Machine Learned Model Quality Monitoring in Fast Data and Streaming Applications

Emre Velipasaoglu

Lightbend

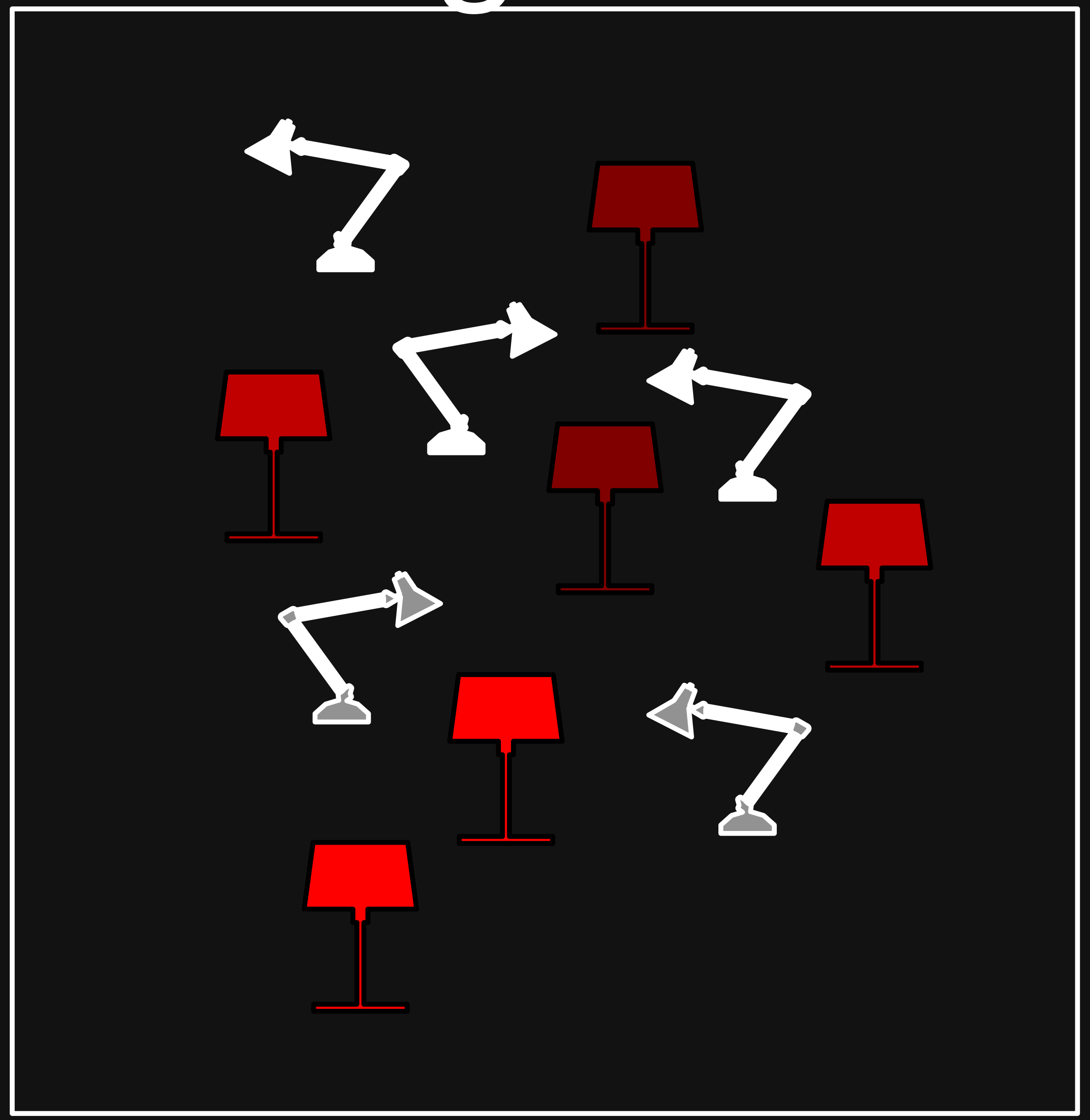
Strata

DATA CONFERENCE

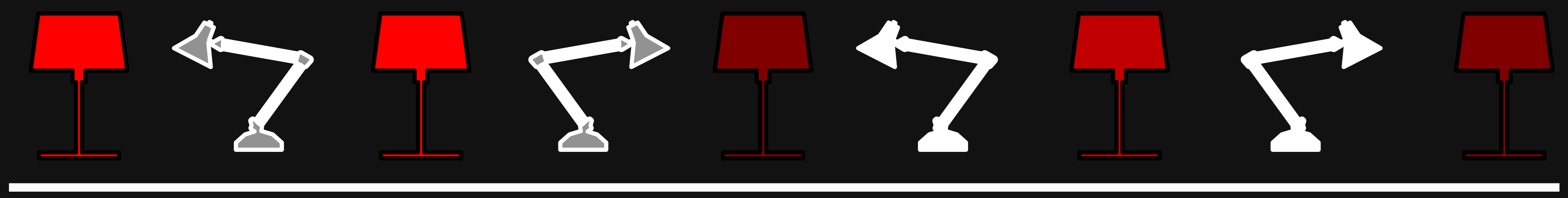
model quality

core problem

training set



$\stackrel{*}{=}$

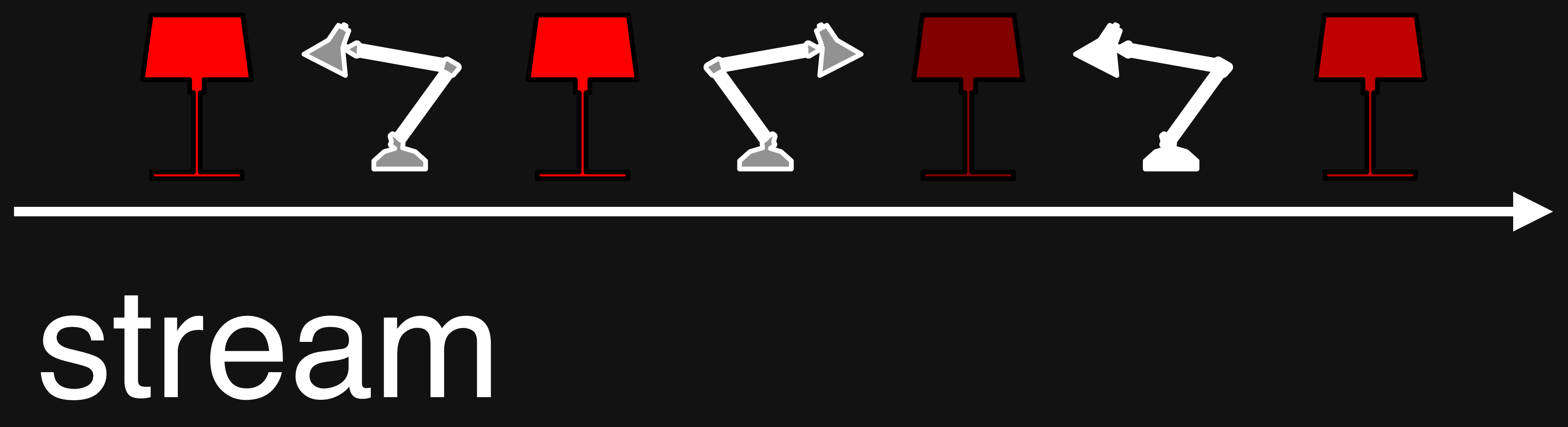


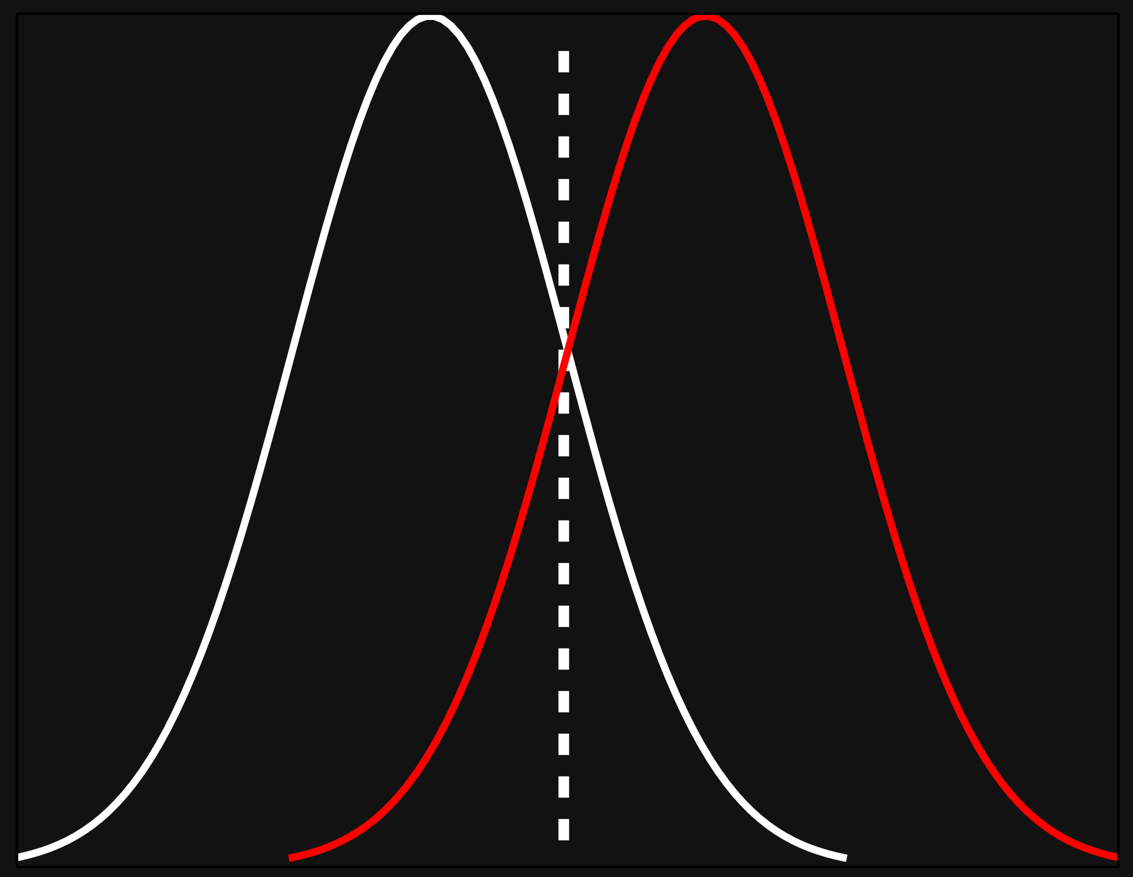
operation

* same data generating distribution

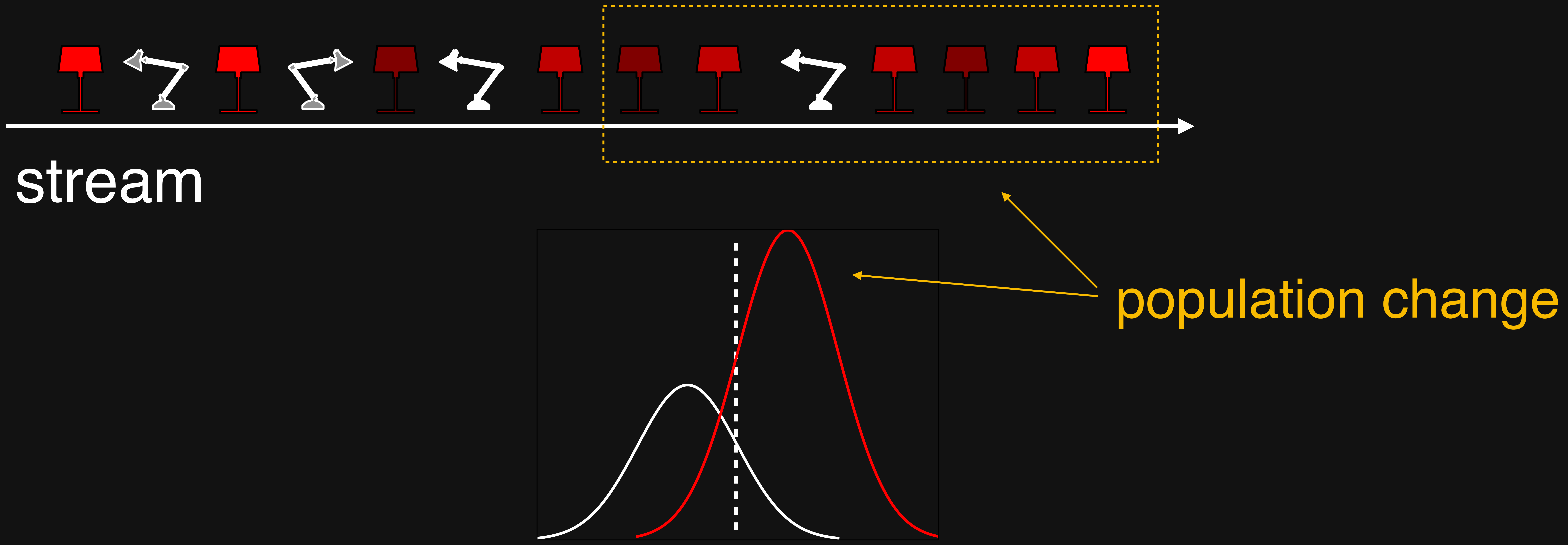
(Some algorithms tolerate violation of this to a certain degree.)

