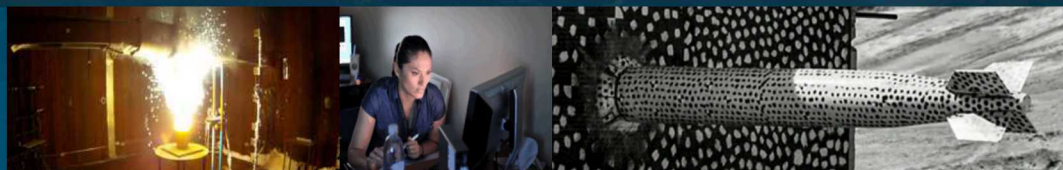
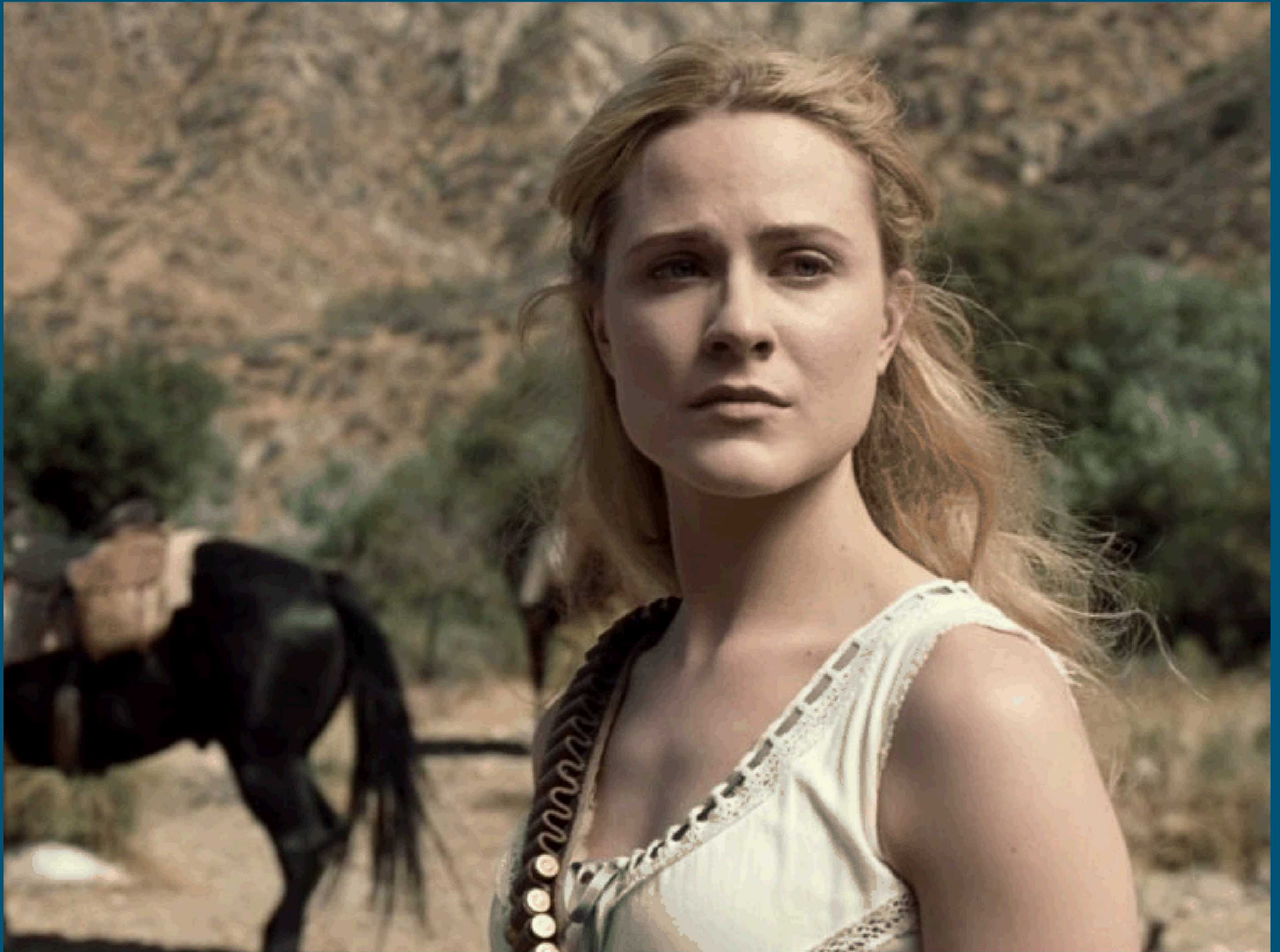


I could see your lips move.



