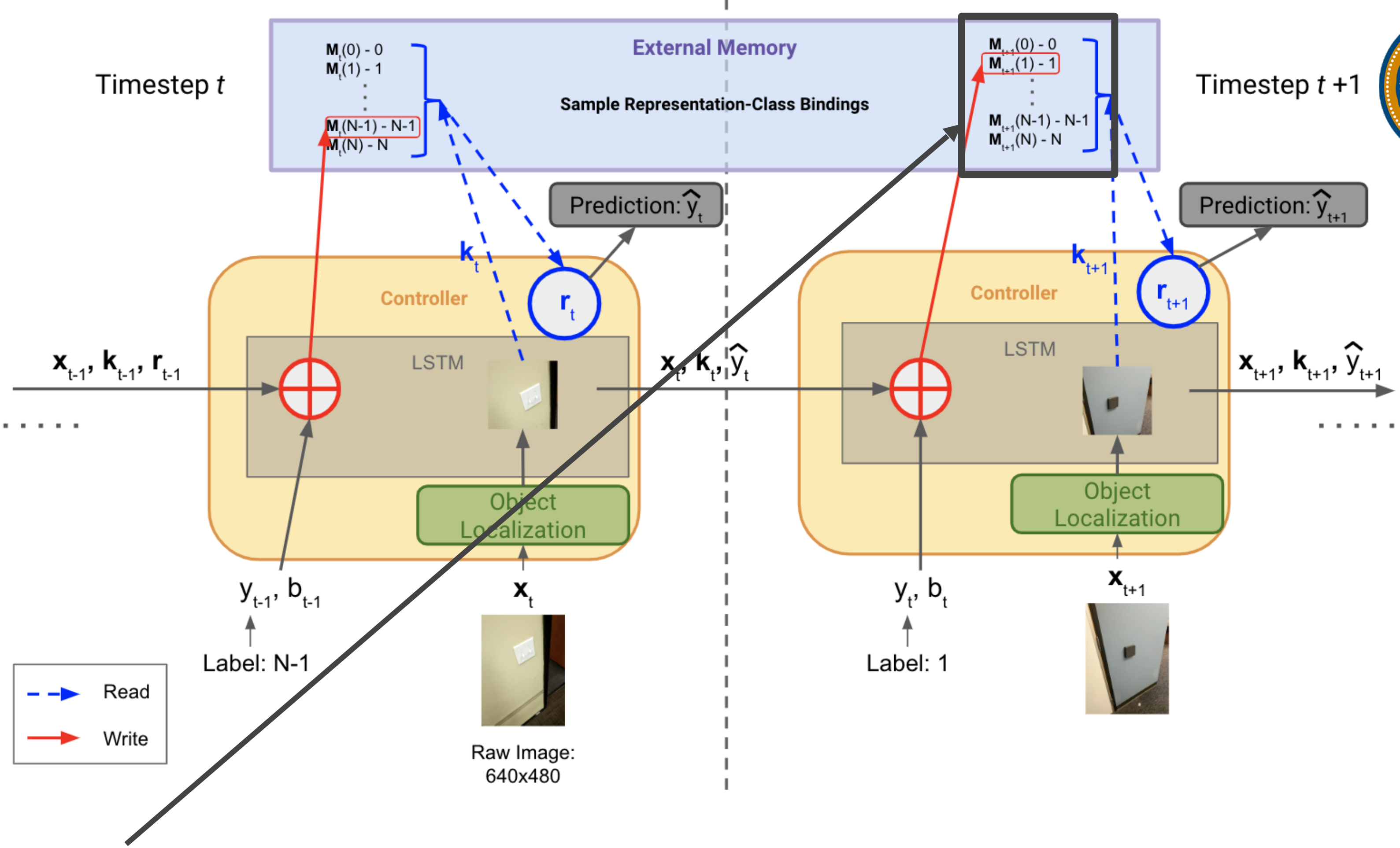
- $\hat{y}_t$ - predicted label for image at time *t* and corresponds to input image $\mathbf{x}_t$