core problem





core problem



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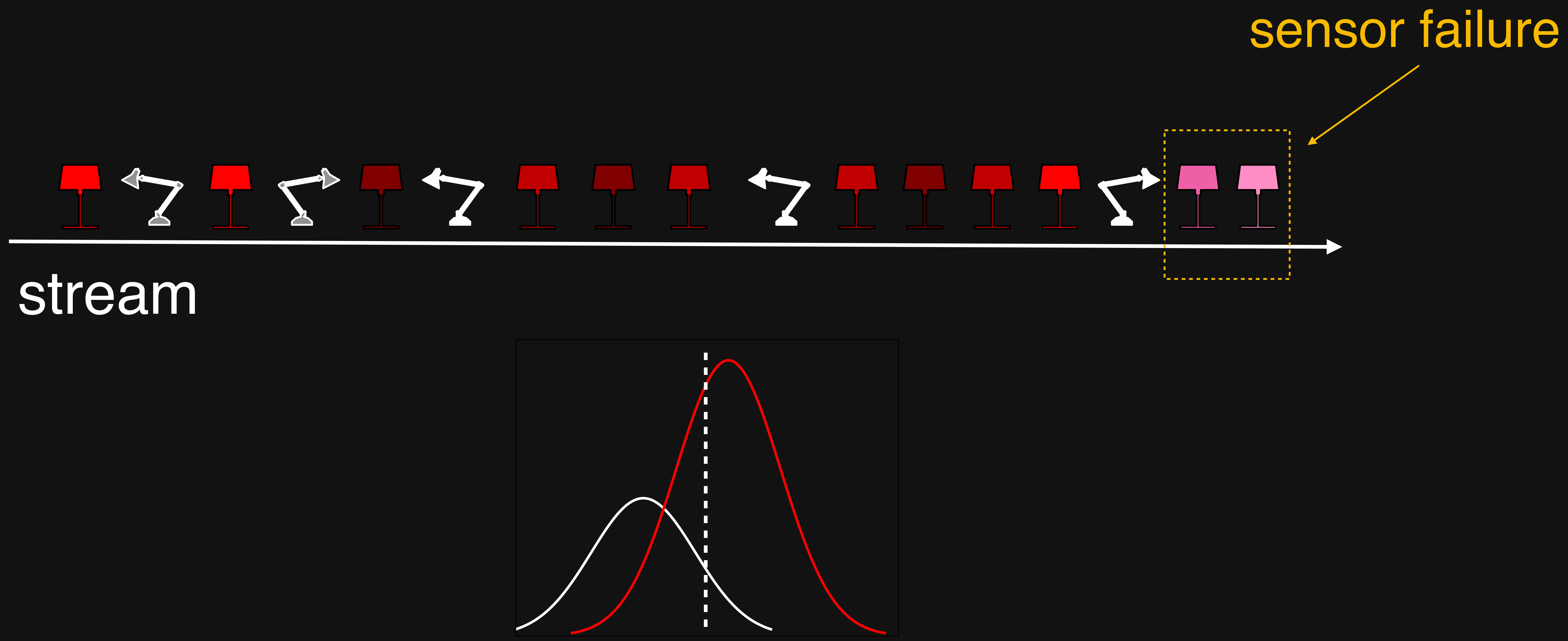

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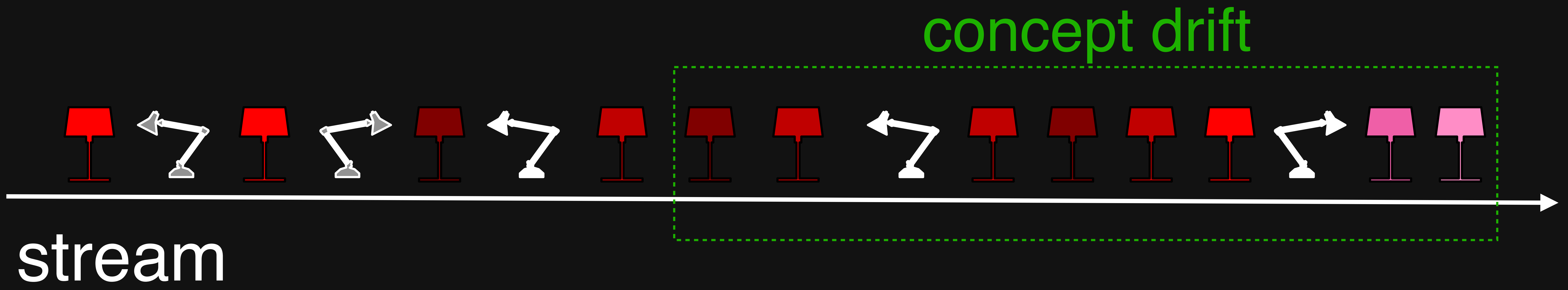

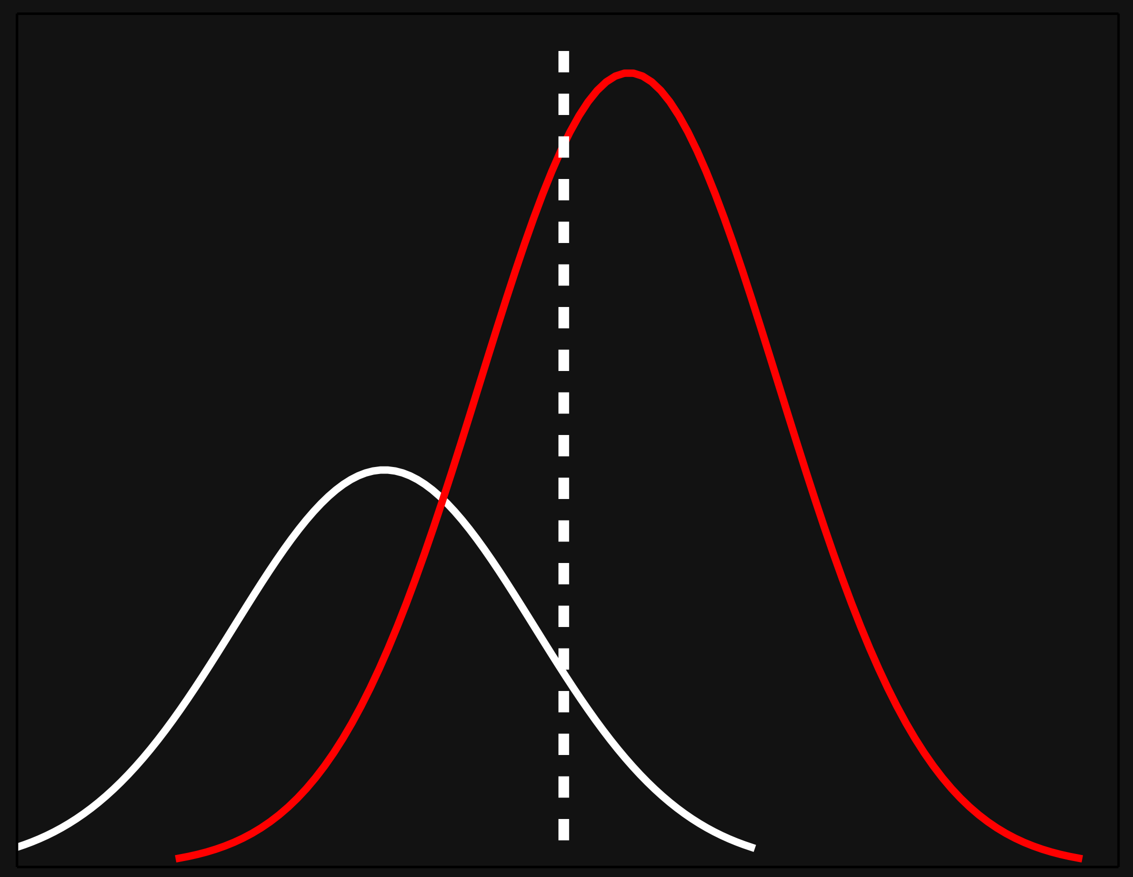

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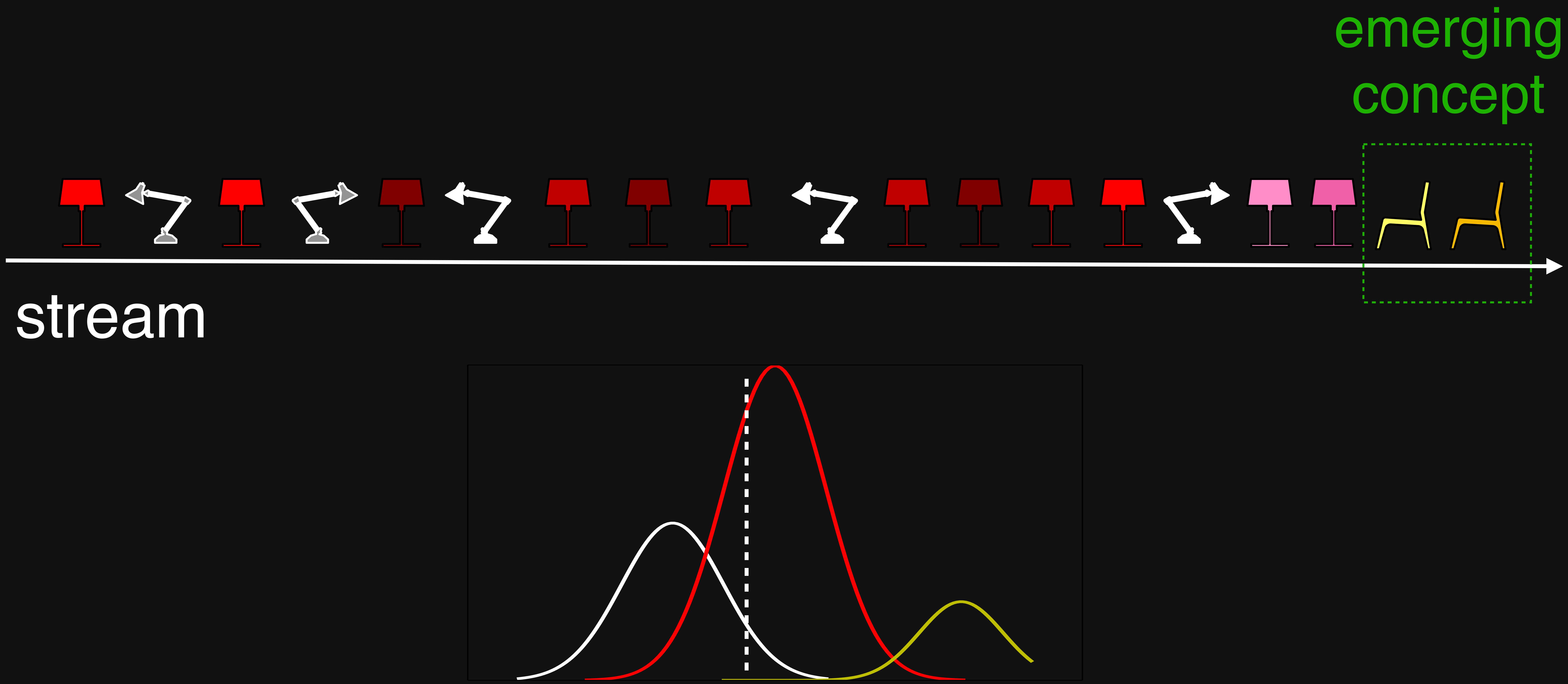
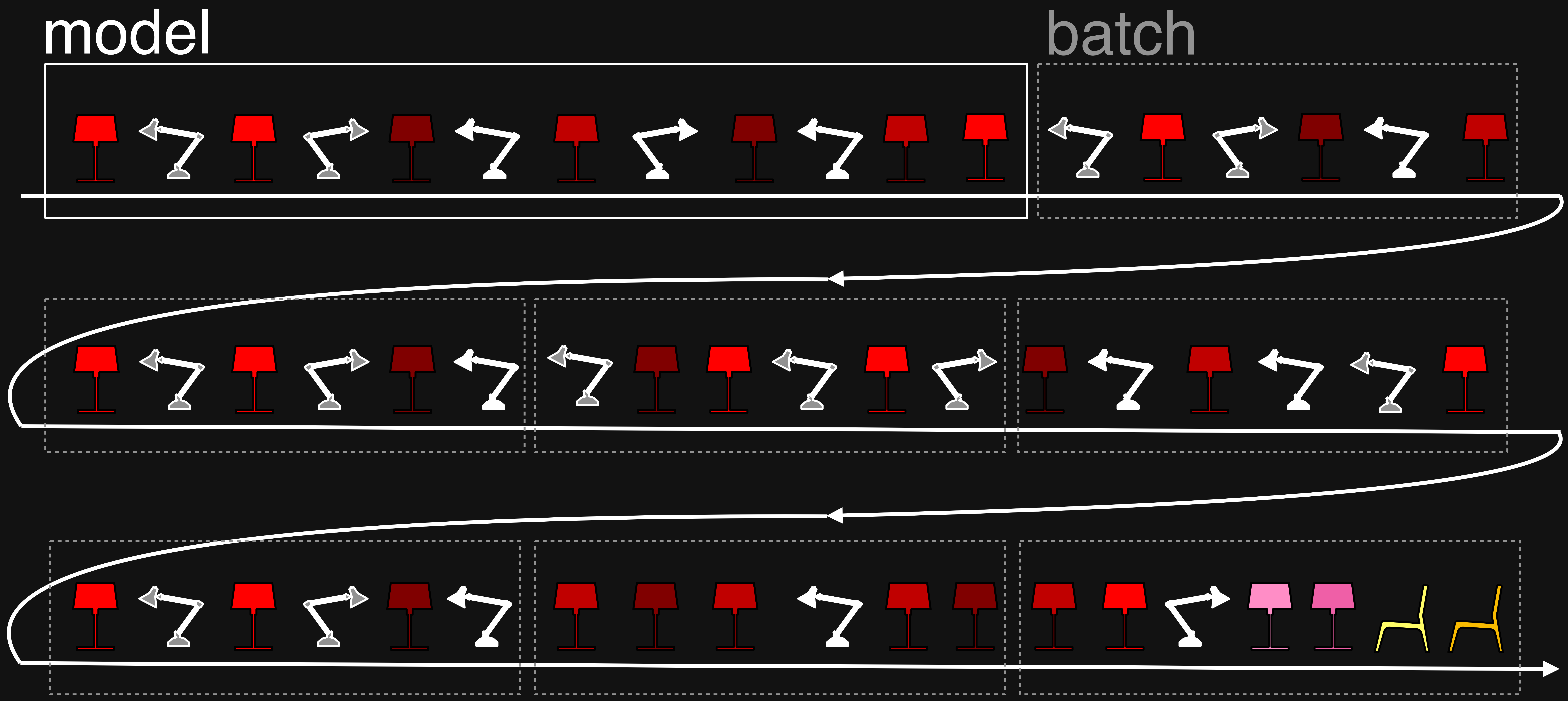
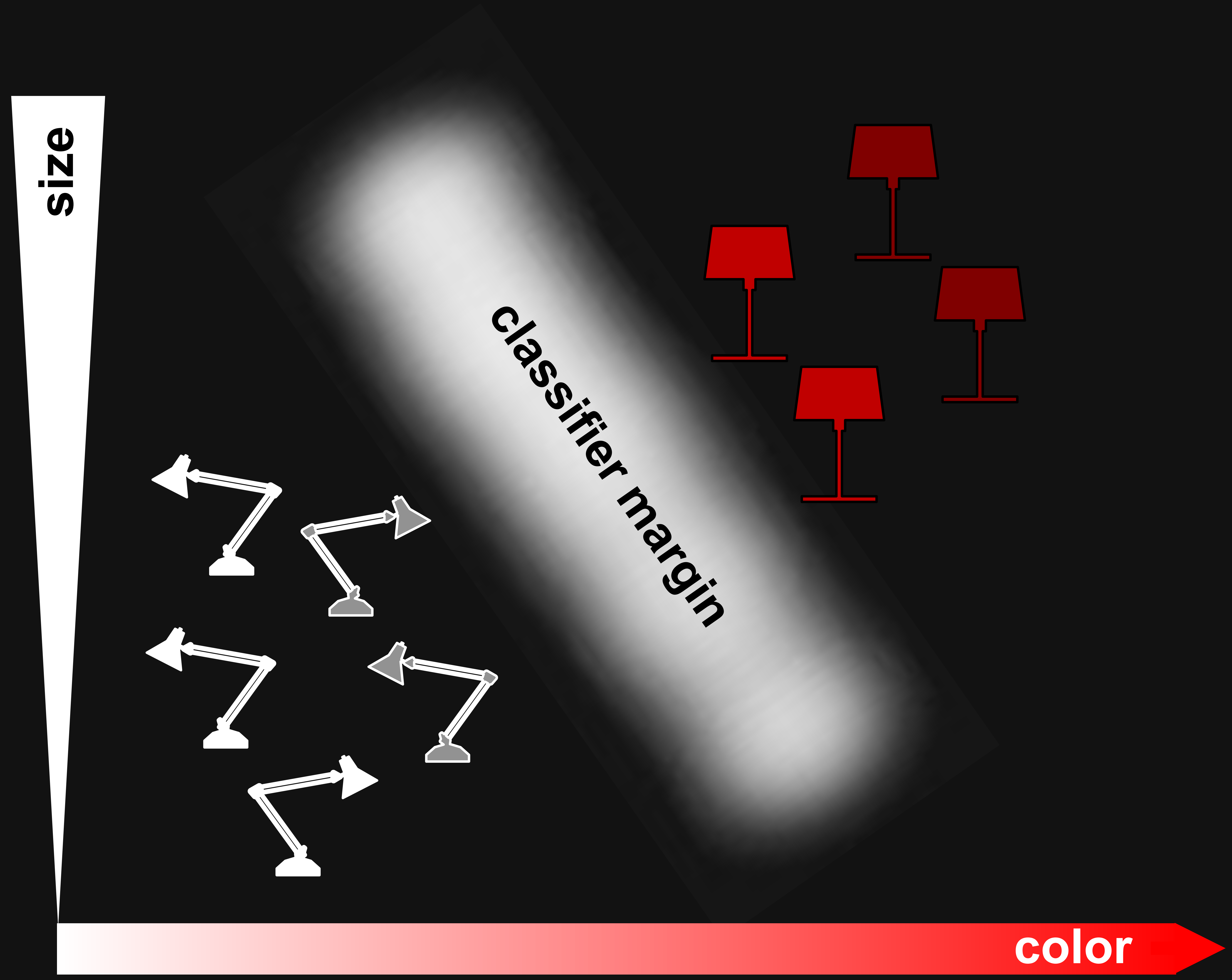