PRESENTED BY

JD Doak to CCD on 6/30/2020

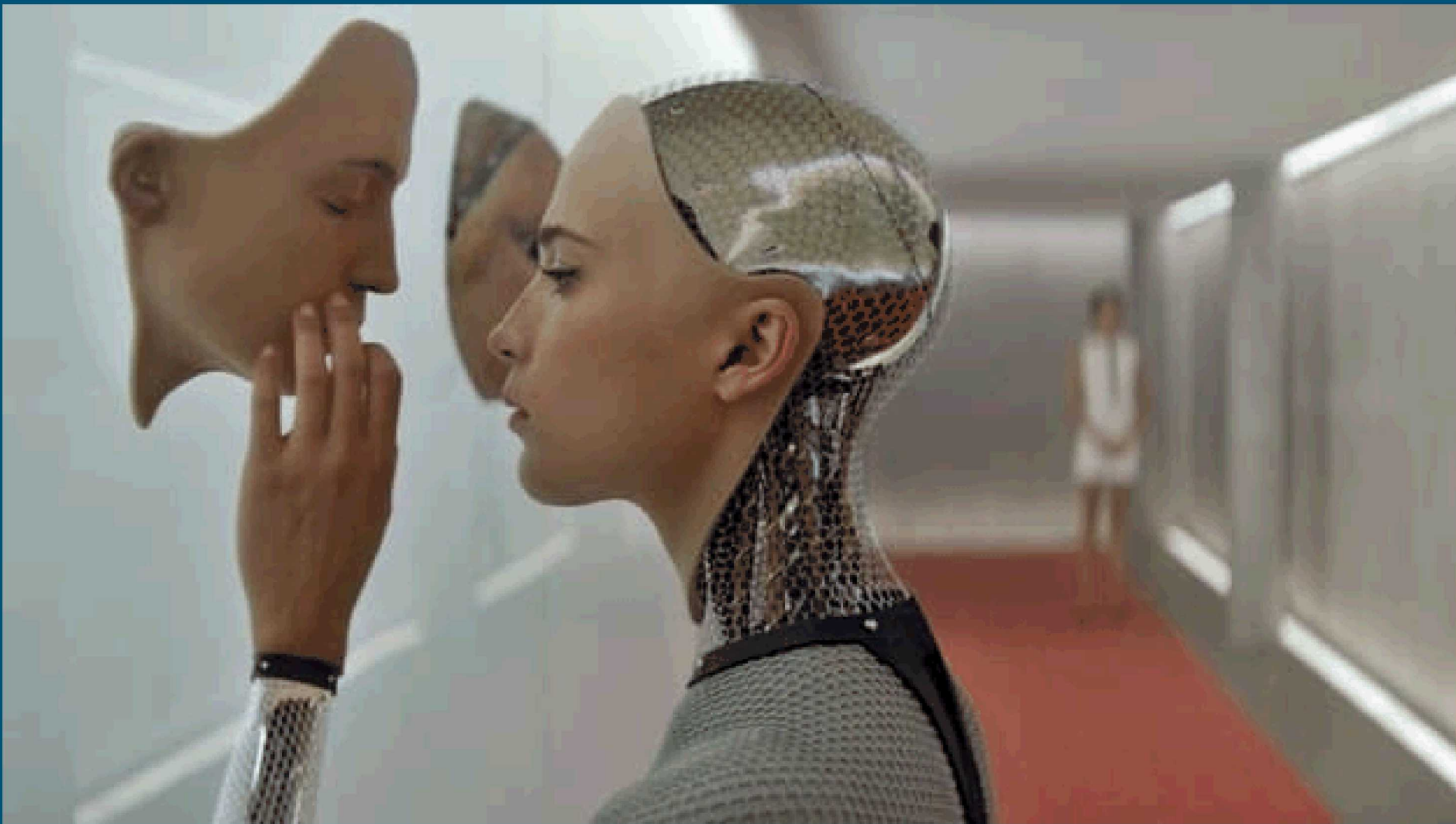


<https://www.thisisinsider.com/westworld-season-2-episode-1-analysis-spoilers-2018-4>

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<https://www.spotern.com/en/wanted/movie/blade-runner/32790/the-cigarette-of-rachel-sean-young-in-blade-runner>
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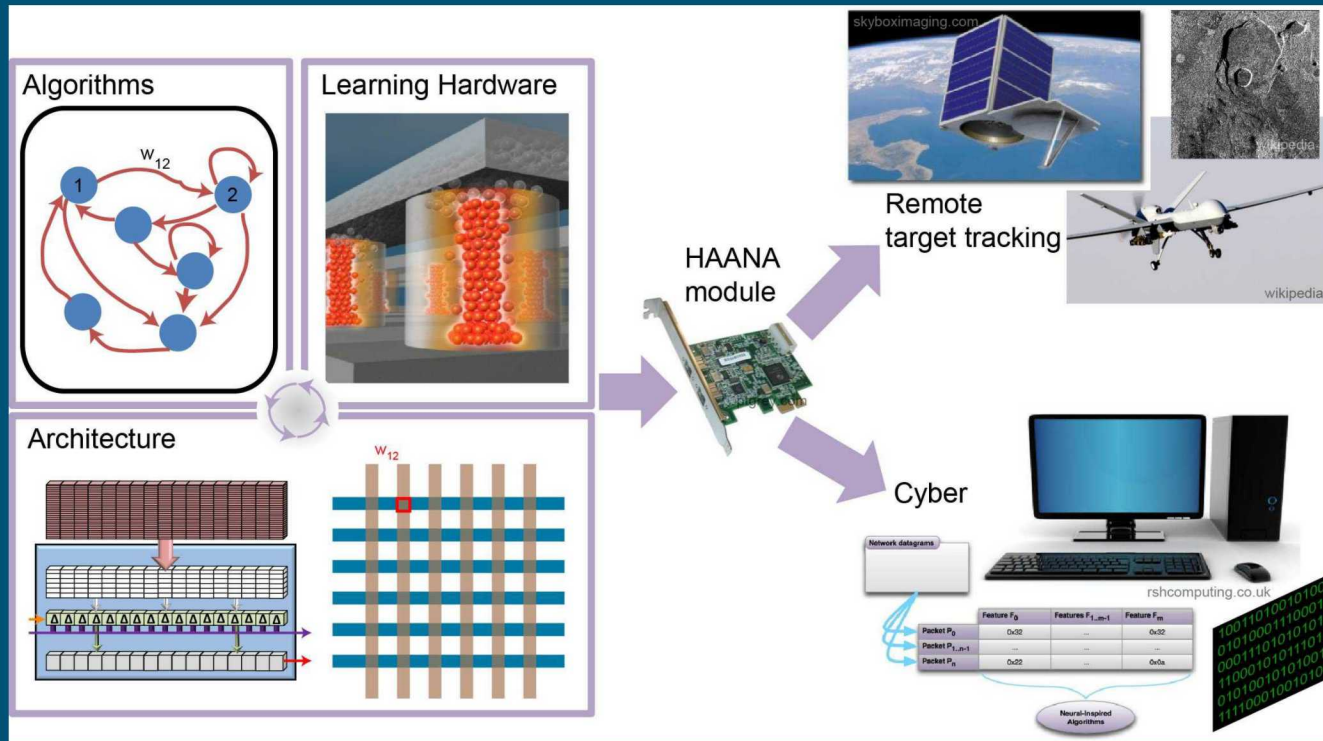
<https://vaguevisages.com/2017/04/14/the-original-sin-in-ex-machina-ava-is-the-origin/>
This is a still image from Ex Machina reproduced for educational purposes only. Copyright belongs to original owners.

