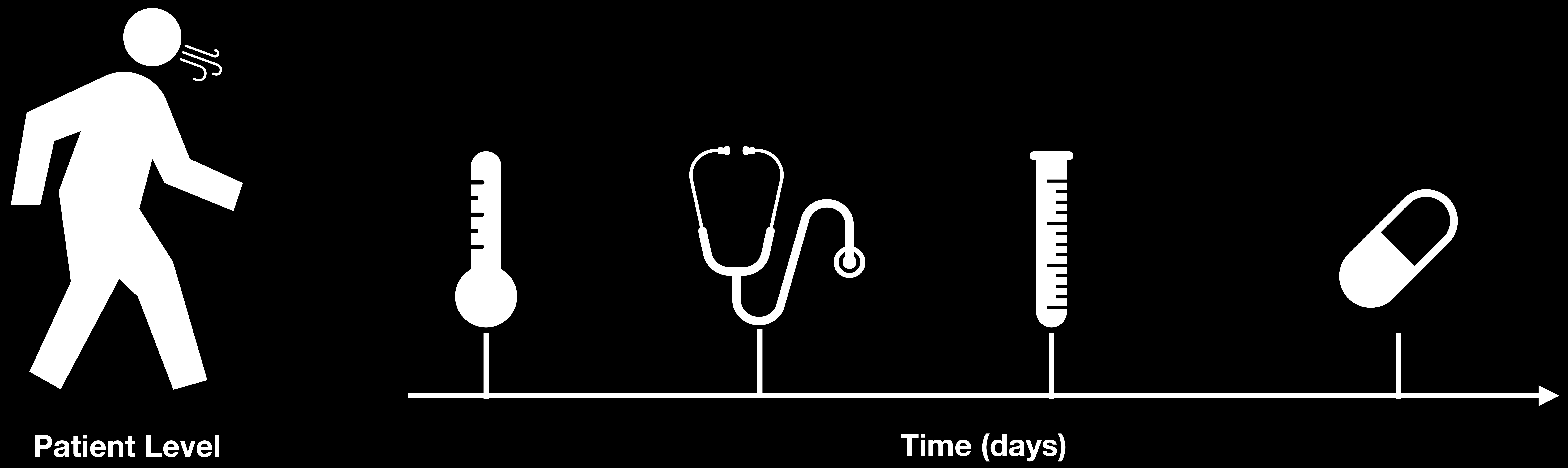
Machine Learning for Healthcare

Lessons From Across The Healthcare ML Lifecycle

WPI Business Week
Erkin Ötleş
October 2023

Time plays an important role in medicine.