common poor solution



can active learning help?



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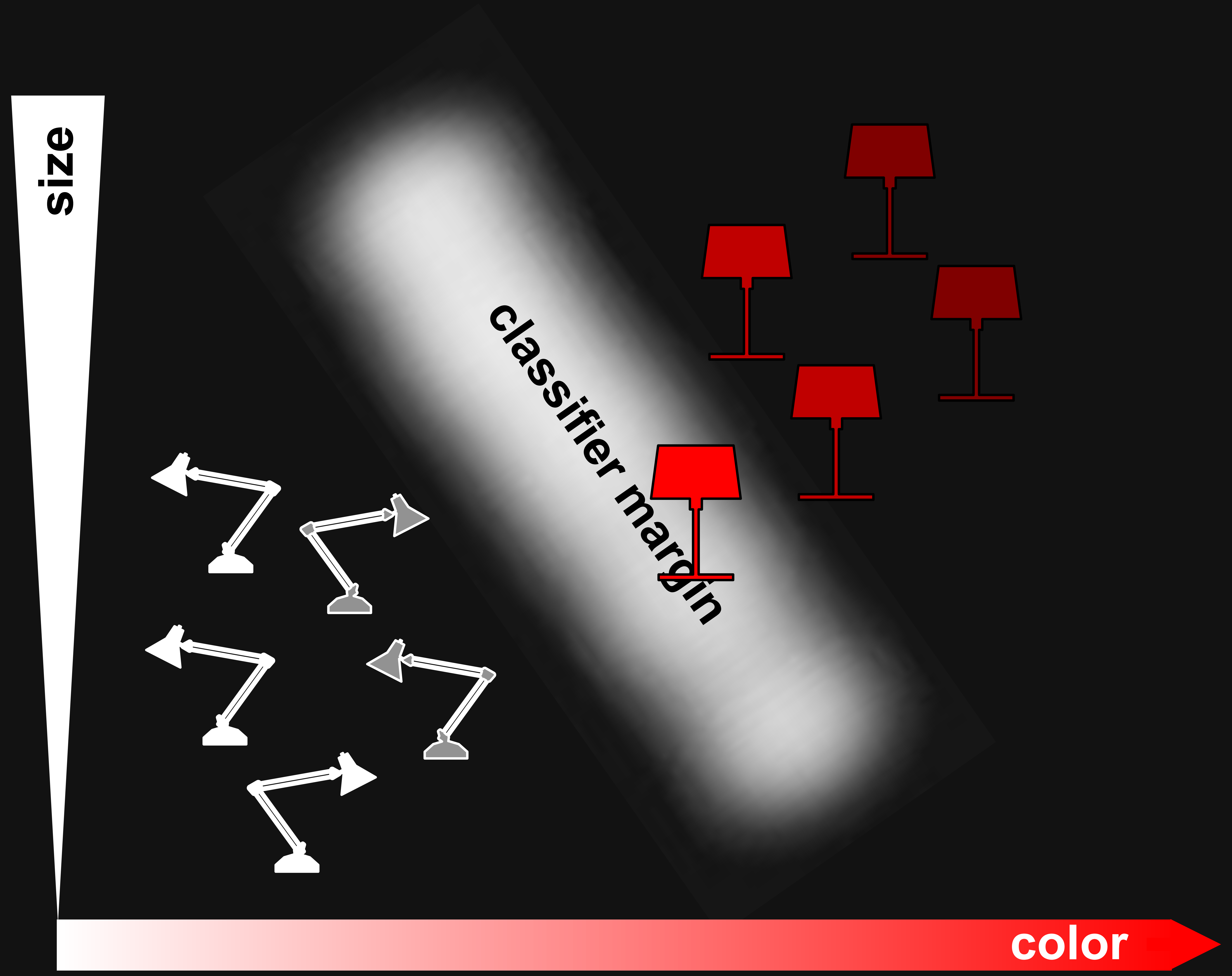

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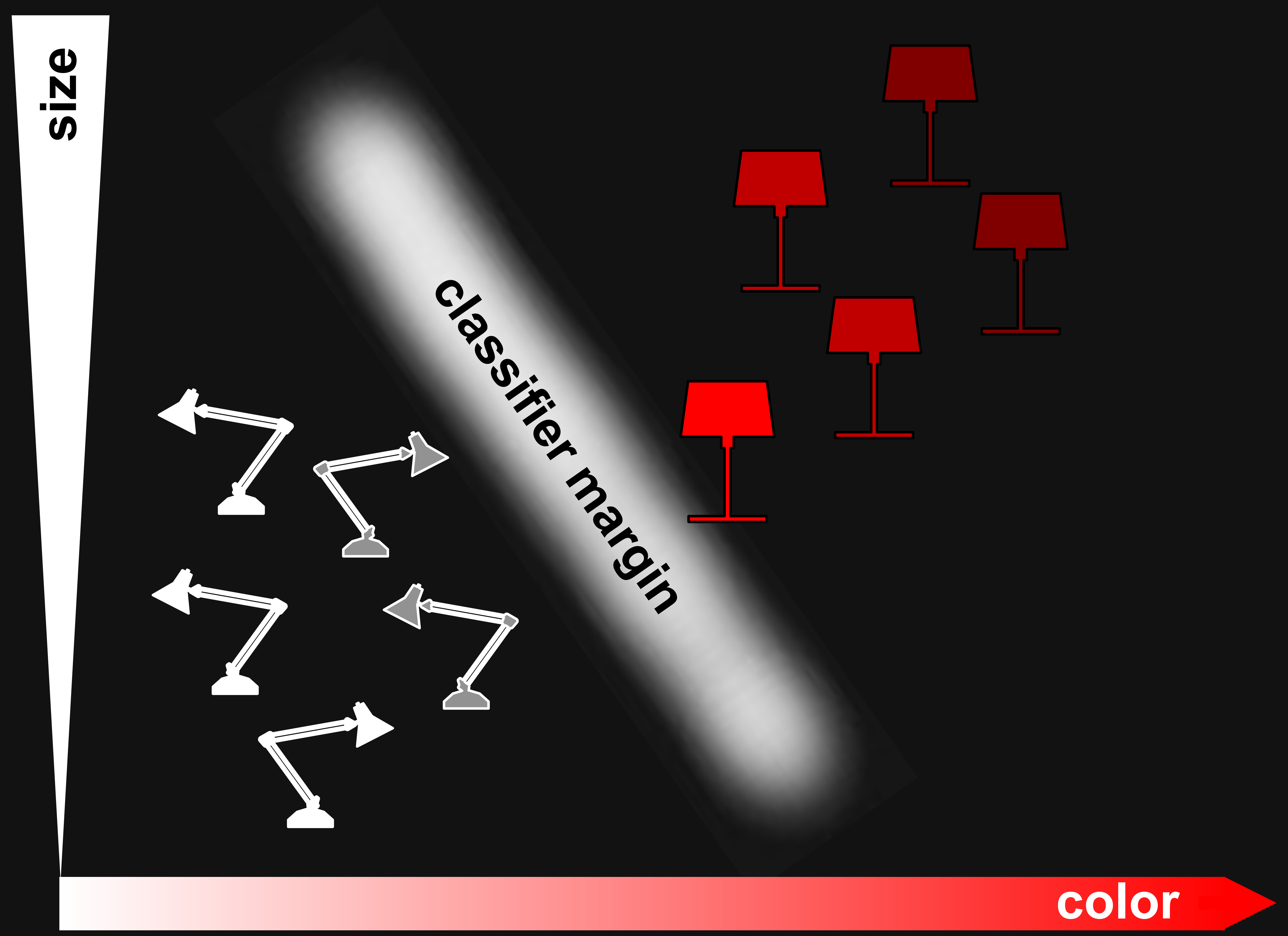

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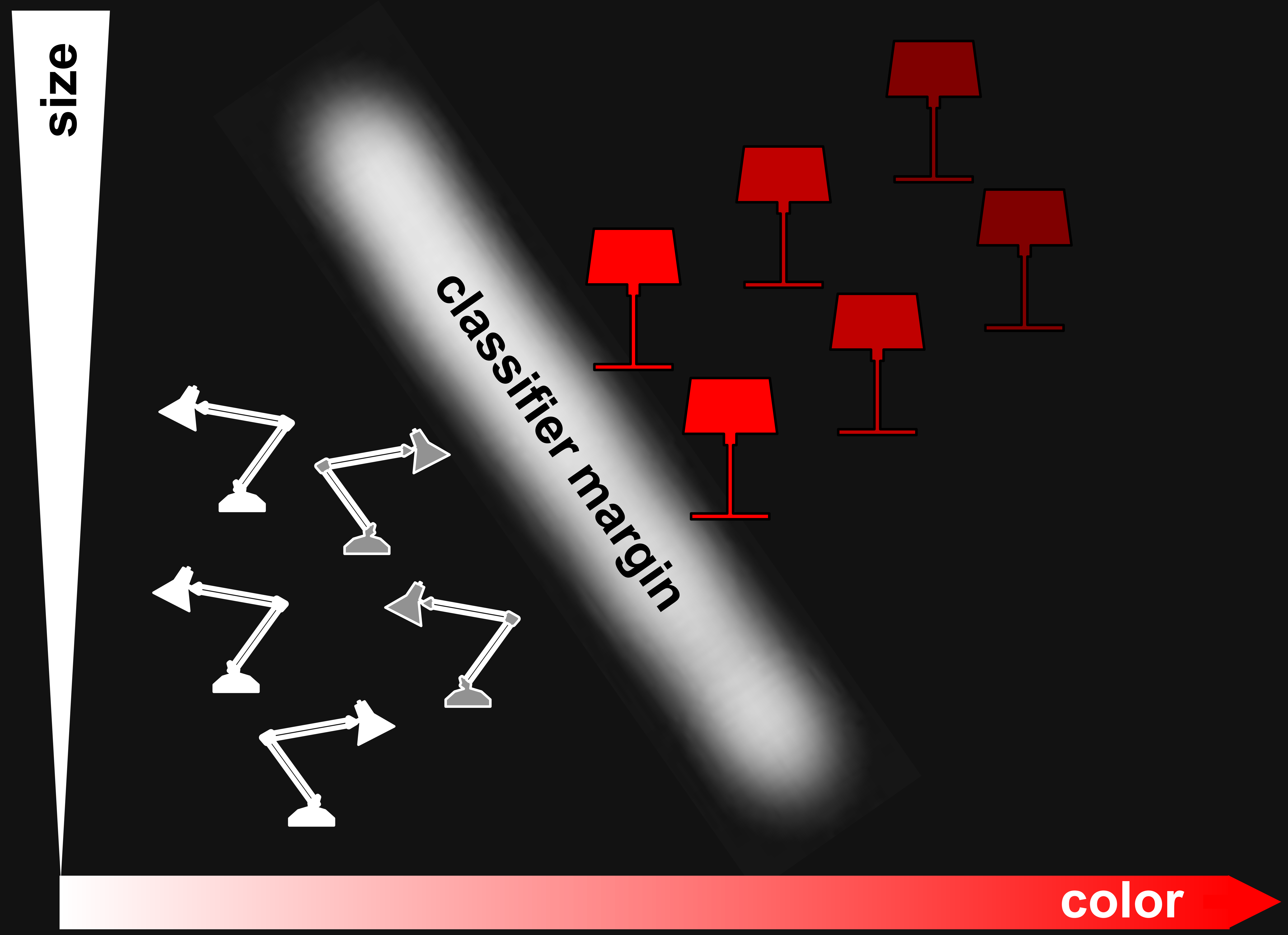