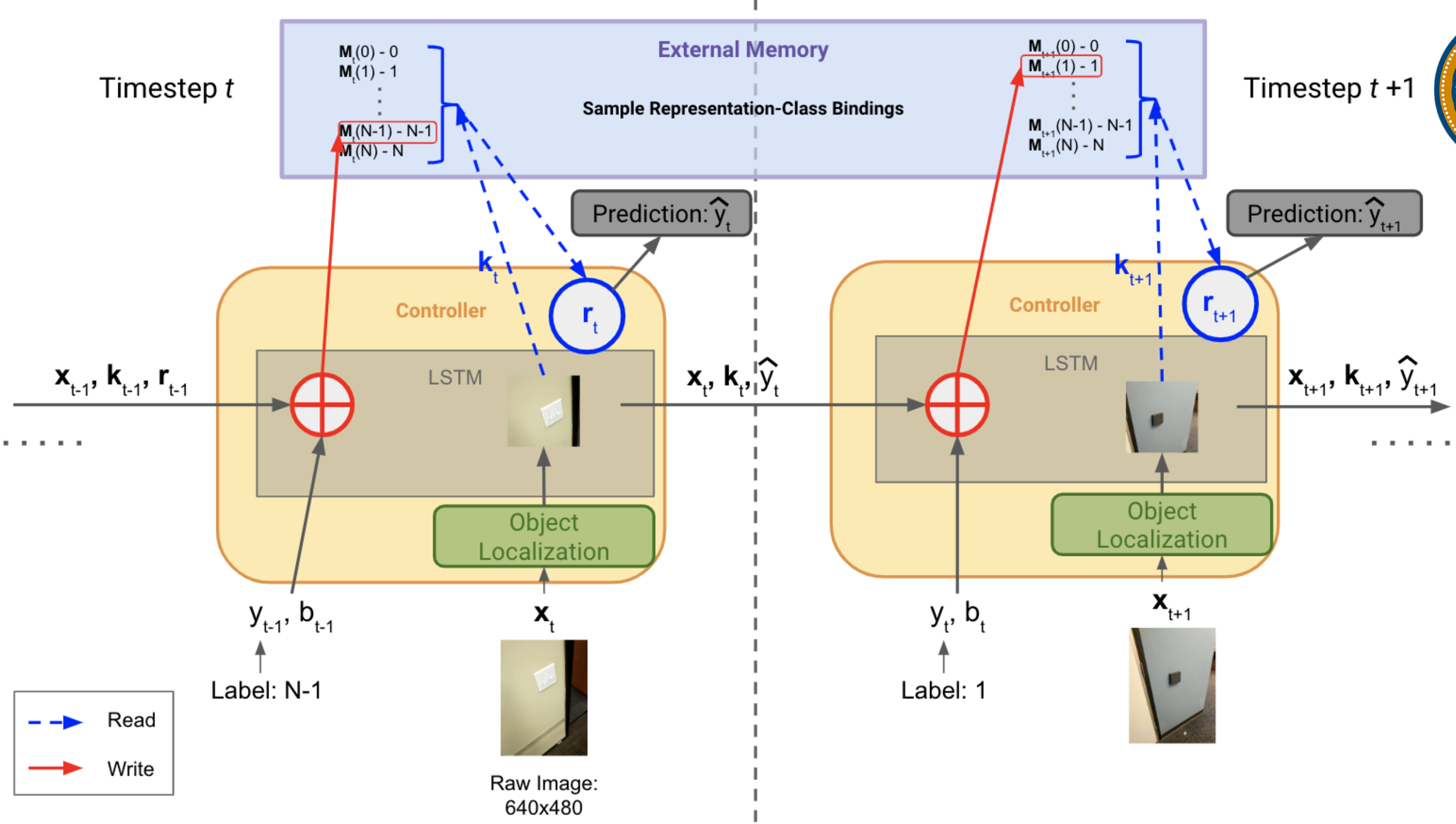
- y_t - ground truth label passed in to model at time t+1 and corresponds to input image $\mathbf{x}_t$



- b_t – bounding box provided at time *t+1* and corresponds to input image $\mathbf{x}_t$



- $\mathbf{M_{t+1}}$ - the $N \times M$ memory matrix at time $t + 1$



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Model Update Flow

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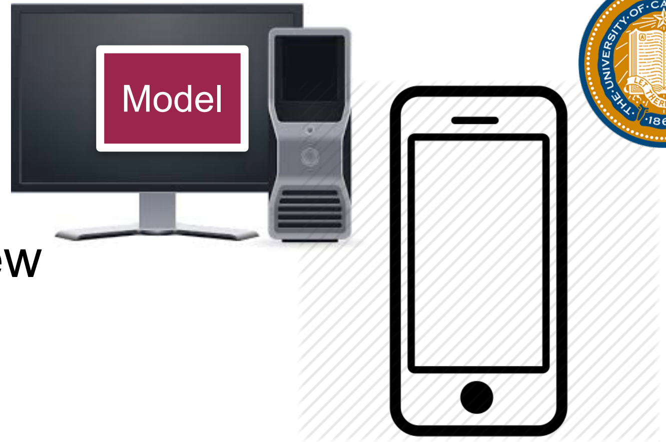

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Back to step 1

Choices in Offline Training Method

- Should we train on only the negative, or incorrectly classified, examples?
- Should we retain short-term memory across sessions?