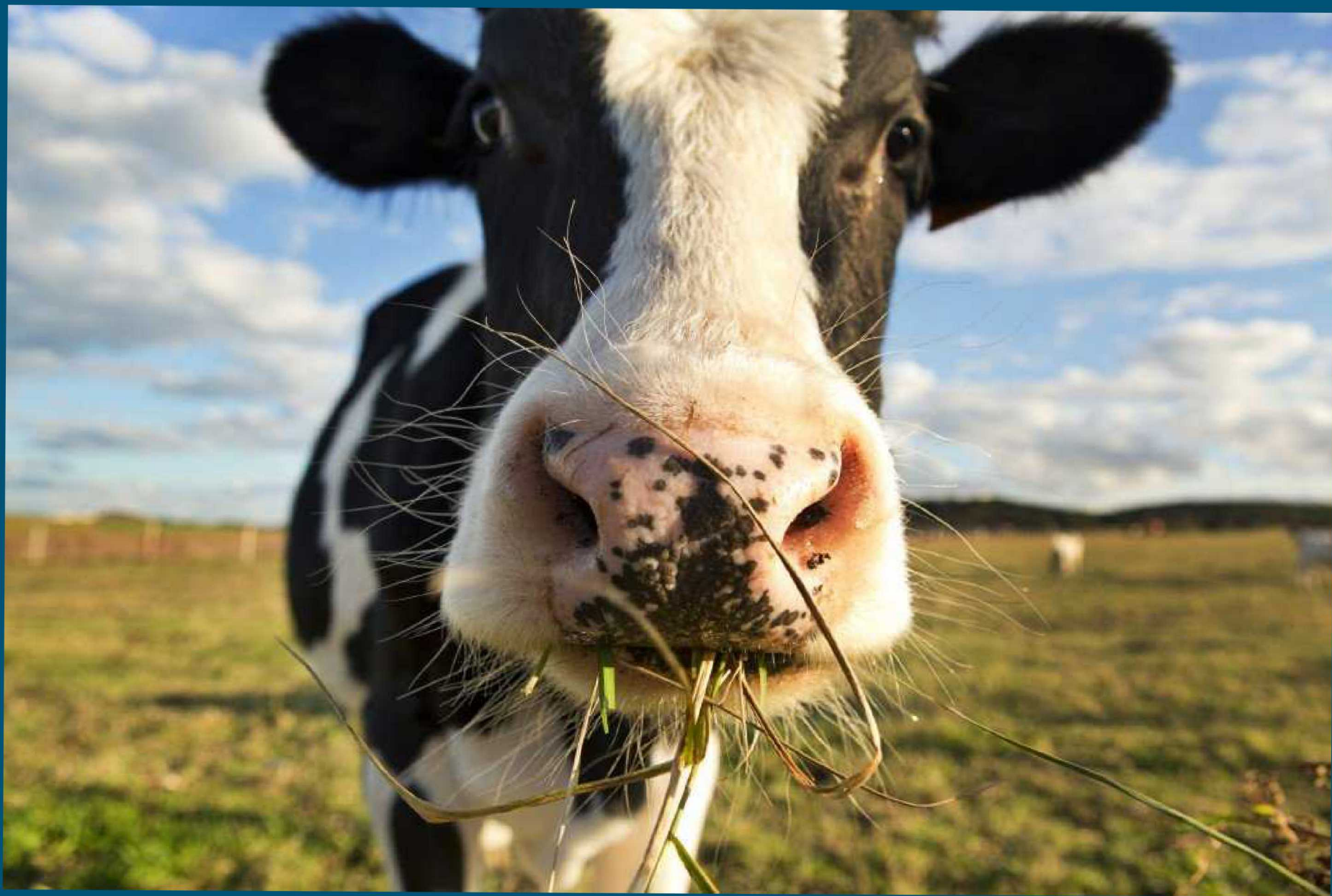


<https://www.dexlabanalytics.com/blog/amazon-launches-deepracer-an-autonomous-machine-learning-car>

<http://www.artificialhumancompanions.com/autonomous-deep-learning-robot-the-missing-instructions/>

Hardware Acceleration of Adaptive Neural Algorithms (HAANA)





<https://steemit.com/blog/@lapilipinas/why-does-a-cow-chew-its-cud>

Algorithm 1: Algorithm for Self-Updating Existing Model

Input: Current model, m ; Window size, w ;

Data stream, D ; Algorithm, A

Output: Updated model: \hat{m}

$P = \{\}$

$N = \{\}$

for $i = 1$ *to* w **do**

$x \sim D$ \triangleright Draw event from stream

$\hat{y} = m(x)$ \triangleright Get model's prediction

if $\hat{y} == 1$ **then**

\triangleright Add event to positive set

$P = P \cup \{x\}$

else

\triangleright Add event to negative set

$N = N \cup \{x\}$

end

end

$\hat{m} = m \cup A(P, N)$ \triangleright Update model

return \hat{m}



<https://www.ebay.com/itm/Boot-hooks-bootstrap-pulls-pullers-lifters-western-riding-wraparound-pair-NEW-/311901884182>



<https://www.golfdigest.com/story/breaking-down-tiger-woods-new-swing>

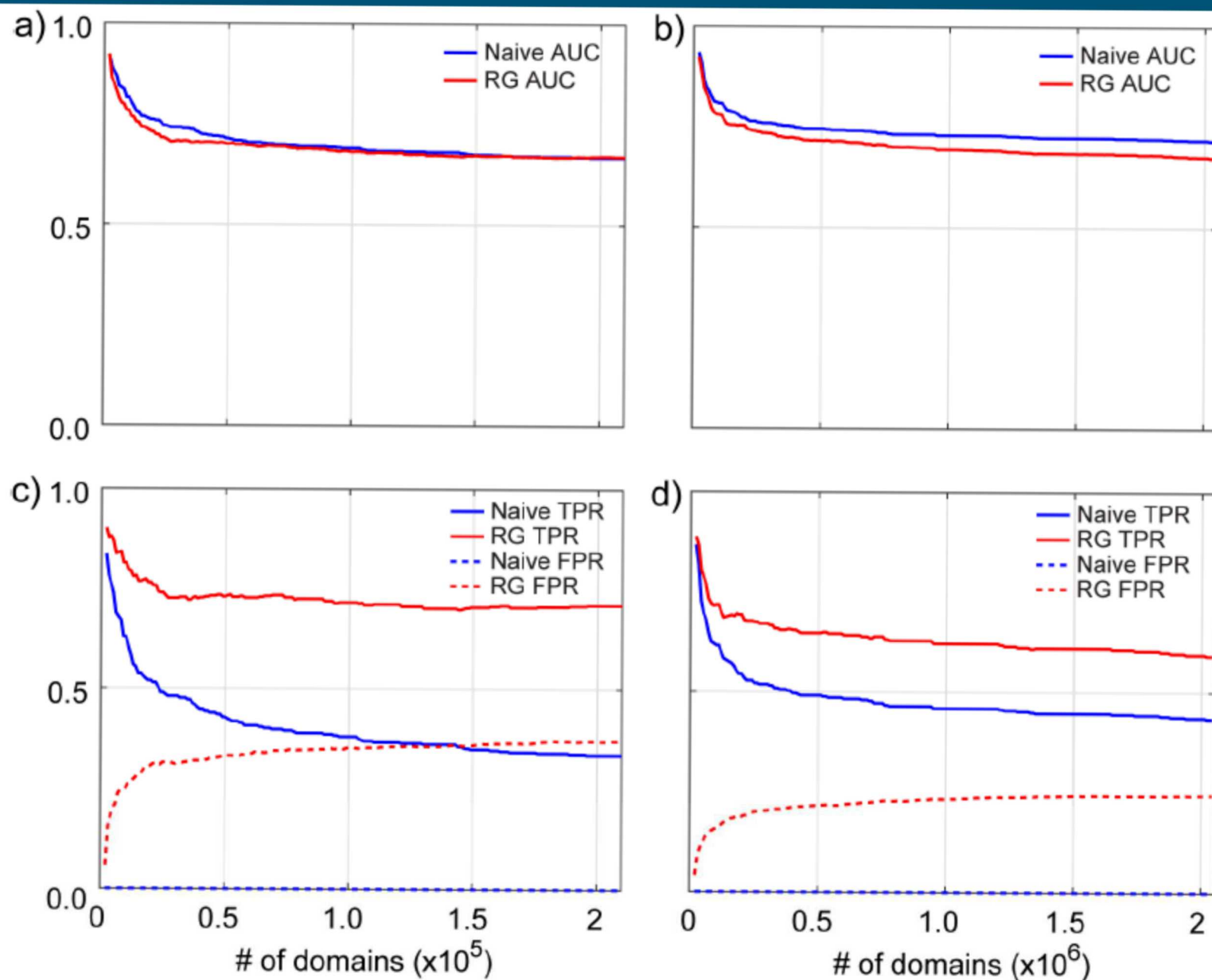


Fig. 3. AUC for a) window size 1,000 and b) window size 10,000. TPR/FPR for c) window size 1,000 and d) window size 10,000.