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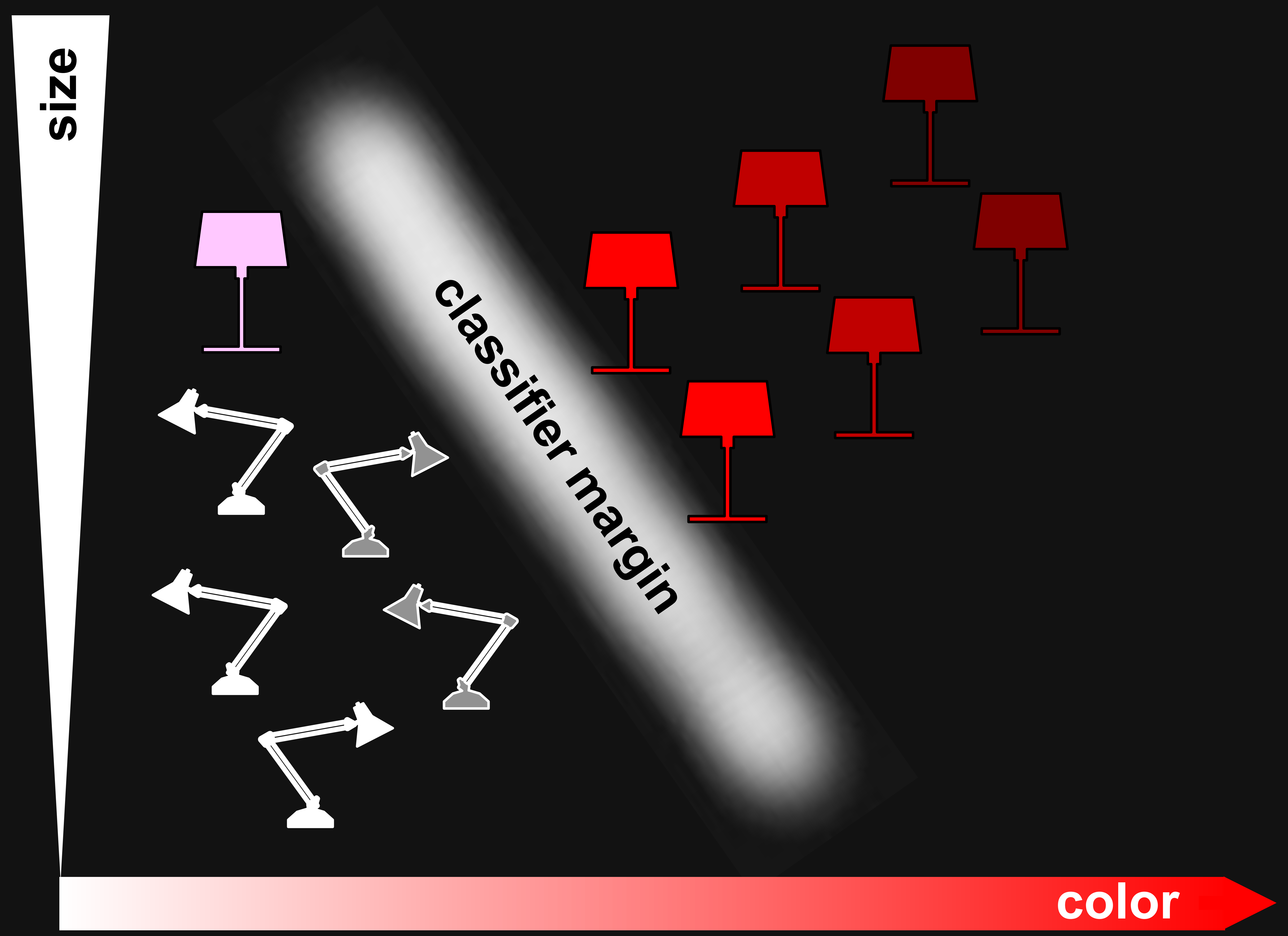

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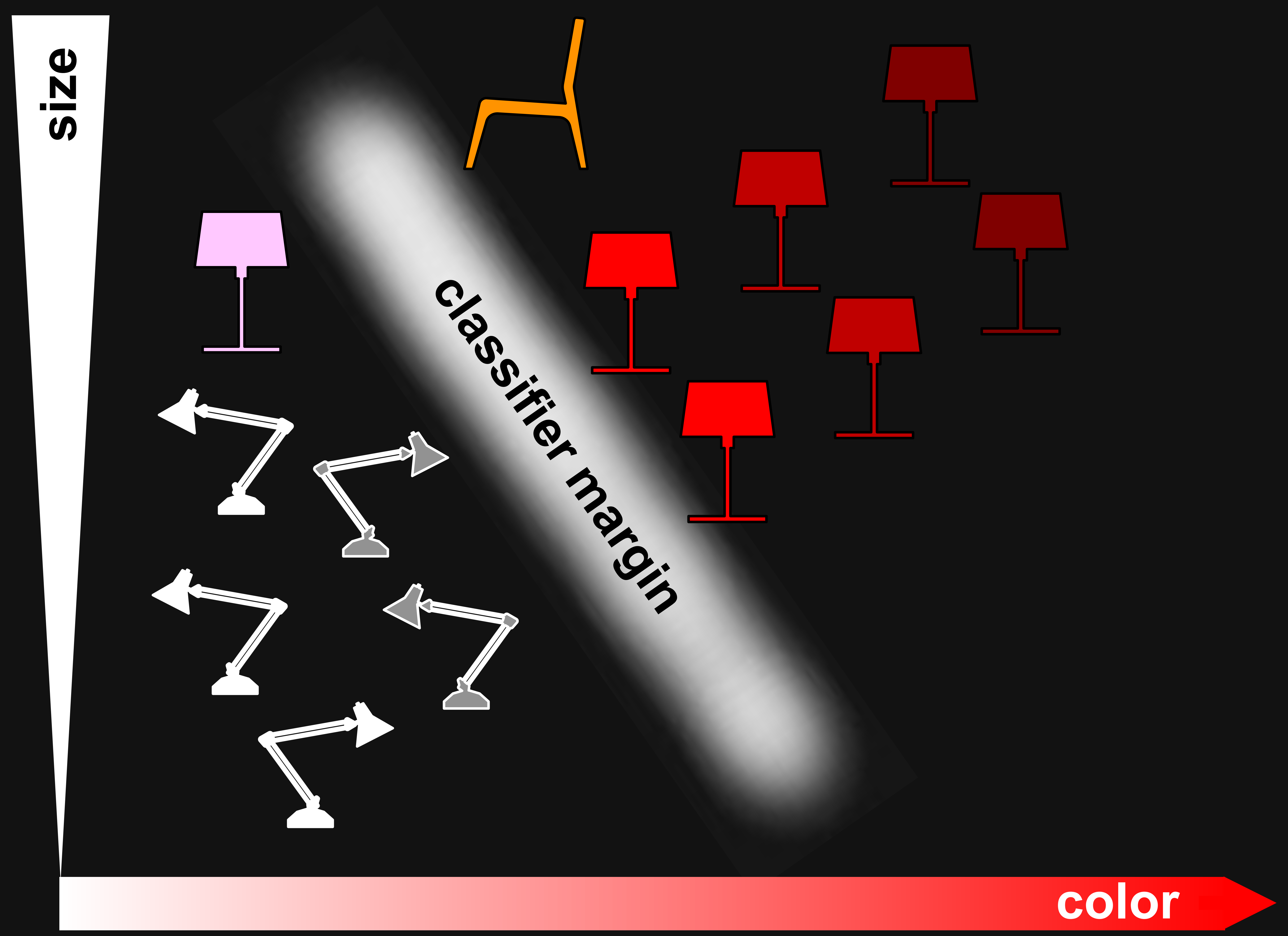
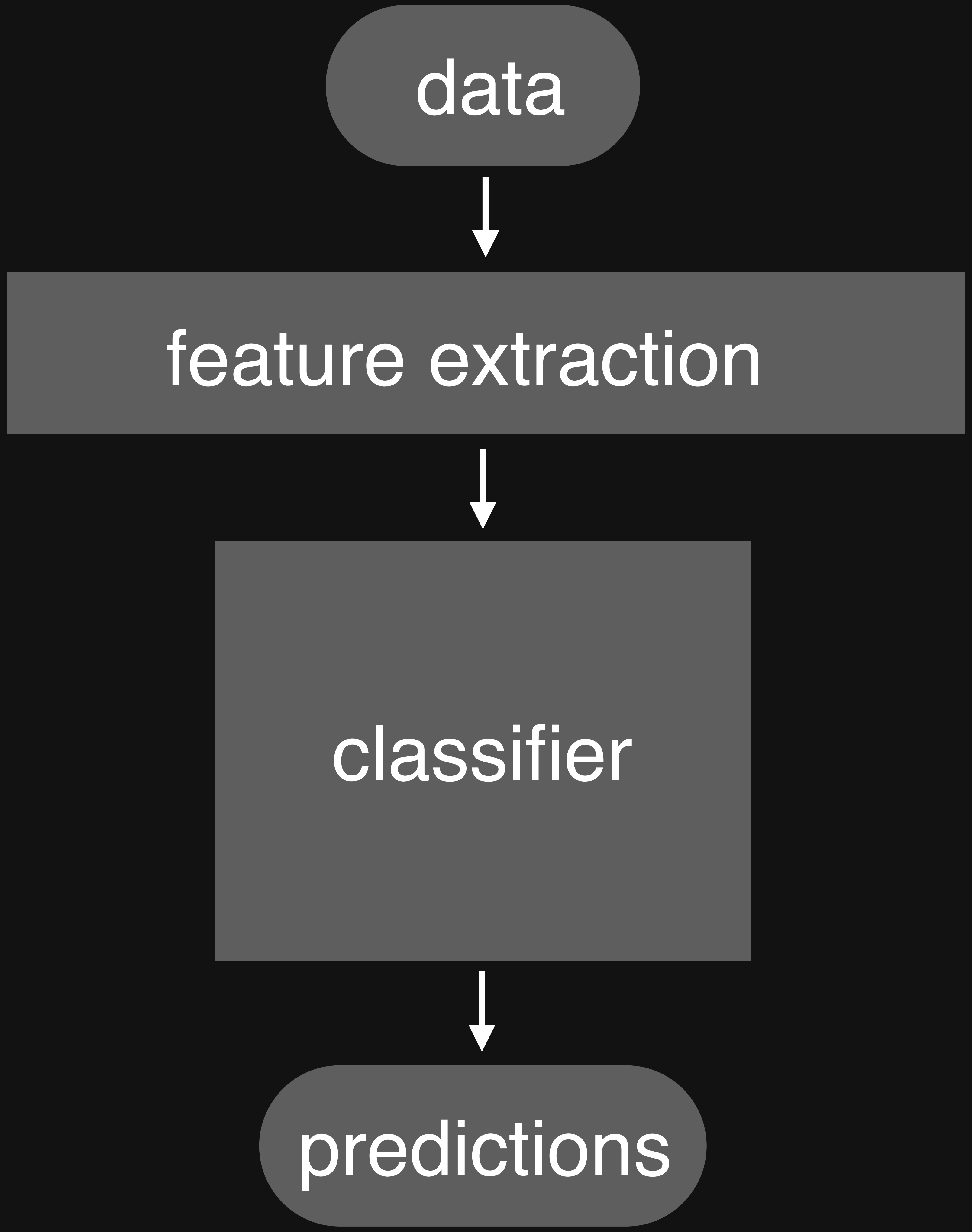


a better solution



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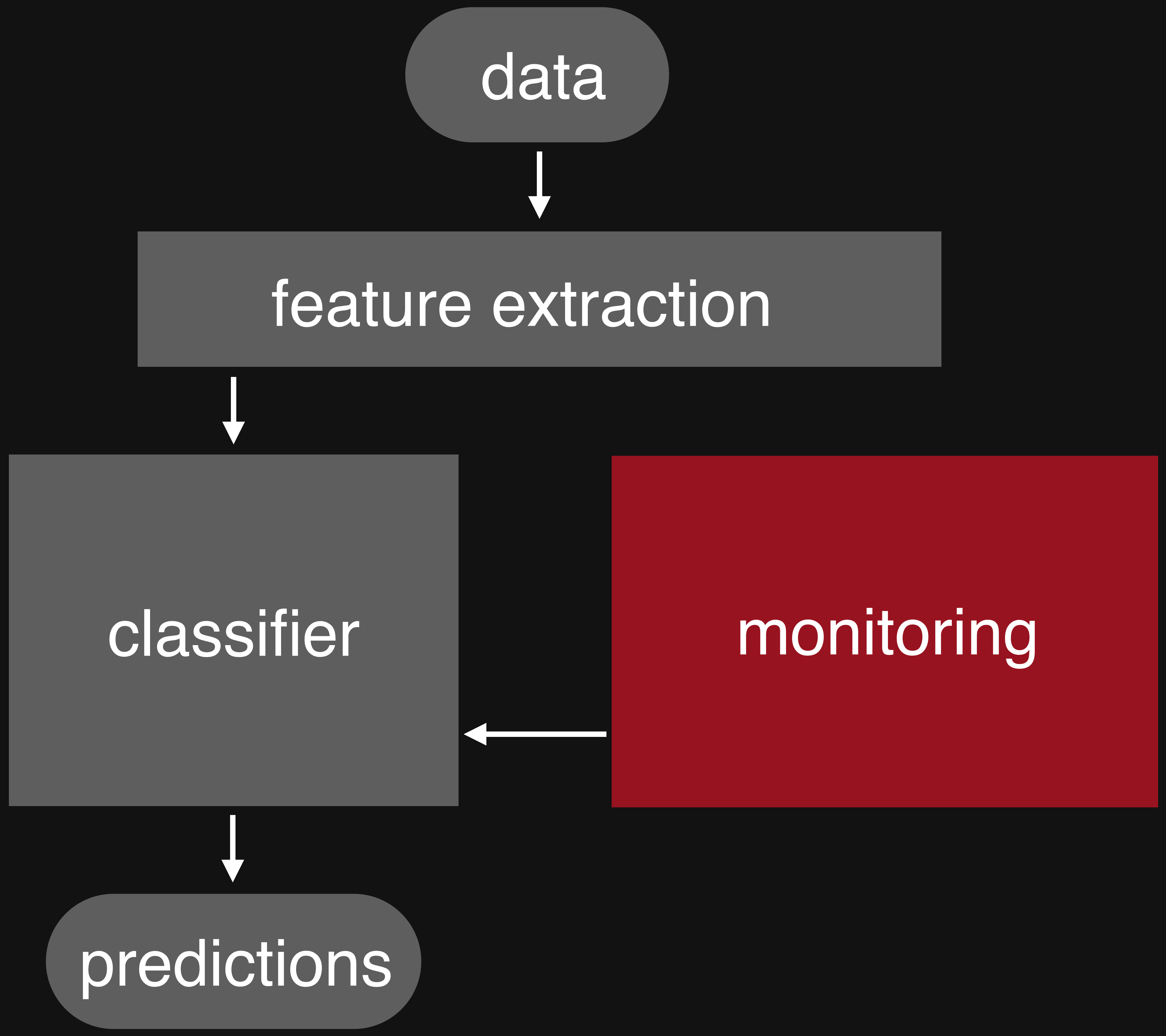