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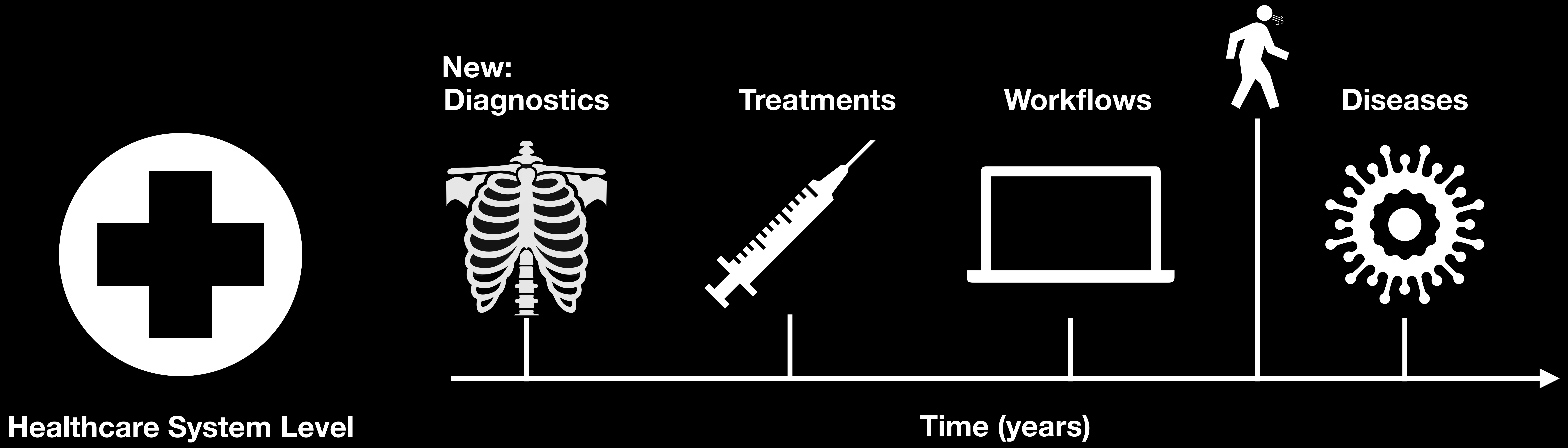
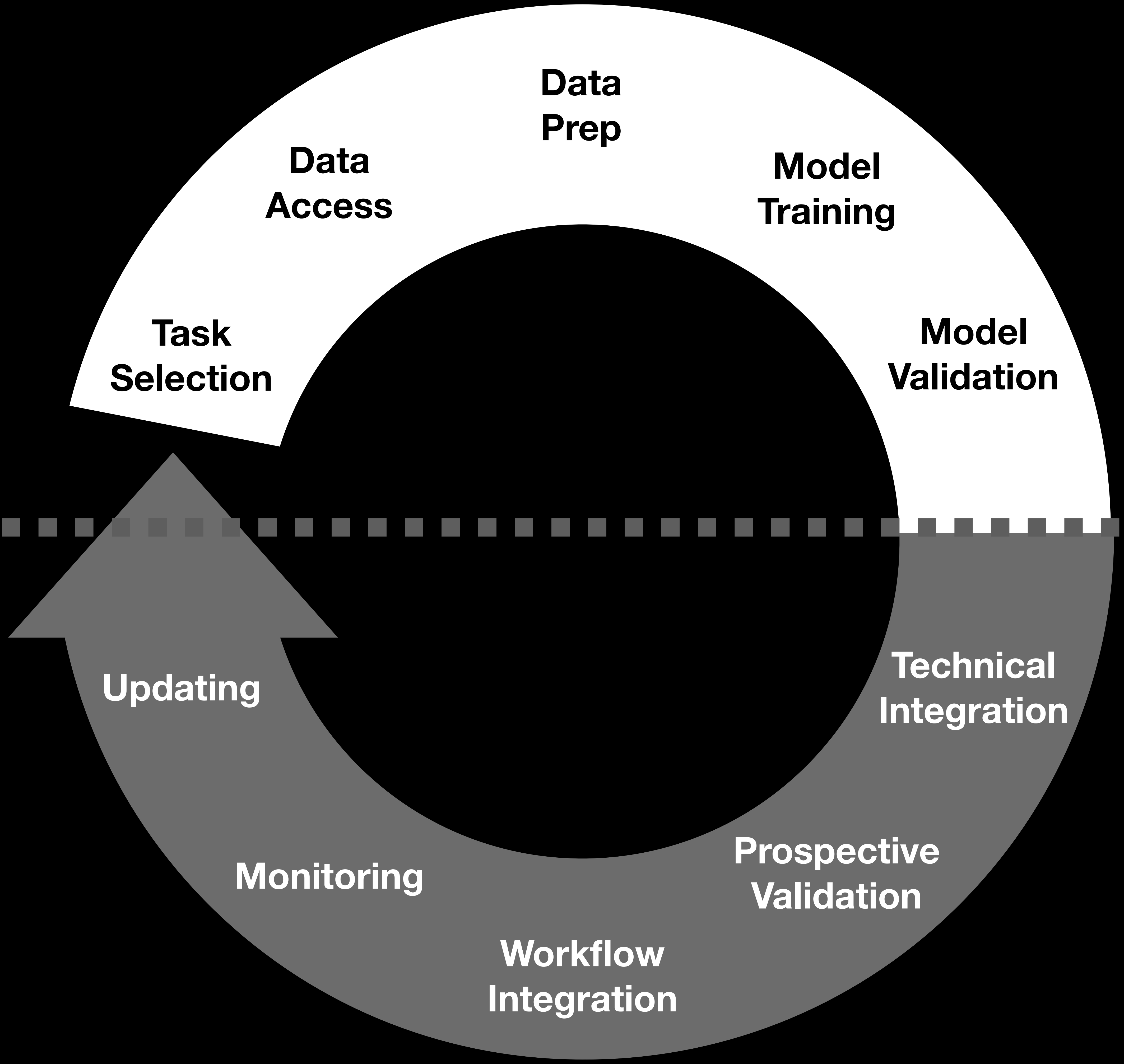