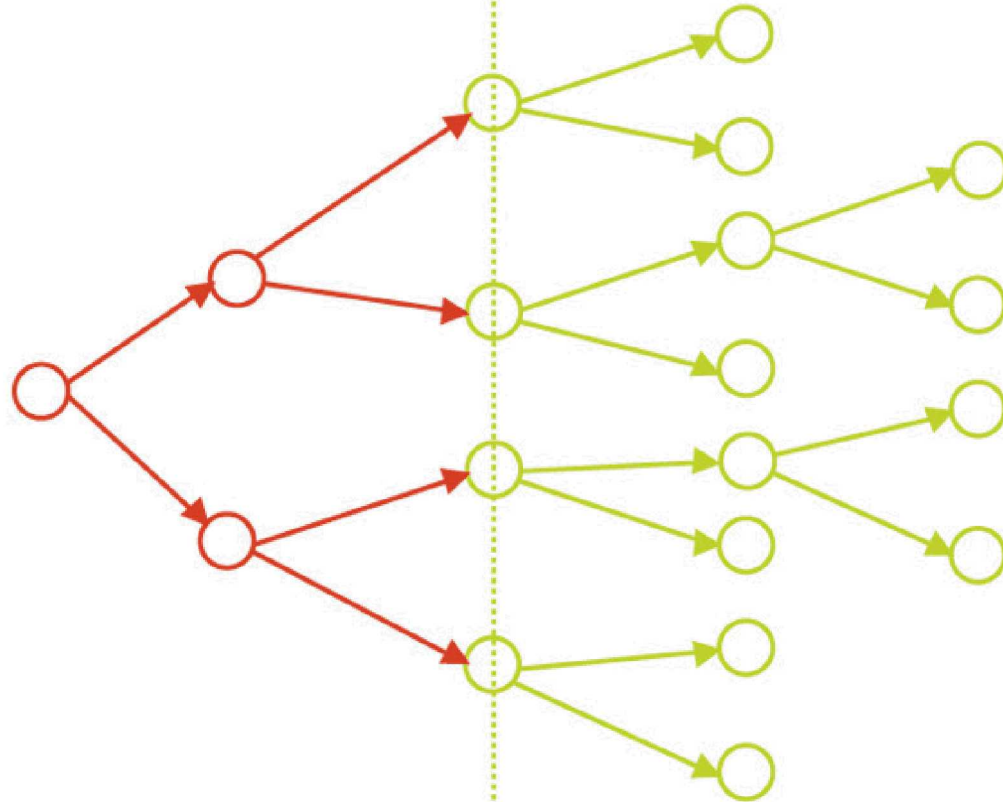


<https://www.mirror.co.uk/news/uk-news/groundhog-day-man-90-minute-memory-6044753>

This is a still image from Groundhog Day reproduced for educational purposes only. Copyright belongs to original owners.

2015 SIAM International Conference on **DATA MINING**

April 30-May 2, 2015



**Pinnacle Vancouver Harbourfront Hotel
Vancouver, British Columbia, Canada**

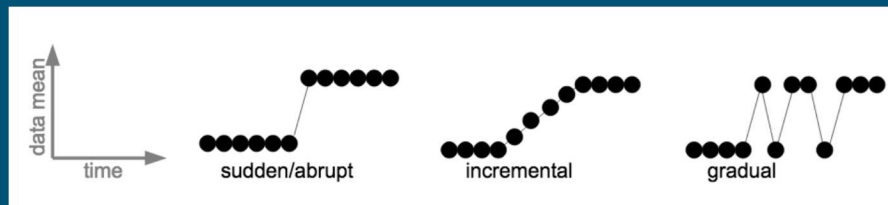
Concept Drift

- Concept drift – unforeseen changes in the relationships between input and output (“concepts”) variables.
 - Can be detrimental to model performance.
 - Can be sudden or gradual.
 - Can be natural or adversarial.