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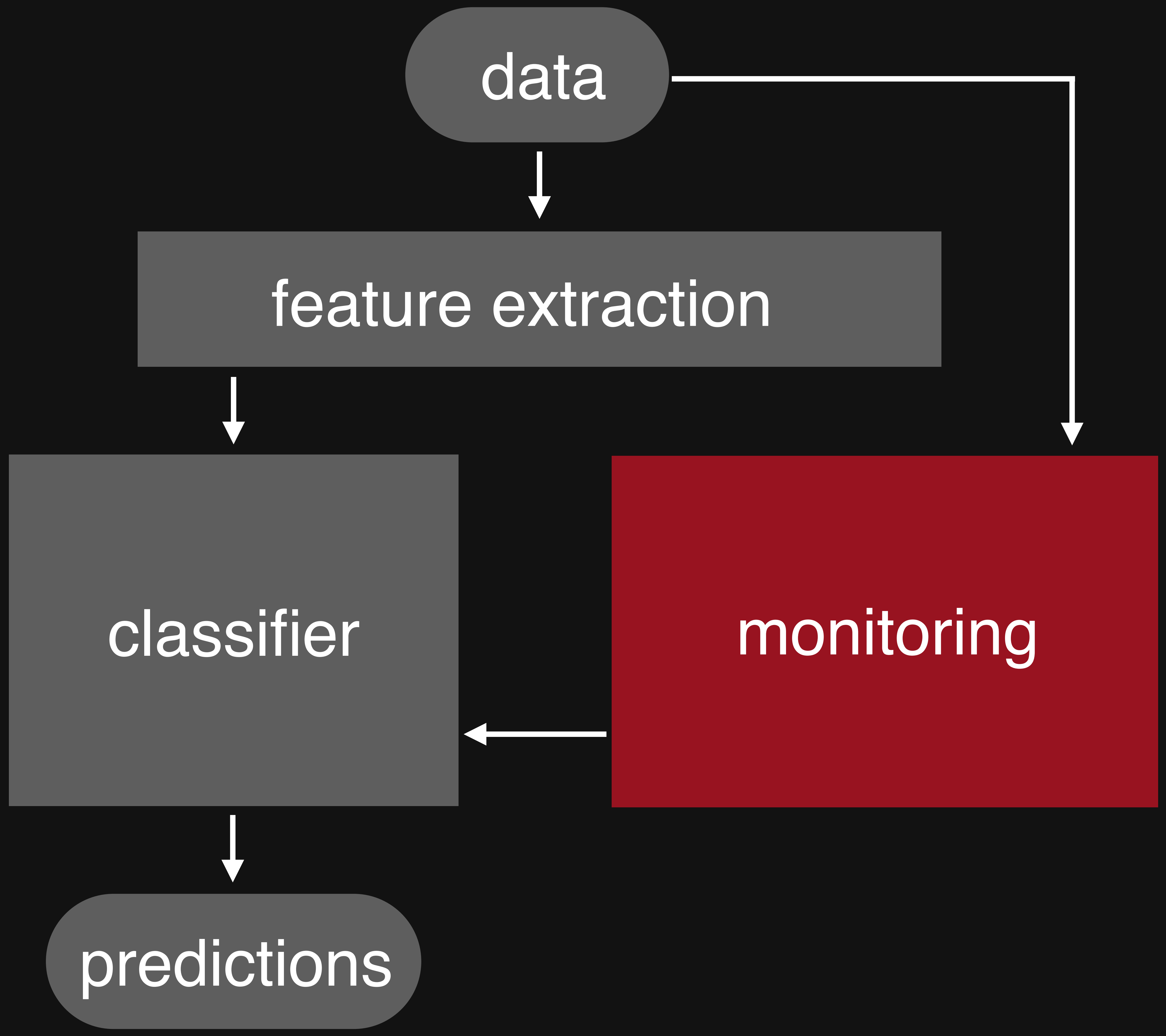

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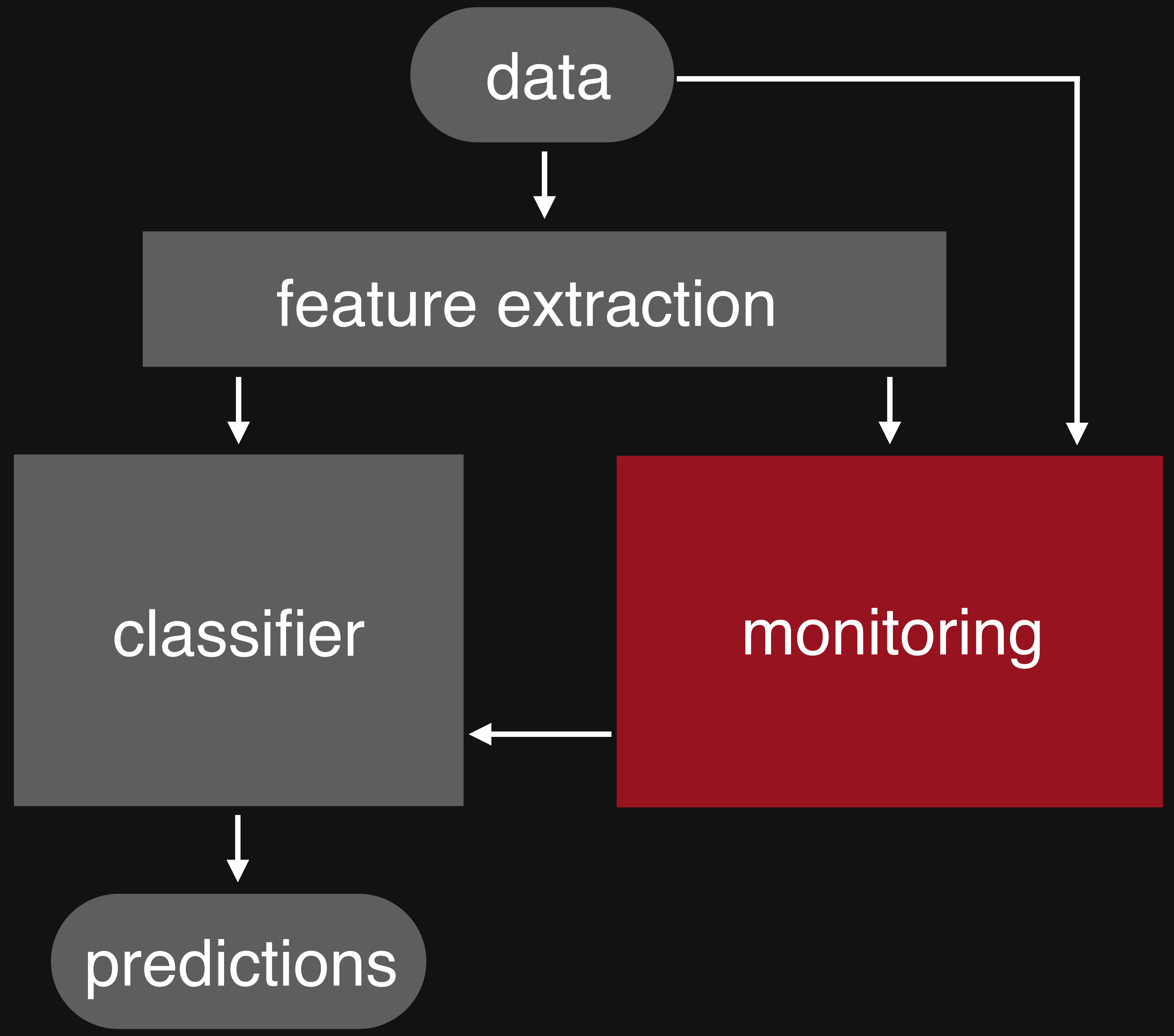

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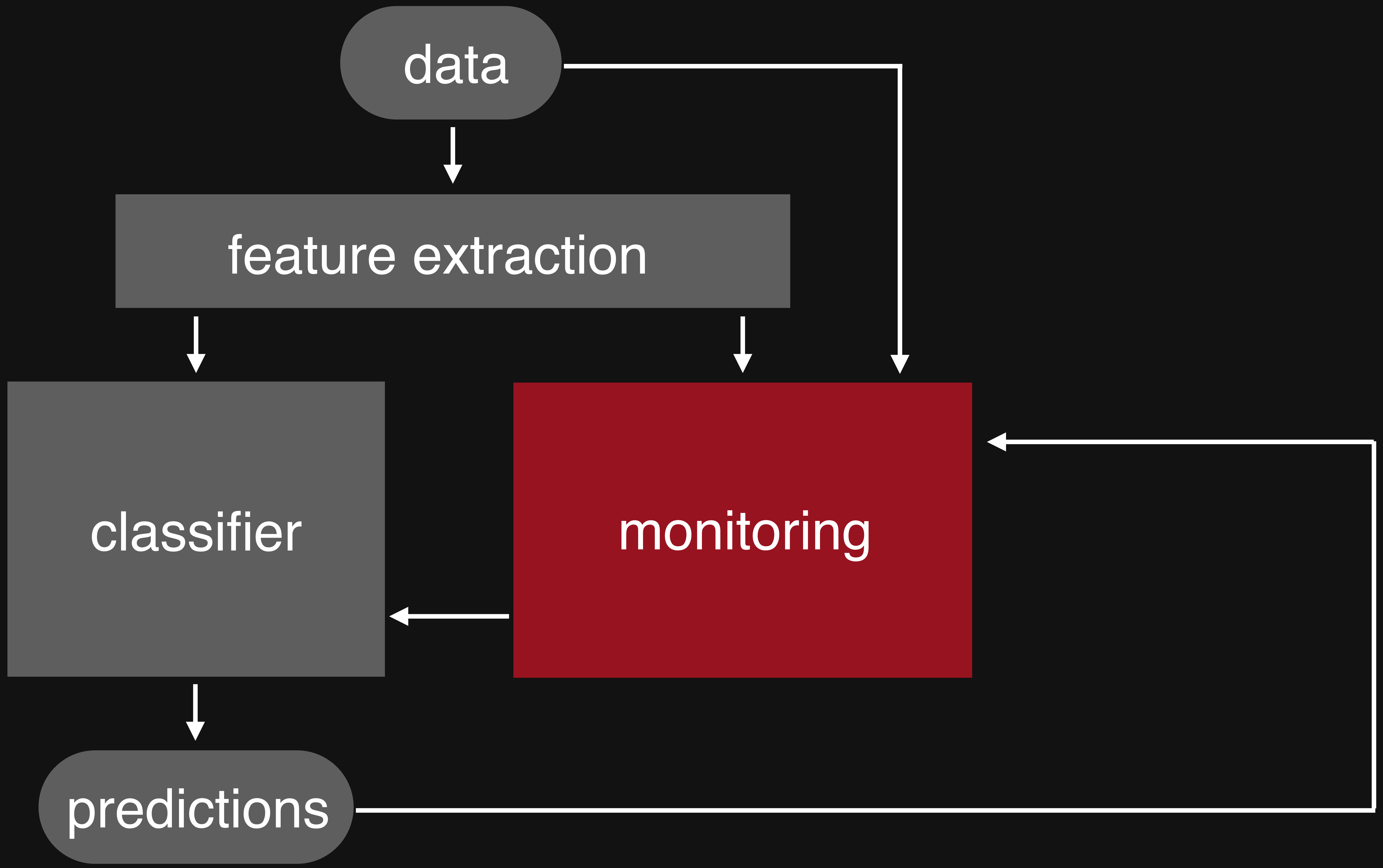

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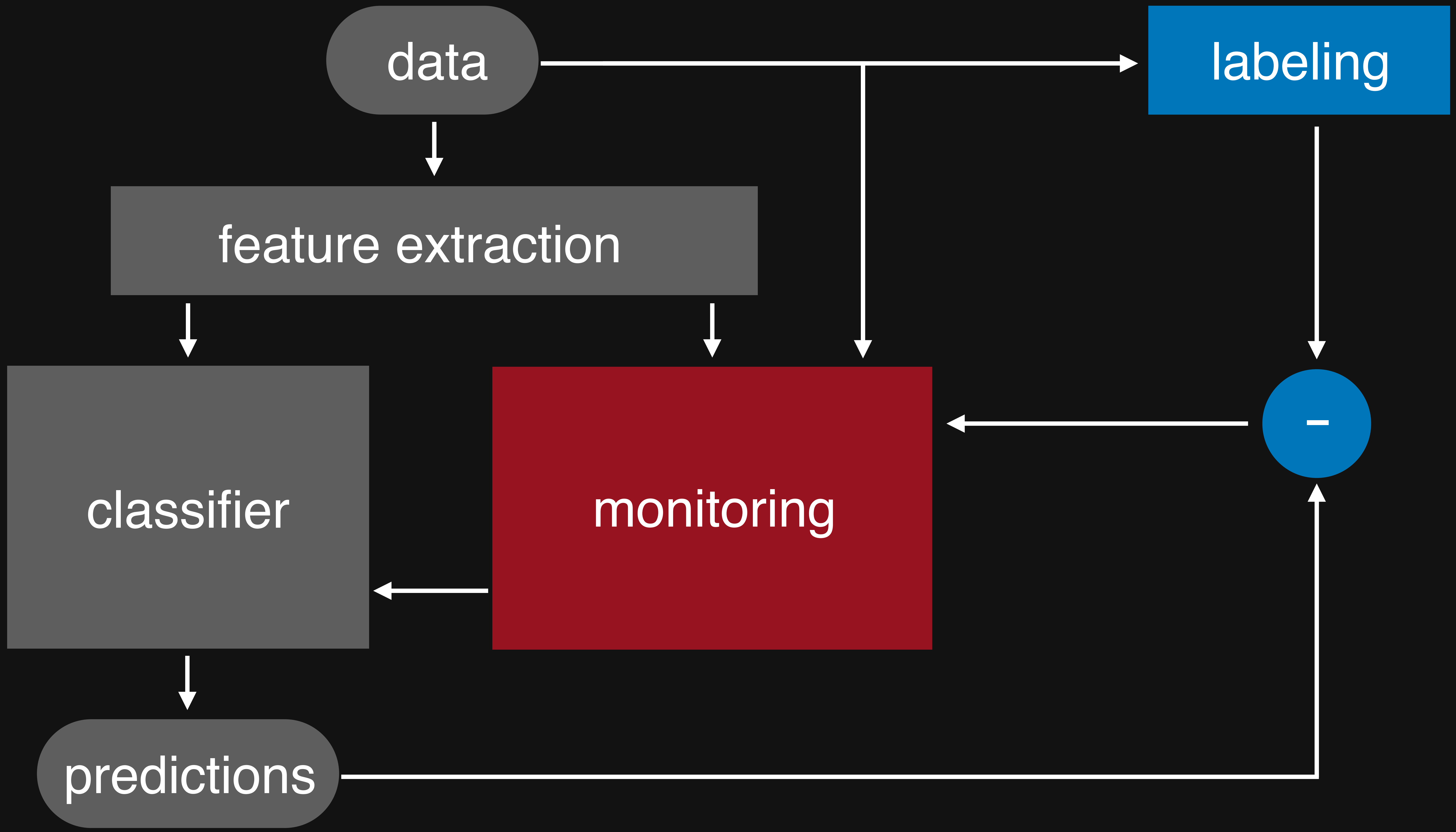