	Clear External Memory	Retain External Memory
(-) Examples	Mode 1	Mode 2
(-/+) Examples	Mode 3	**Mode 4 w/ decaying memory retention**

Results compared to previous method

Model		Day 1 (CH)	Day 2 (CH)	Day 3 (SDH)	Day 3 (EH)	Day 4 (CH)
		Evaluation Set				
SSD [1]		67.2	81.7	74.3	54.7	73.6
Ours						
Mode (1)	Acc.(%)	58.6	60.9	63.5	62.9	69.78
	Std Dev.(%)	0.11	0.08	0.05	0.14	0.03
	Min Acc.(%)	54.1	55.7	60.6	56.2	60.1
	Max Acc.(%)	62.0	64.1	65.8	67.5	70.3
Mode (2)	Acc.(%)	66.7	63.9	67.6	64.33	76.2
	Std Dev.(%)	0.21	0.11	0.08	0.13	0.02
	Min Acc.(%)	59.9	61.3	63.4	60.1	74.0
	Max Acc.(%)	70.0	66.2	69.3	66.7	77.3
Mode (3)	Acc.(%)	73.1	74.3	**76.2**	69.3	77.1
	Std Dev.(%)	0.12	0.13	0.01	0.10	0.008
	Min Acc.(%)	68.8	70.2	75.1	68.8	76.0
	Max Acc.(%)	75.2	75.1	77.1	70.1	77.8
Mode (4)	Acc.(%)	**73.1**	**82.3**	74.7	**69.8**	**79.0**
	Std Dev.(%)	0.07	0.01	0.04	0.08	0.10
	Min Acc.(%)	71.8	77.8	70.9	67.1	77.2
	Max Acc.(%)	76.2	84.1	76.3	71.5	83.6

[1] Kostoeva et. al. "Indoor 3D Interactive Asset Detection Using a Smartphone", SPIE Electronic Imaging 2018

TFLite Model Results for Mode 4:

Tensorflow Model (150 MB) converted to TFLite Model (80 MB) to port onto phone

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Model	Day 1 (CH)	Day 2 (CH)	Day 3 (SDH)	Day 3 (EH)	Day 4 (CH)
SSD [1]	67.2	81.7	74.3	54.7	73.6
Ours (TFLite)	71.8	81.8	74.0	68.8	77.9
Ours (Full TF)	**73.1**	**82.3**	**74.7**	**69.8**	**79.0**
Δ Ours (Full TF) - Ours (TFLite)	+1.3	+0.5	+0.7	+1.0	+1.1
Δ Ours (TFLite) - SSD	+4.6	+0.1	-0.3	+14.1	+4.3

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- Little loss from TF model to TFLite from conversion
- TFLite model outperforms SSD by up to 14 points

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Comparison of Offline Training Times

	Offline Training		Online Training		Online Inference	
Data Set	SSD (Kostoeva et al.)	Ours (Mode 4)	SSD [1]	Ours	SSD [1]	Ours
Day 0	18hr 29m	5hr 27m	–	–	–	–
Day 1	20hr 11m	4hr 17m	–	1.13 s	0.084 s	0.064 s
Day 2	20hr 56m	3hr 4m	–	1.06 s	0.082 s	0.041 s
Day 3	22hr 40m	4hr 13m	–	1.00 s	0.081 s	0.050 s
Day 4	–	4hr 9m	–	1.21 s	0.084 s	0.034 s

- Up to 7x speedup in offline training times
- Up to 2x speedup in online inference times

[1] Kostoeva et. al. "Indoor 3D Interactive Asset Detection Using a Smartphone", SPIE Electronic Imaging 2018

Conclusions & Future Work

- **Proposed Online Learning Method for Asset Detection:**
  - Better Accuracy
  - Improved Latencies
  - Real-time Learning
  - Shorter Offline Training time

- **Future Work:**
  - Extend to hundreds of asset categories → scalability
  - Adapt to previously unseen asset classes in real-time