Model – what is output y , given input x

$$P(y|x) = \frac{P(x, y)}{P(x)} = \frac{P(x|y)P(y)}{P(x)}$$

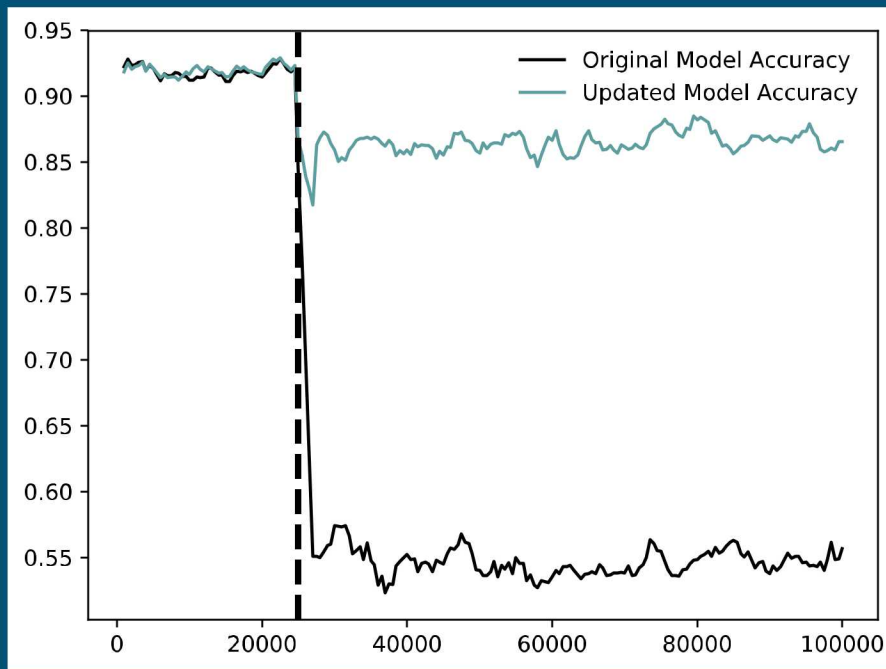
Probability of input x , given output y



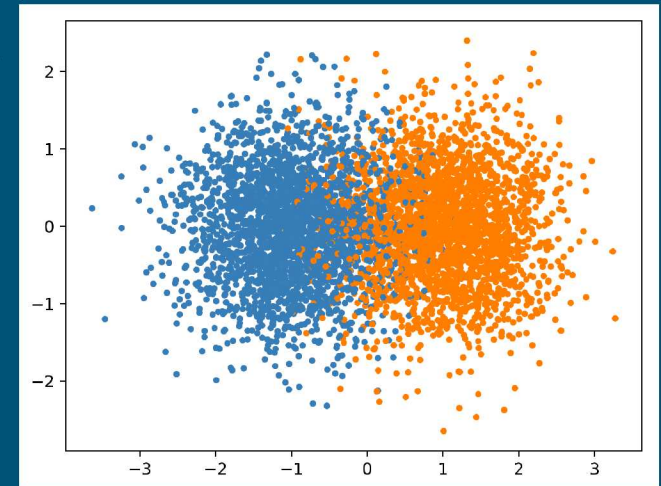
Different rates of concept drift

Effect of Concept Drift

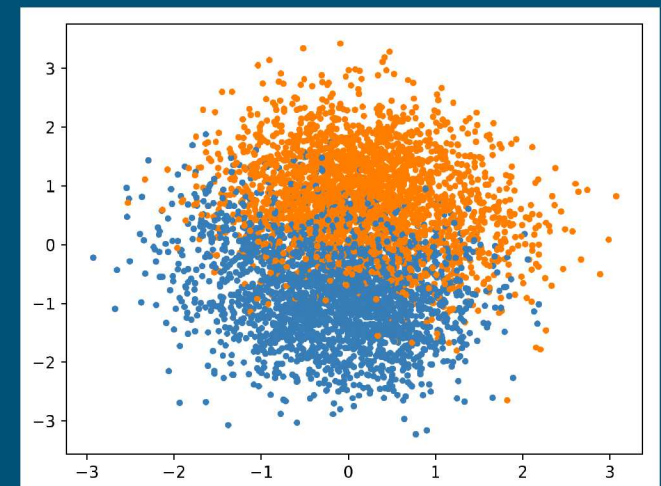
- **Takeaway:** need to update or adapt models to maintain performance.



Performance under drift in $P(x|y)$ over time



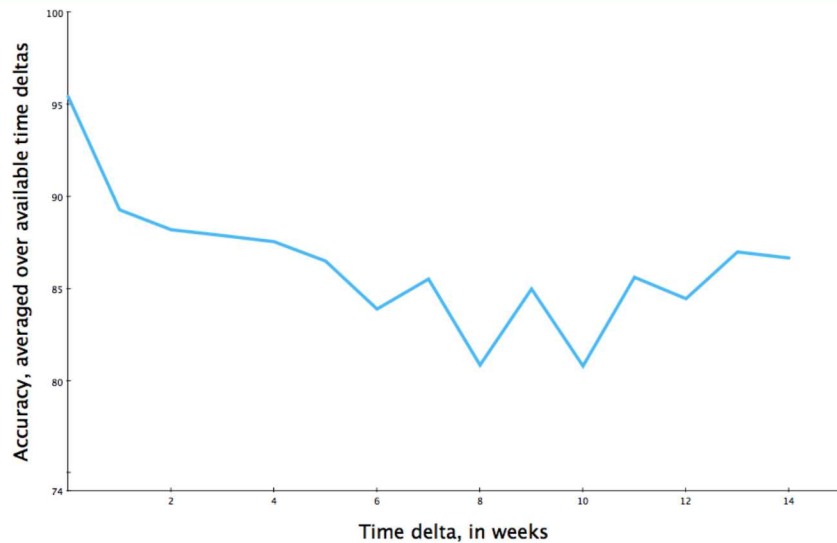
$t=0$



$t=25000$

Example: Malware Detection

- Developed model in 2012 to detect malicious software.
- Revisited in 2018 and updated model.
 - Updated (2018) model accuracy: 96%
 - Original (2012) model accuracy: 63%



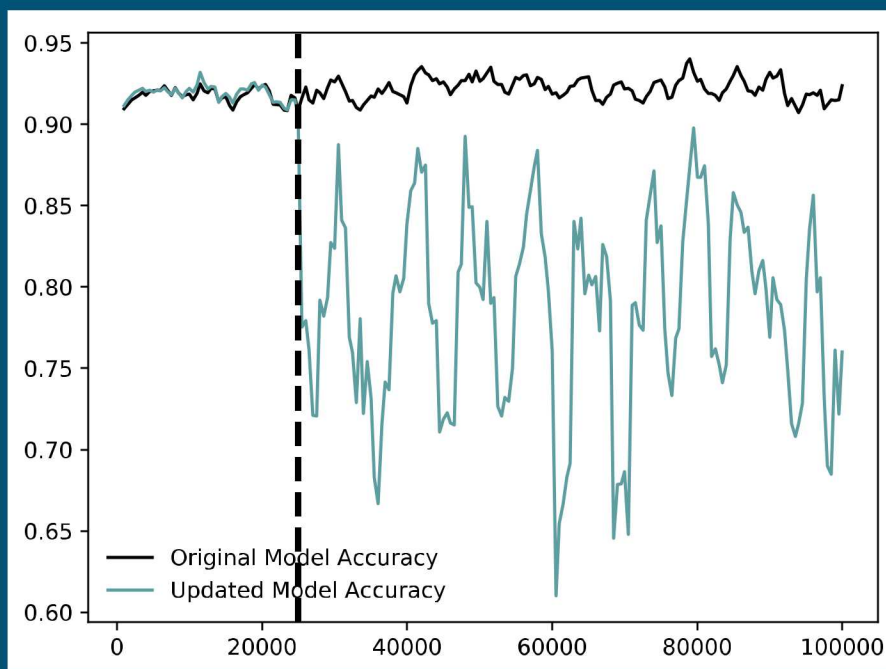
Natural concept drift



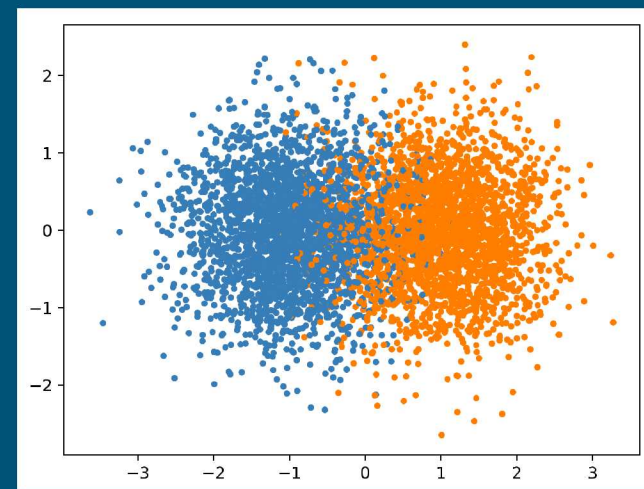
Adversarial concept drift

Effect of Label Noise

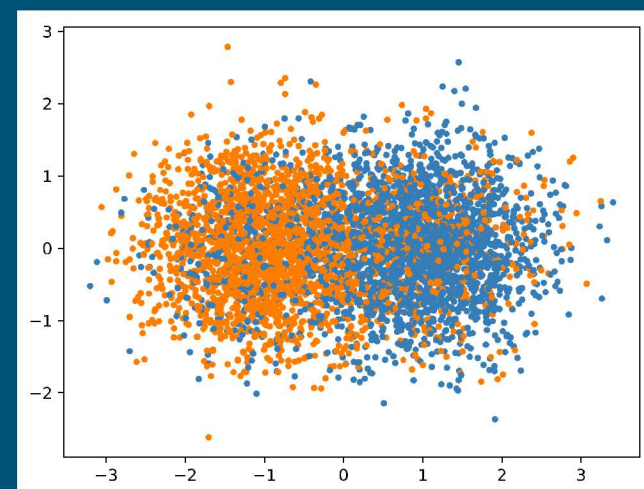
- Label noise – data is mislabeled.
- **Takeaway:** need *correctly* update or adapt models to maintain performance.