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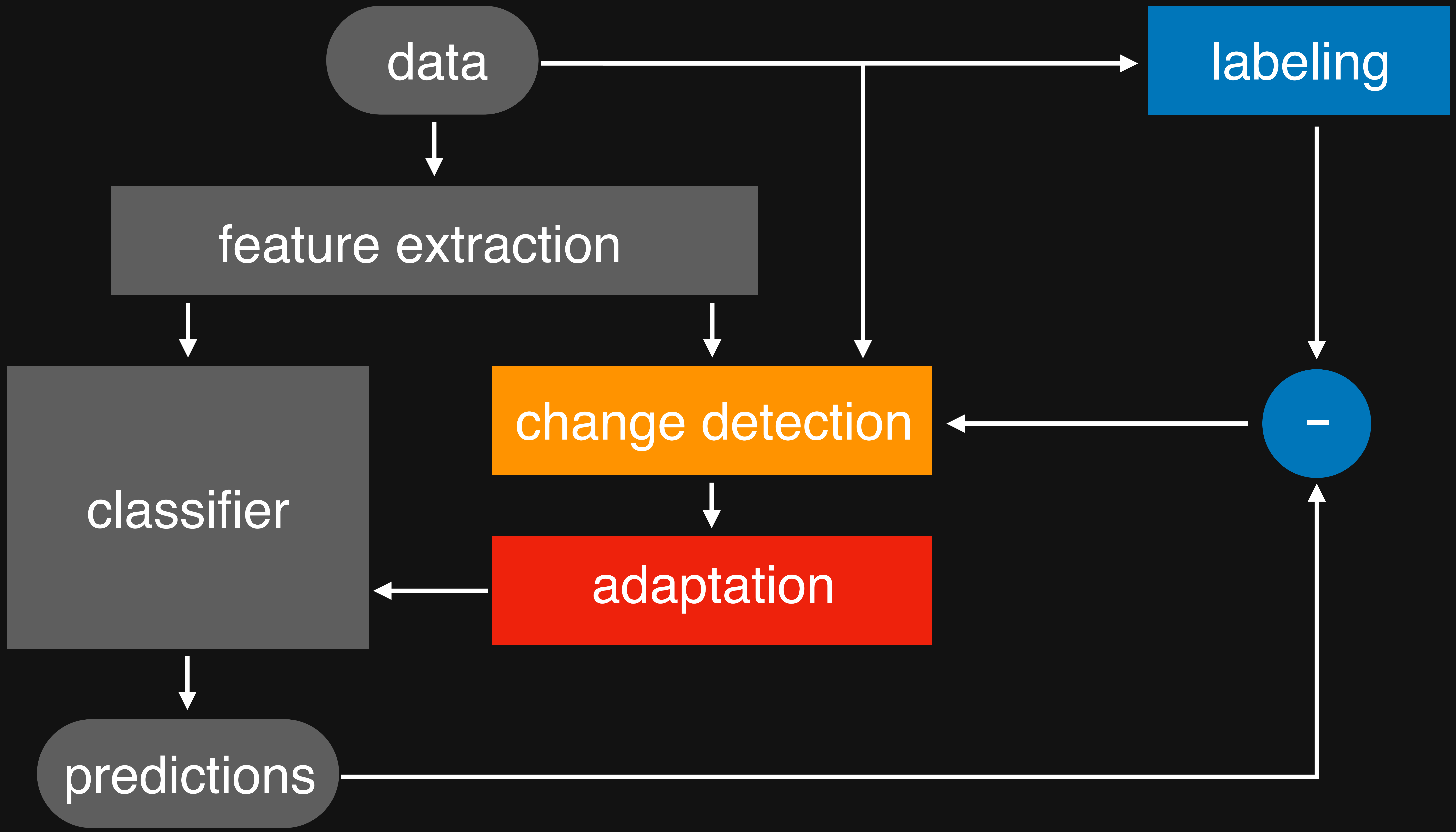

monitor how?

- supervised
  - statistical process control
  - sequential analysis
  - error distribution monitoring
- unsupervised
  - clustering / novelty detection
  - feature distribution monitoring
  - model-dependent monitoring

adapt how?

- explicit mechanisms
  - windowing
  - weighting
  - sampling
- implicit mechanisms
  - pure methods
  - ensemble methods

which method?

monitor how?

supervised

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ML theory: samples ↑ errors ↓

statistical process control

- Drift Detection Method [DDM]
  - # of errors is Binomial:

$$\mu = np_t$$

$$\sigma = \sqrt{\frac{p_t(1 - p_t)}{n}}$$

  - alert:

$$p_t + \sigma_t \geq p_{min} + 3\sigma_{min}$$

statistical process control

- Drift Detection Method [DDM]
  - # of errors is Binomial:

$$\mu = np_t$$

$$\sigma = \sqrt{\frac{p_t(1-p_t)}{n}}$$

  - alert:

$$p_t + \sigma_t \geq p_{min} + 3\sigma_{min}$$

- Early Drift Detection Method [EDDM]
  - distance between errors
    better for gradual drift
  - warn & start caching:

$$\frac{p_t + 2\sigma_t}{p_{max} + 2\sigma_{max}} < 0.95$$

  - alert and reset max:

$$\frac{p_t + 2\sigma_t}{p_{max} + 2\sigma_{max}} < 0.90$$

monitor how?

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model-dependent monitoring

sequential analysis

- Linear Four Rates [LFR]
  - stationary data => constant contingency table

Predicted \ True	0	1
0	TN	FN
1	FP	TP

sequential analysis

- Linear Four Rates [LFR]
  - stationary data => constant contingency table
  - calculate four rates

True / Predicted	0	1
0	TN	FN
1	FP	TP

$$P_{npv} = \frac{TN}{TN + FN}$$

$$P_{ppv/precision} = \frac{TP}{TP + FP}$$

$$P_{tnr/specificity} = \frac{TN}{TN + FP} \qquad P_{tpr/recall} = \frac{TP}{TP + FN}$$

sequential analysis

- Linear Four Rates [LFR]
  - stationary data => constant contingency table
  - calculate four rates
  - incremental updates

Predicted \ True	0	1
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$$P_*{}^t \leftarrow \eta_* P_*{}^{t-1} + (1 - \eta_*) I_{y_t = \hat{y}_t}$$

sequential analysis

- Linear Four Rates [LFR]
  - stationary data => constant contingency table
  - calculate four rates
  - incremental updates
  - test for change
    - Monte Carlo sampling for significance level
    - Bonferoni correction for correlated tests
  - O(1)
  - Better than (E)DDM for class imbalance

True / Predicted	0	1
0	TN	FN
1	FP	TP

$$P_{npv} = \frac{TN}{TN + FN}$$

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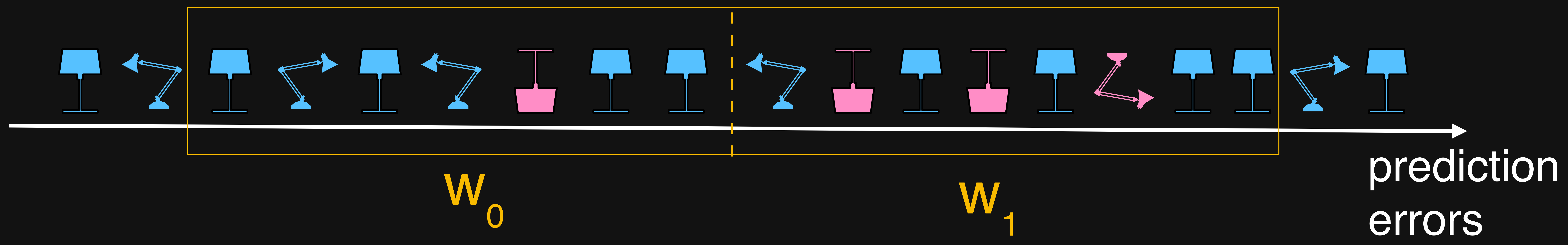
model-dependent monitoring

error distribution monitoring

- ADaptive WINdowing [ADWIN]
  - Consider all partitions of a window



  - Drop the last element if any

$$|\mu_0 - \mu_1| > \theta_{Hoeffding}$$

  - Efficient version O(log W)
    - Data structure for windows ~ exponential histograms
    - Drop last window rather than last element

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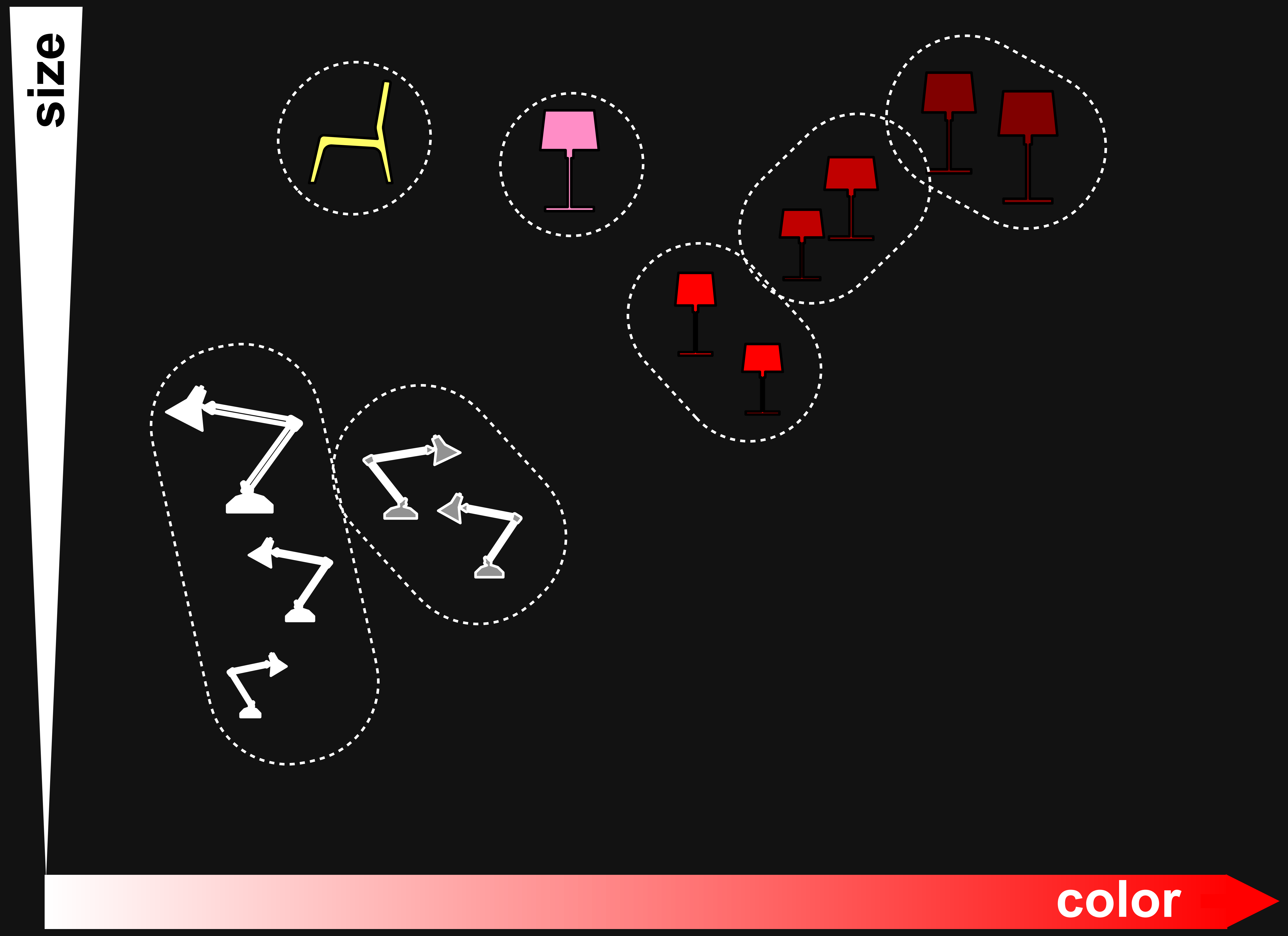
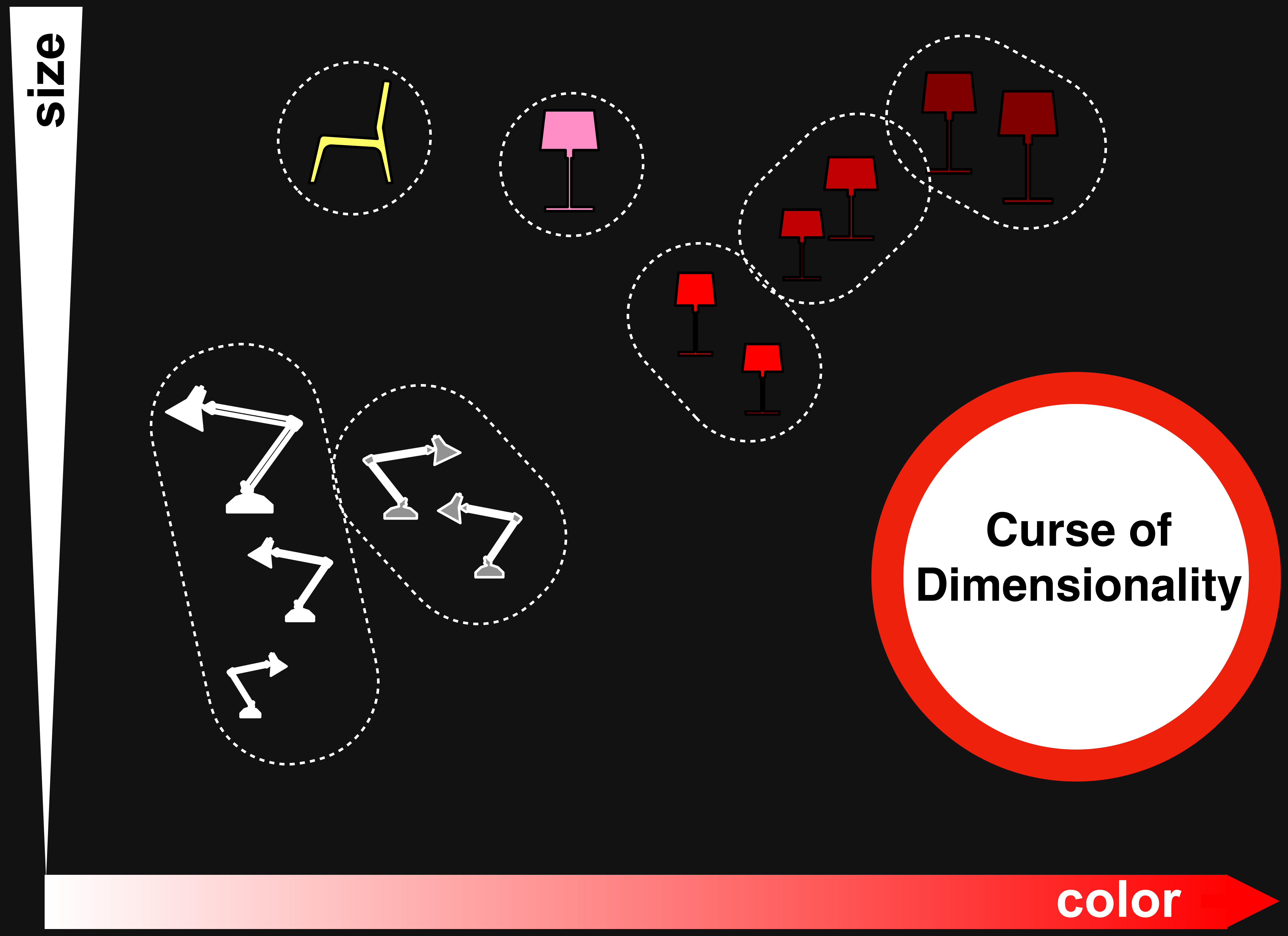
clustering / novelty detection