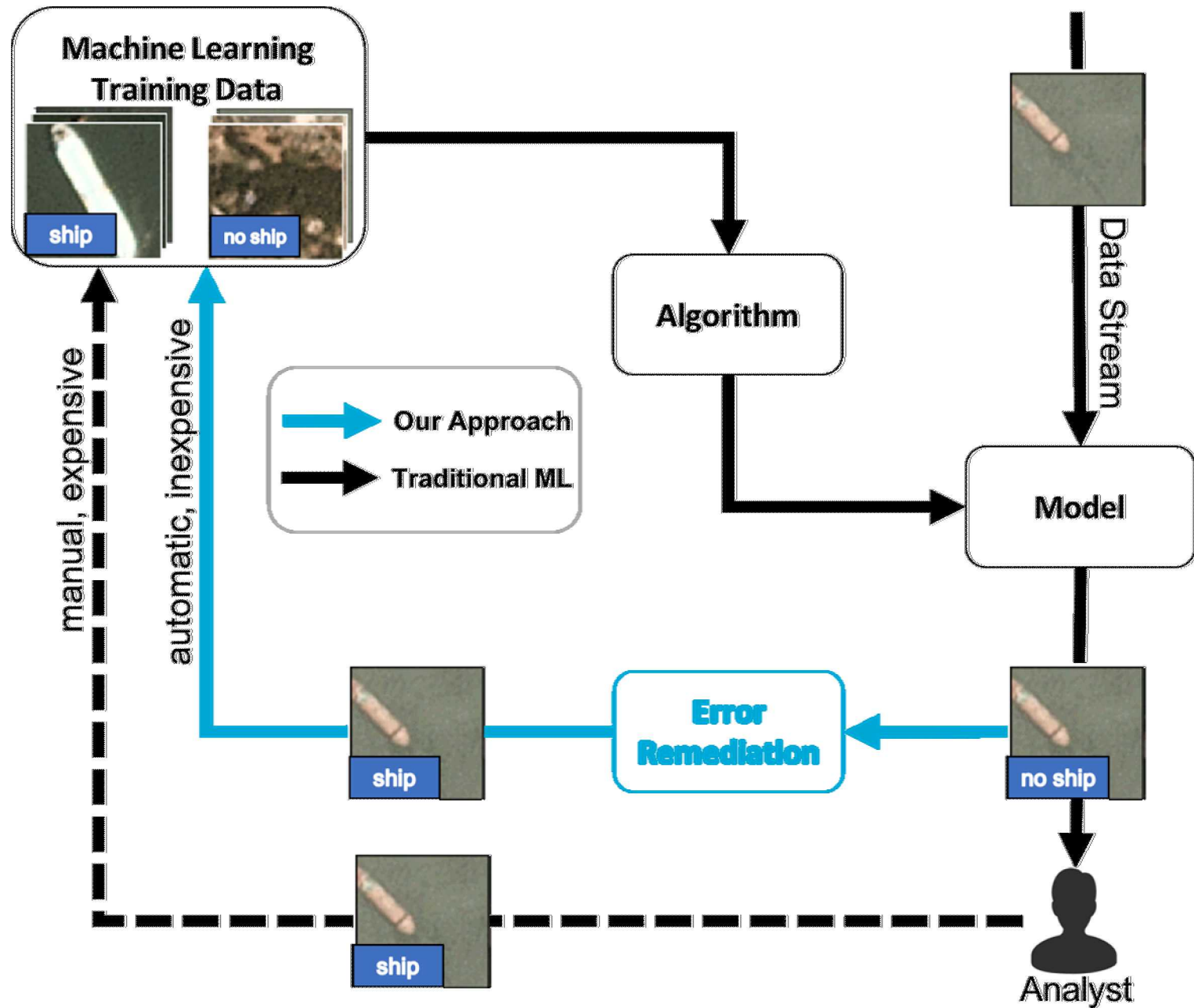
Performance with label noise over time and no underlying drift



t=0

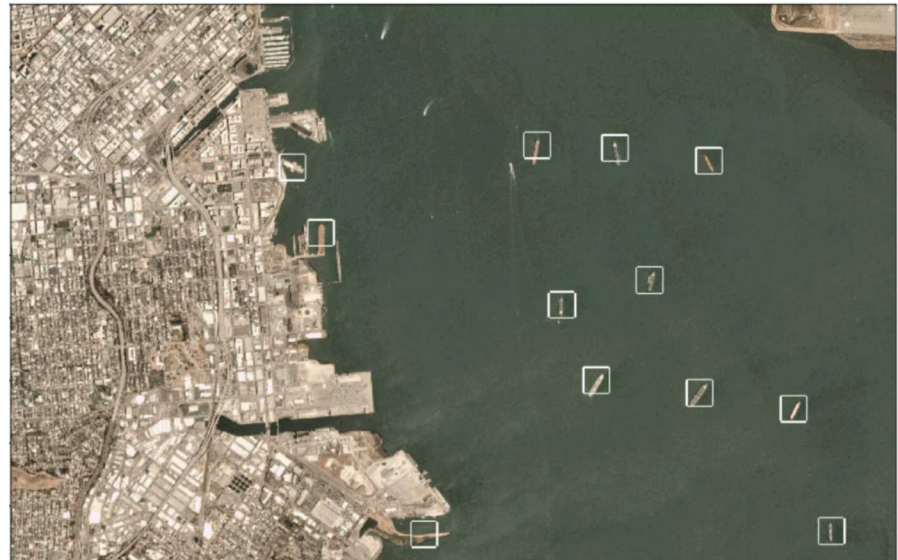
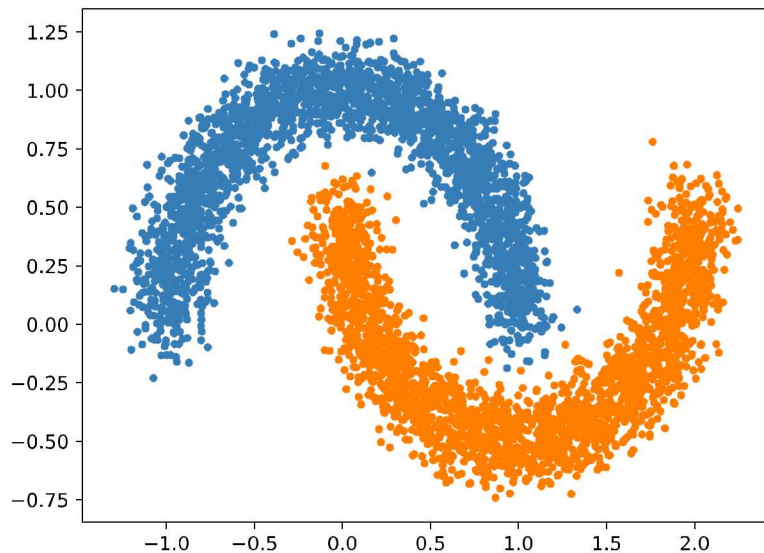


t=25000, corrupted data



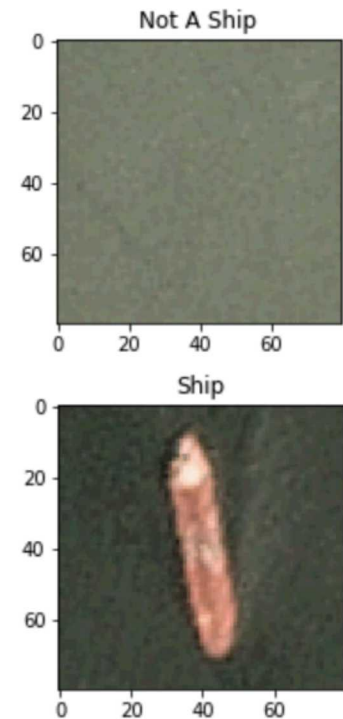
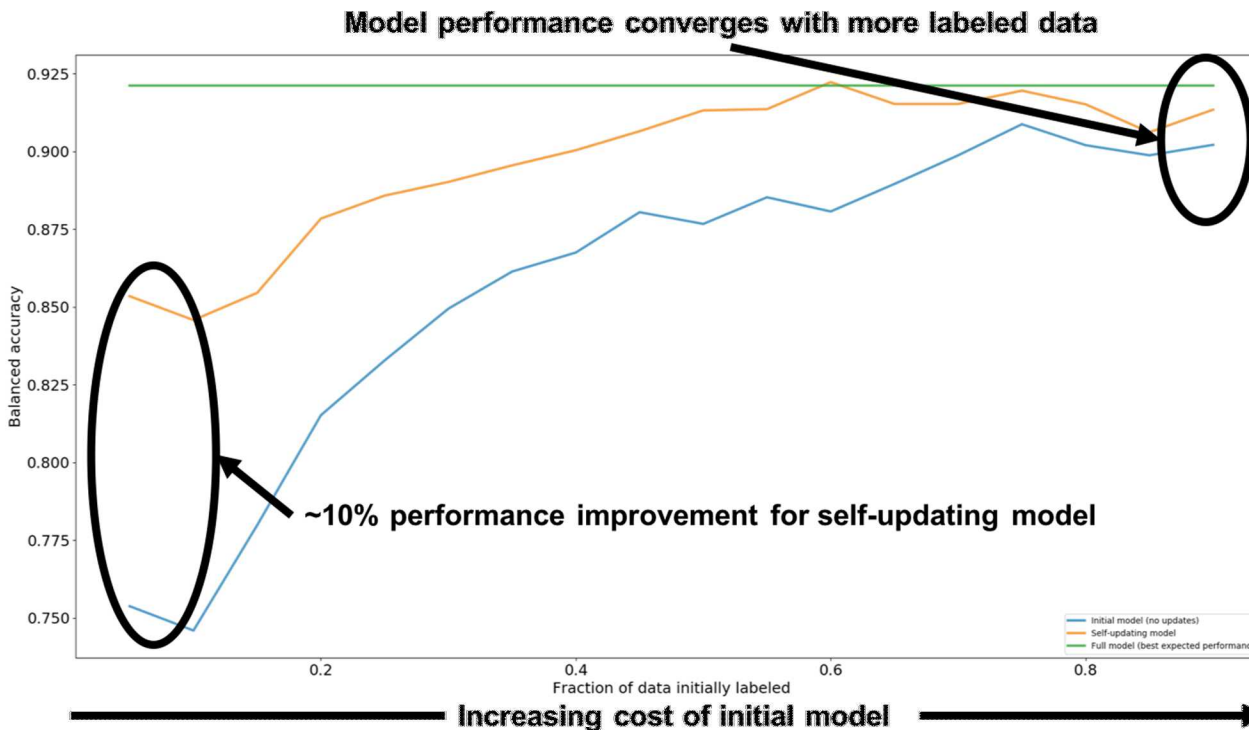
Description of the data used

- Synthetic, two-dimensional data with mechanisms to introduce label errors and concept drift
- Kaggle “Ships in Satellite Imagery” dataset:
 - Features – 19,200 integers representing pixel intensities in red, green, and blue channels (6,400 values for each)
 - Ships – 1,000 images (25% of data)
 - Non-ships – 3,000 images (75% of data)



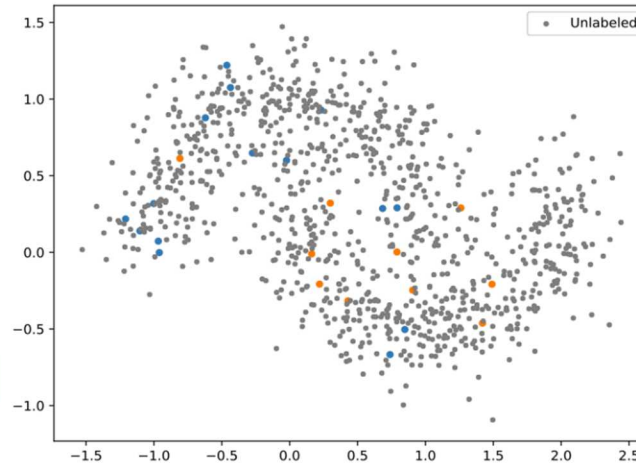
Results – Benefit(s) of Self-updating

- Self-updating (orange line) provides performance boost over not utilizing unlabeled data (blue line).
 - Benefit is more pronounced with less initially-labeled data.
- Self-updating also approaches performance upper-bound (green line) much faster.

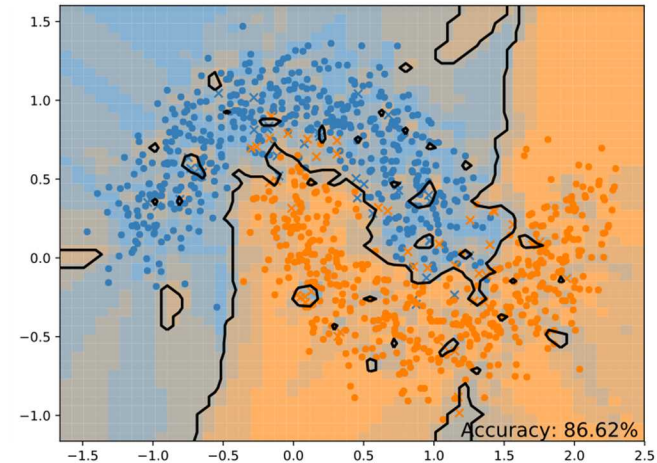


Results – Benefits of SUMER

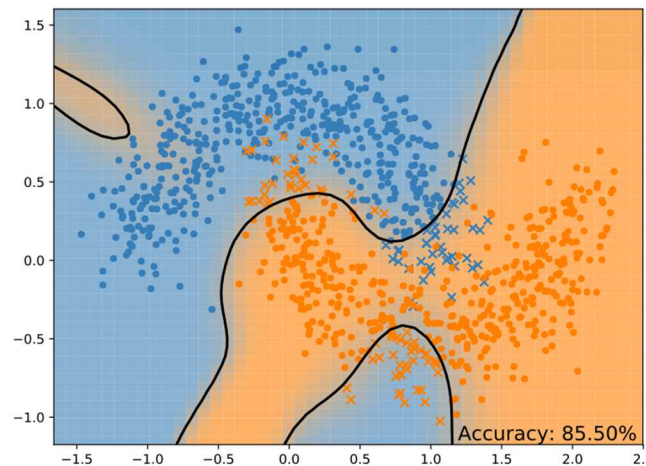
- Self-updating with error remediation increased performance by 5% and improved decision boundary.