- OLINDDA: K-means, periodically merge unknown to known or flag
- MINAS: micro-clusters, incremental stream clustering
- DETECTNOD: Discrete Cosine Transform to estimate distances efficiently
- Woo-ensemble: Treat outliers as potential emerging class centroids
- ECSMiner: Store and use cluster summary efficiently
- GC3: Grid based clustering

clustering / novelty detection



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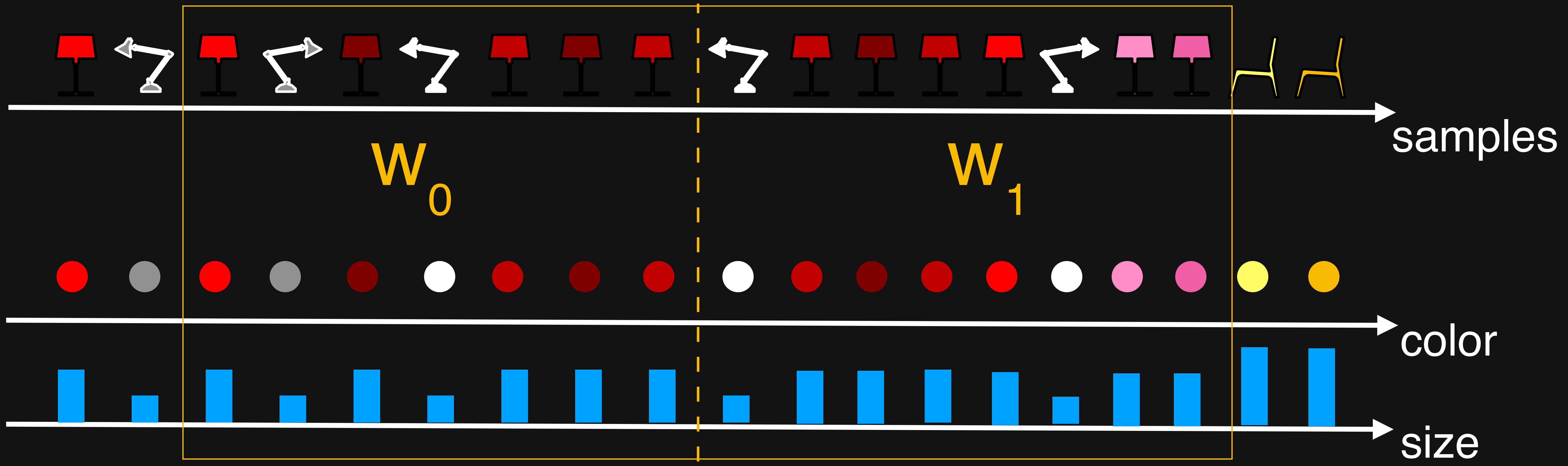
feature distribution monitoring



- Monitor individual features
- Many ways to compare:
  - Pearson correlation [Change of Concept - CoC]
  - Hellinger distance [HDDDM] ~ O(DB)
- Use PCA to reduce the number of features to track (top [PCA-1] or bottom [PCA-2] n%)

monitor how?

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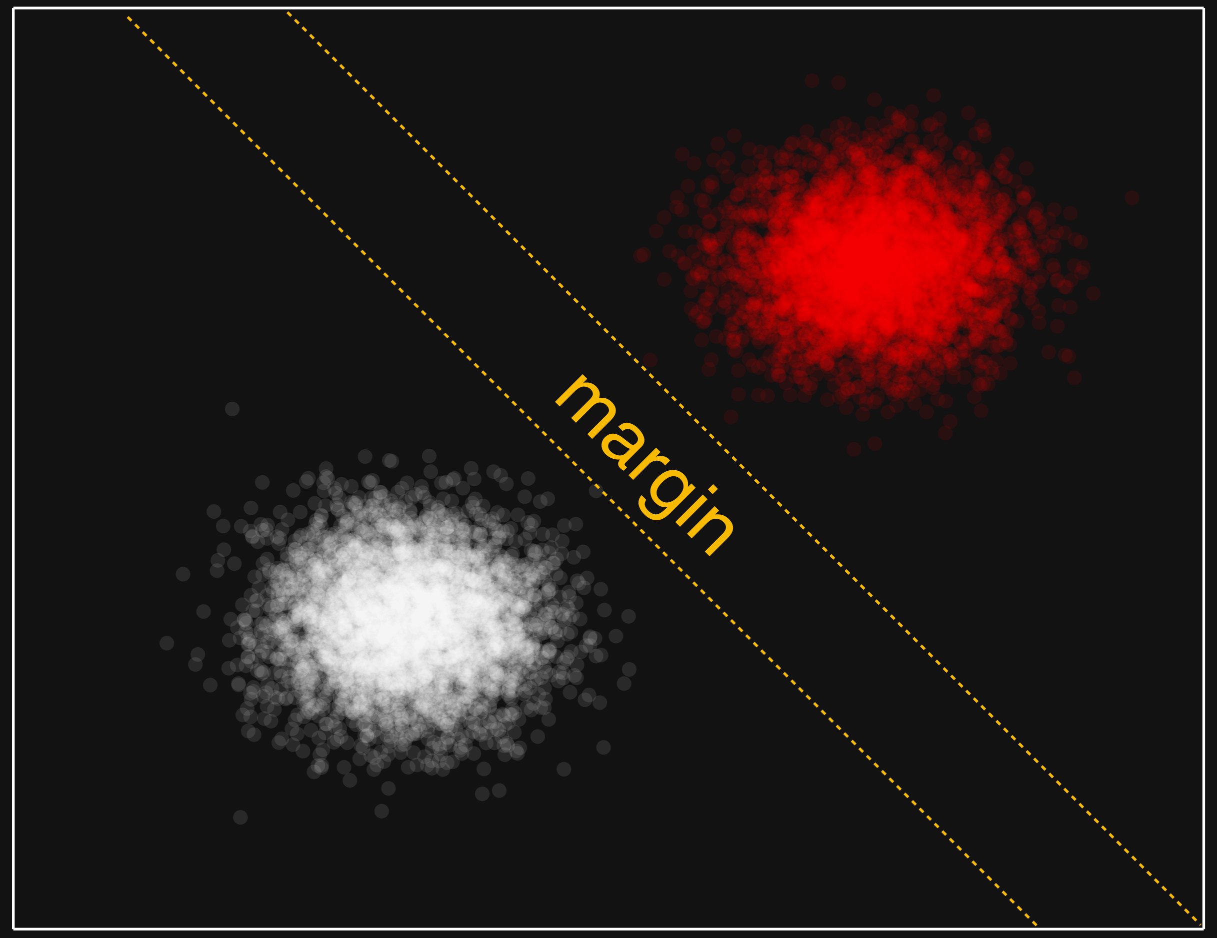
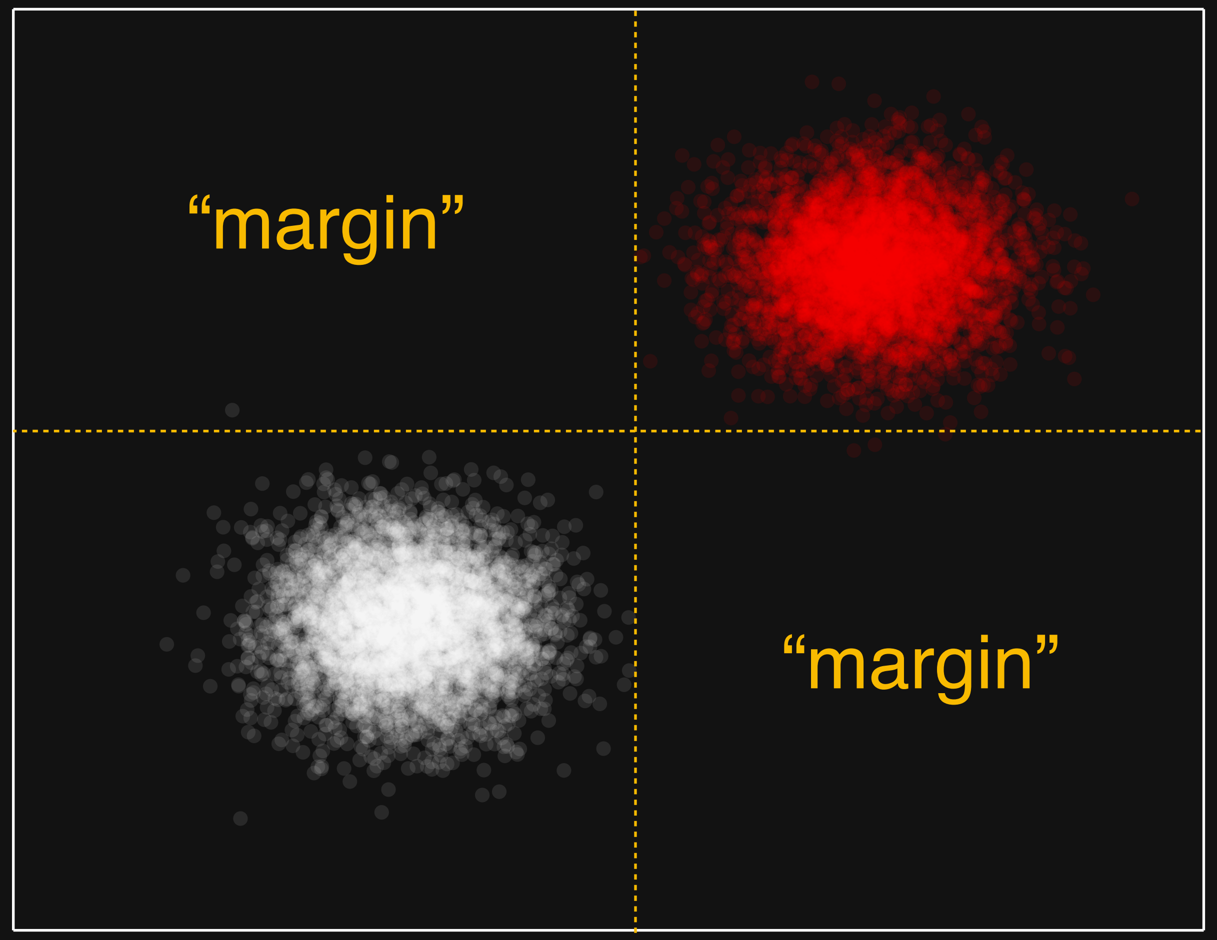
model-dependent monitoring

- Not all changes matter
- Posterior probability estimate
  - Use [A-distance] ~ generalized KS distance
    - designed to be less sensitive to irrelevant changes

model-dependent monitoring

- Not all changes matter
- Posterior probability estimate
  - Use [A-distance] ~ generalized KS distance
    - designed to be less sensitive to irrelevant changes
- Margin distribution
  - Compare average [Margin]s of 1-norm SVM
  - Generalized margin [MD3]:
    - Embed base classifier in a Random Feature Bagged Ensemble
    - Margin == high disagreement region of the ensemble





adapt how?