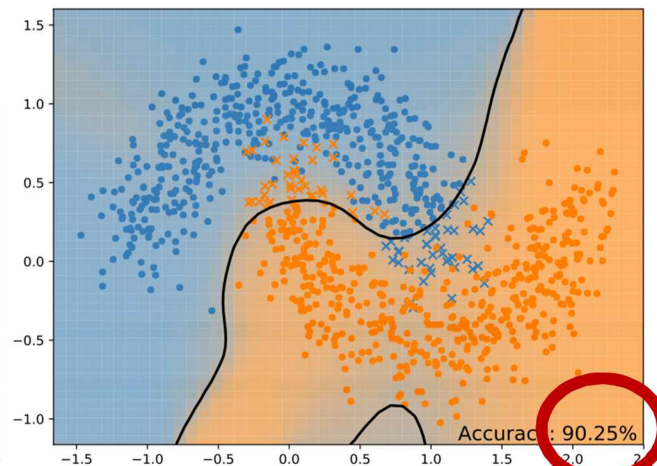
Initial data w/ 20% label noise



Model w/o self-updating/remediation



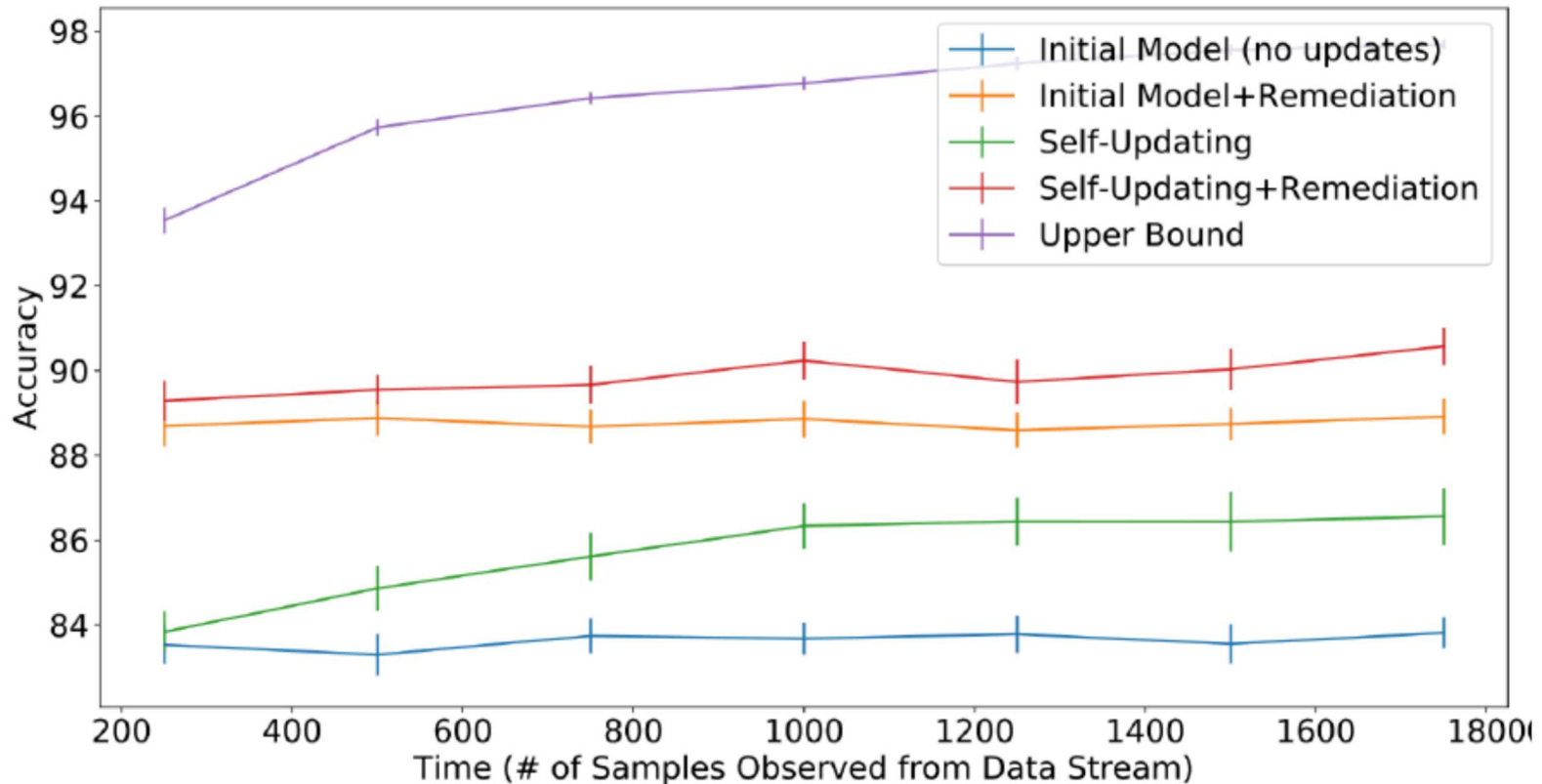
Self-updating without remediation



Self-updating with remediation

Results – Benefits of SUMER over Time

- Self-updating by itself only provides marginal improvement.
- Upper Bound Performance – model is updated with ground-truth labels (i.e., label noise is removed).
- Self-updating with remediation provides best performance.



Potential Issues with SUMs and Label Correction

SUMs: the initially labeled data points can dramatically impact performance.

- We saw as much as a 15% difference in performance based on the specific points that were initially labeled.

Label correction: if the prediction model and the label correction model are “coupled”, i.e., they make the same predictions on all or nearly all of the data points, then little value is provided by label correction.

- $P(\hat{Y}|Y) \sim 0$ and $P(\hat{X}|X) \sim 0$
- One possible solution to “model coupling” is to build the prediction and label correction models with different views of the data.

The MAGE Project and Future Work



MAGE

- Take in overhead imagery of multiple modalities and highlight objects that may be of interest to analysts/operators.
- Automate machine learning pipeline as much as possible.
- Determine how to improve pipeline given feedback from humans-in-the-loop.
- Integrates a variety of techniques, e.g., few-shot learning, SUMs, label correction, active learning (modified), and model calibration.

Future Work

- Research the use of model calibration to improve confidences output by model. This facilitates the use of a threshold to determine if a prediction should be used as a label.
- Experiment with various approaches for novel concept detection.
- Implement and test other promising label correction techniques.
- Develop detectors for feature and label distribution shifts.
- Obtain funding to generate and test hypotheses for solving the model coupling problem.



Questions? Comments?