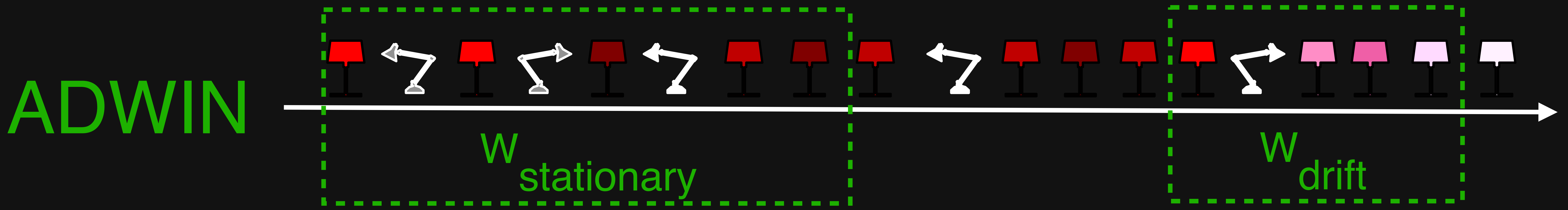
explicit mechanisms

- windowing
- weighting
- sampling

implicit mechanisms

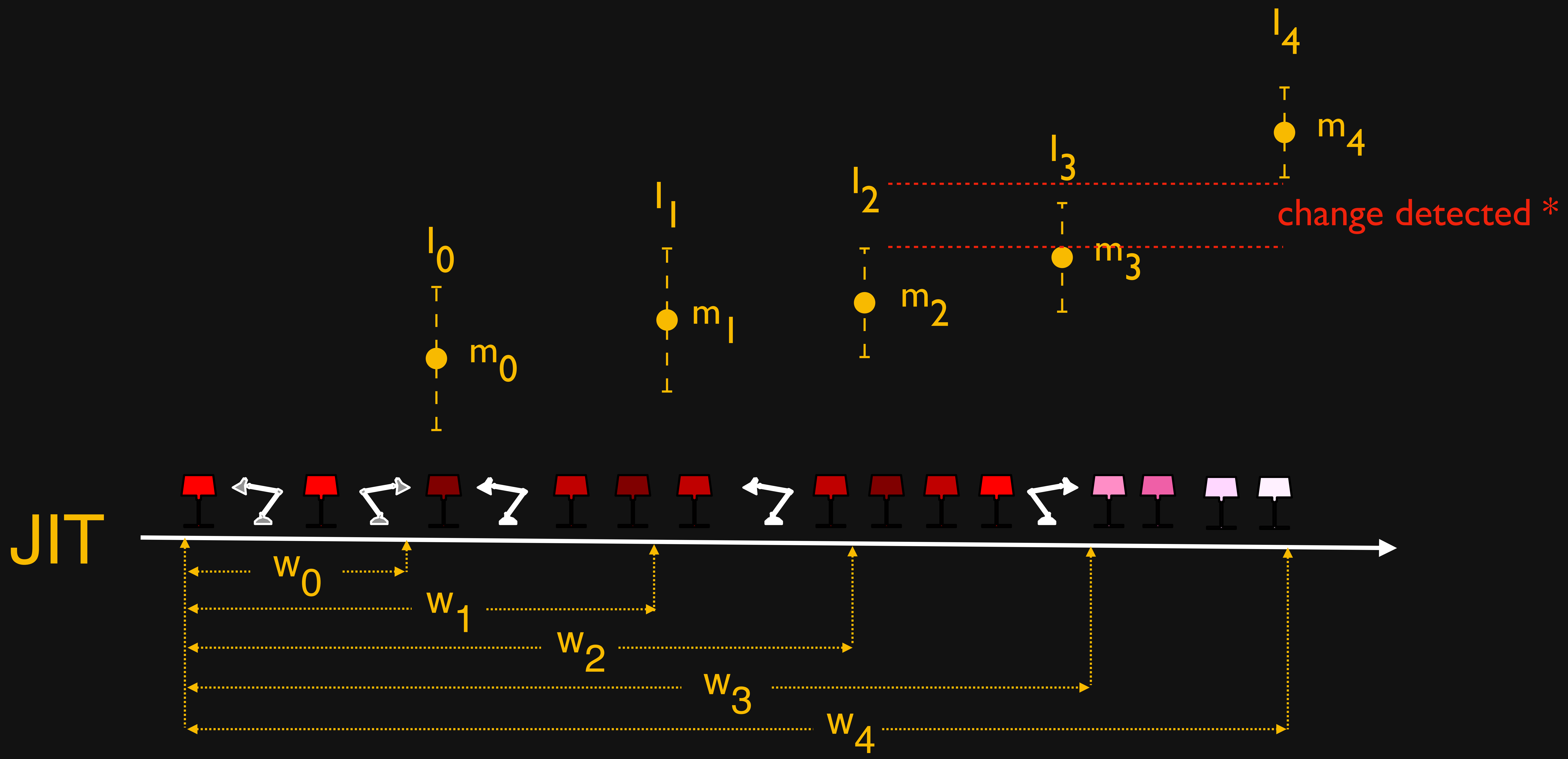
- pure methods
- ensemble methods

explicit mechanisms for adaptation



Drop the last sub-window if threshold is exceeded. = Adaptively shrink window during drift.

explicit mechanisms for adaptation



* Adaptation goes through a similar refinement process.

adapt how?

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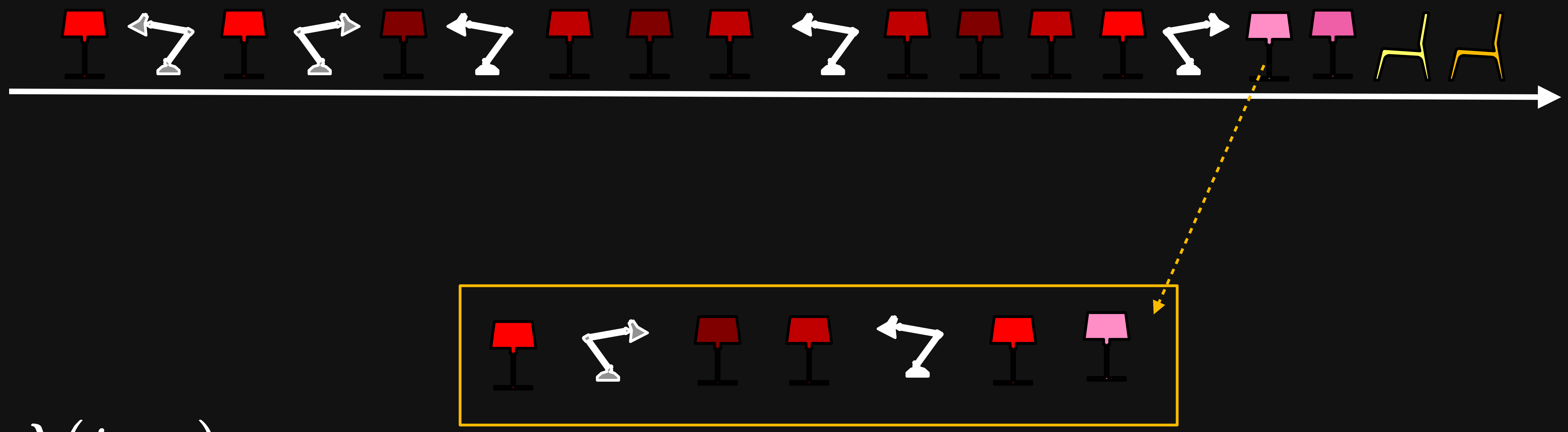
explicit mechanisms for adaptation

Biased Reservoir Sampling



bias: $f(r,t) = e^{-\lambda(t-r)}$

capacity: $N = \frac{1}{\lambda}$

overwrite / exchange

randomly w/ Prob{ $\%_{\text{full}}$ }

or append

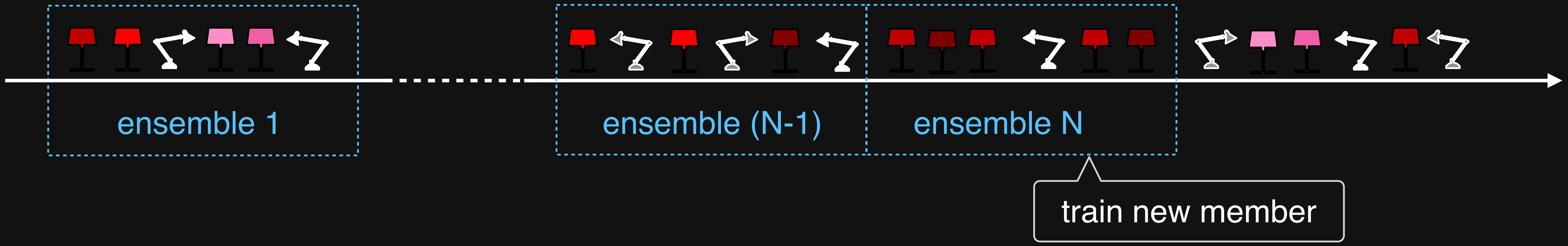
adapt how?

explicit mechanisms
- windowing
- weighting
- sampling

implicit mechanisms
- pure methods
- ensemble methods

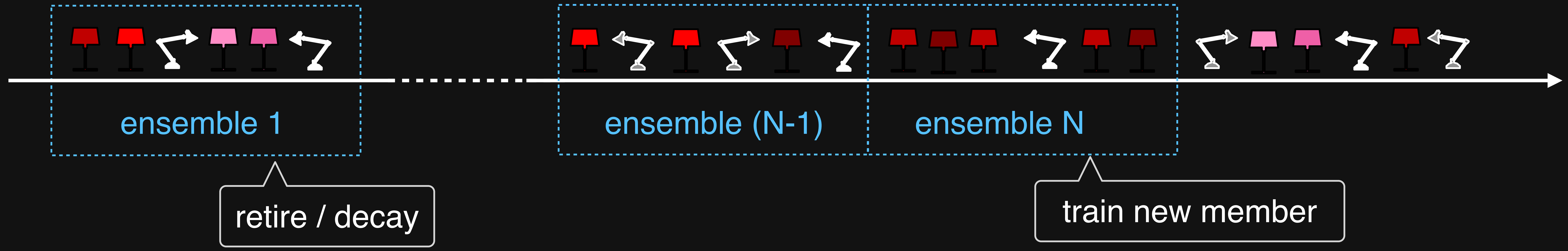
implicit mechanisms for adaptation

Ensemble Based Adaptation



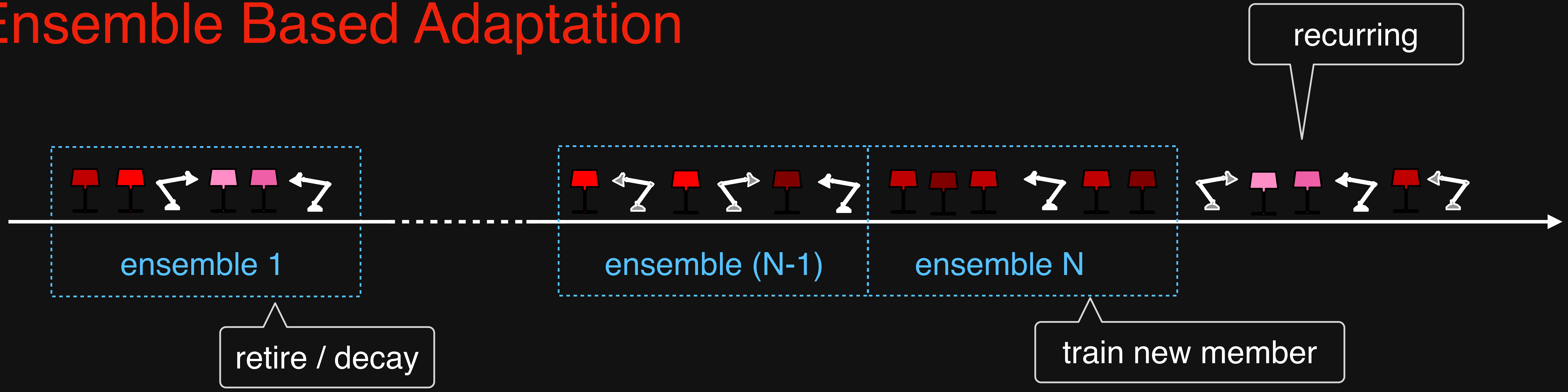
implicit mechanisms for adaptation

Ensemble Based Adaptation



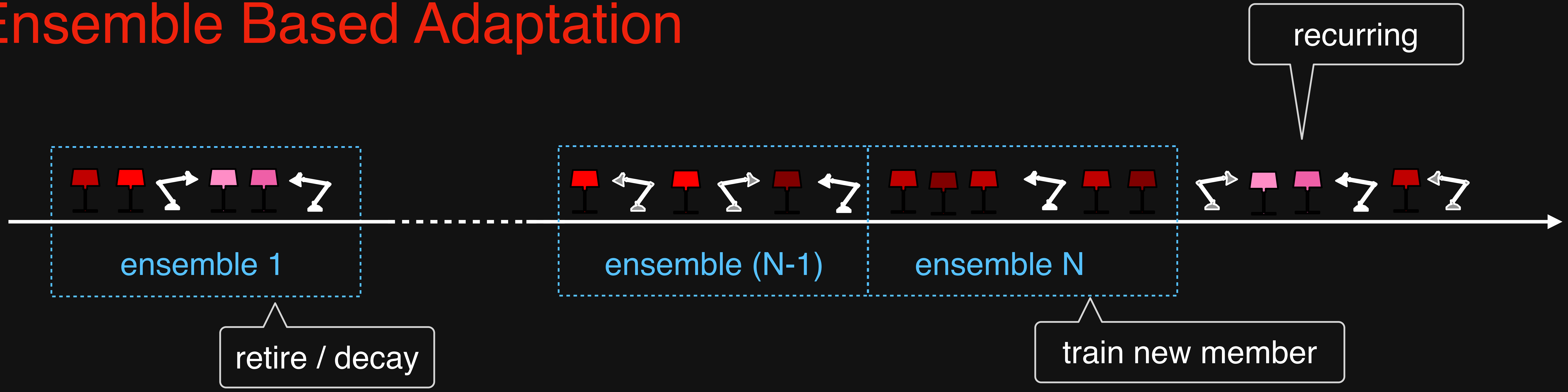
implicit mechanisms for adaptation

Ensemble Based Adaptation



implicit mechanisms for adaptation

Ensemble Based Adaptation



- Online NonStationary boosting [ONSboost]
- NonStationary Random Forests [NSRF]
- Dynamic Weighted Majority [DWM]
- Learn++ for NonStationary Environments [Learn++.NSE]

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which method?

Method	Efficiency	Pros	Cons	Notes
DDM/EDDM	O(1)	no data stored	label cost false alarms	sampling necessary in case of fast data, microservices architecture ideal
LFR	O(1)	class imbalance OK	label cost	
ADWIN	O(log W)	better change localization	label cost	
JIT	O(log W)	no labels required	only for abrupt changes	best localization

which method?

Method	Efficiency	Pros	Cons	Notes
ECSMiner / GC3	$O(W^2 / k)$ $O(G \log C)$	emerging concepts	*clusterable* drift only	use if emerging concepts expected
HDDDM	O(DB)	no labels	not for population drift or class imbalance	better when combined with PCA
A-distance	$O(\log W)$	no labels	less false positives compared to HDDDM	good choice for unsupervised
Margin / MD3	Learning, detection, adaptation bundled	reduced false alarms	must use feature bagged ensembles	best choice but must commit to using the specific machine learning algorithms
Ensemble methods		recurring concepts	large batches	

Appendix

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Appendix

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Appendix

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Appendix

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Appendix

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thank you

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