Time complicates ML model development & implementation.

Development

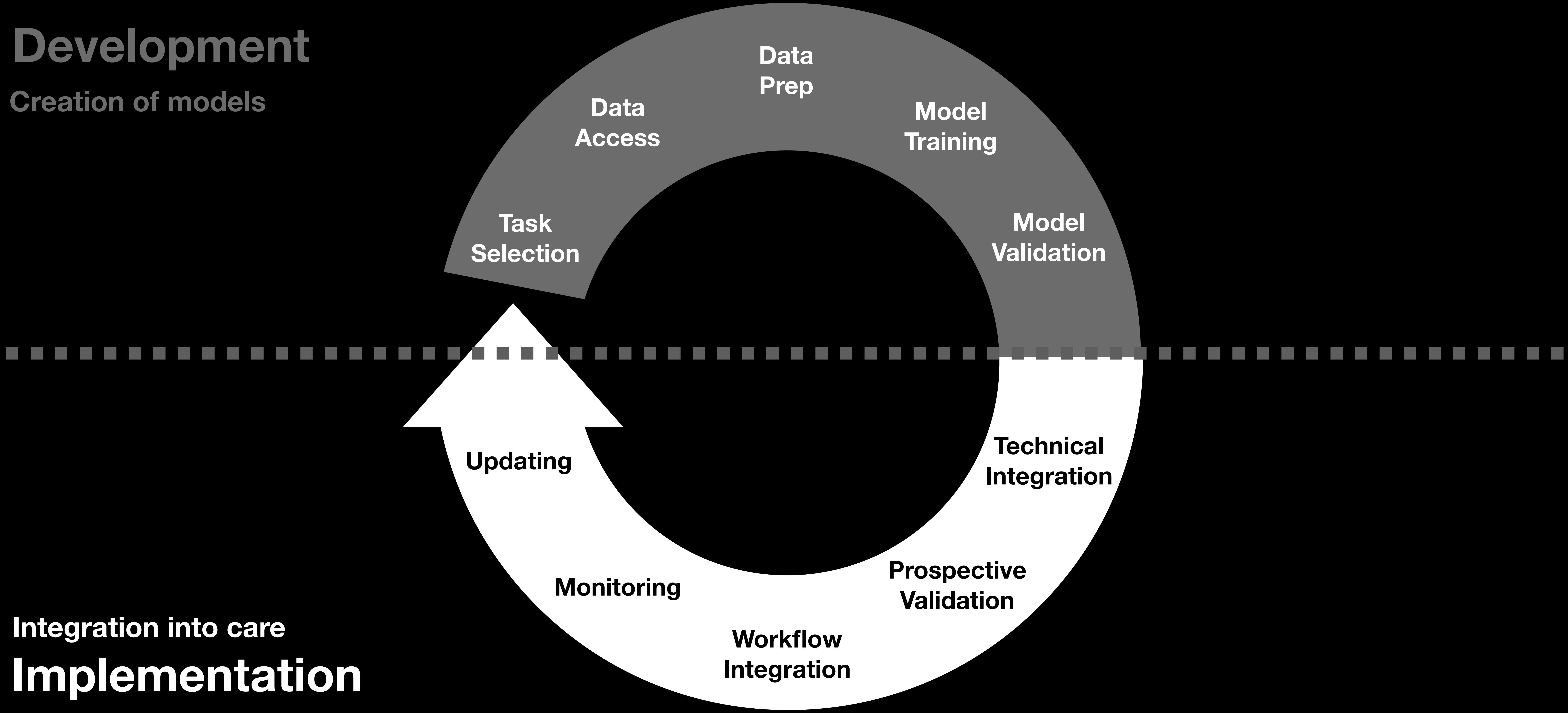
Creation of models



Integration into care

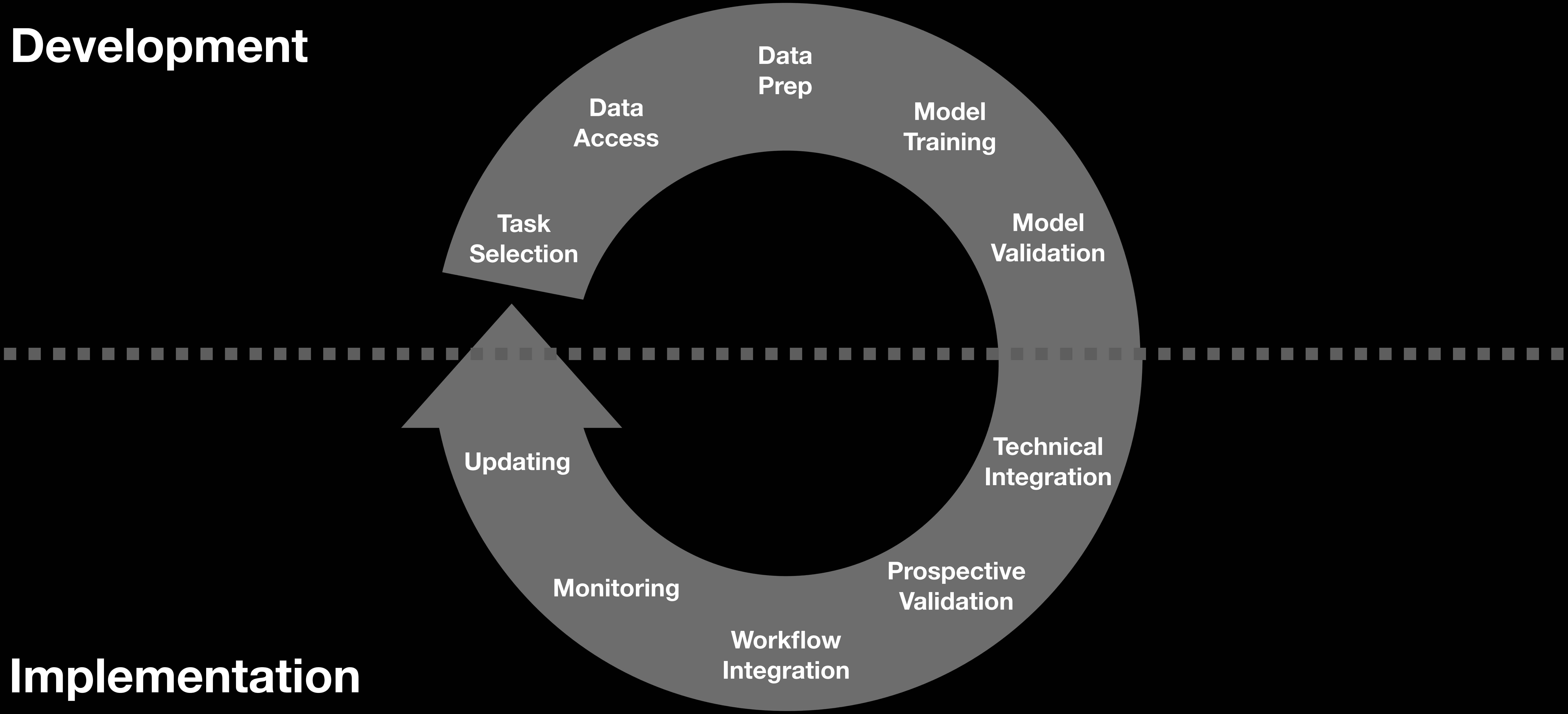
Implementation

Time complicates ML model development & implementation.



Thesis: by focusing on the longitudinal nature of healthcare, we can improve the performance of predictive models during development & implementation.

The ML Lifecycle



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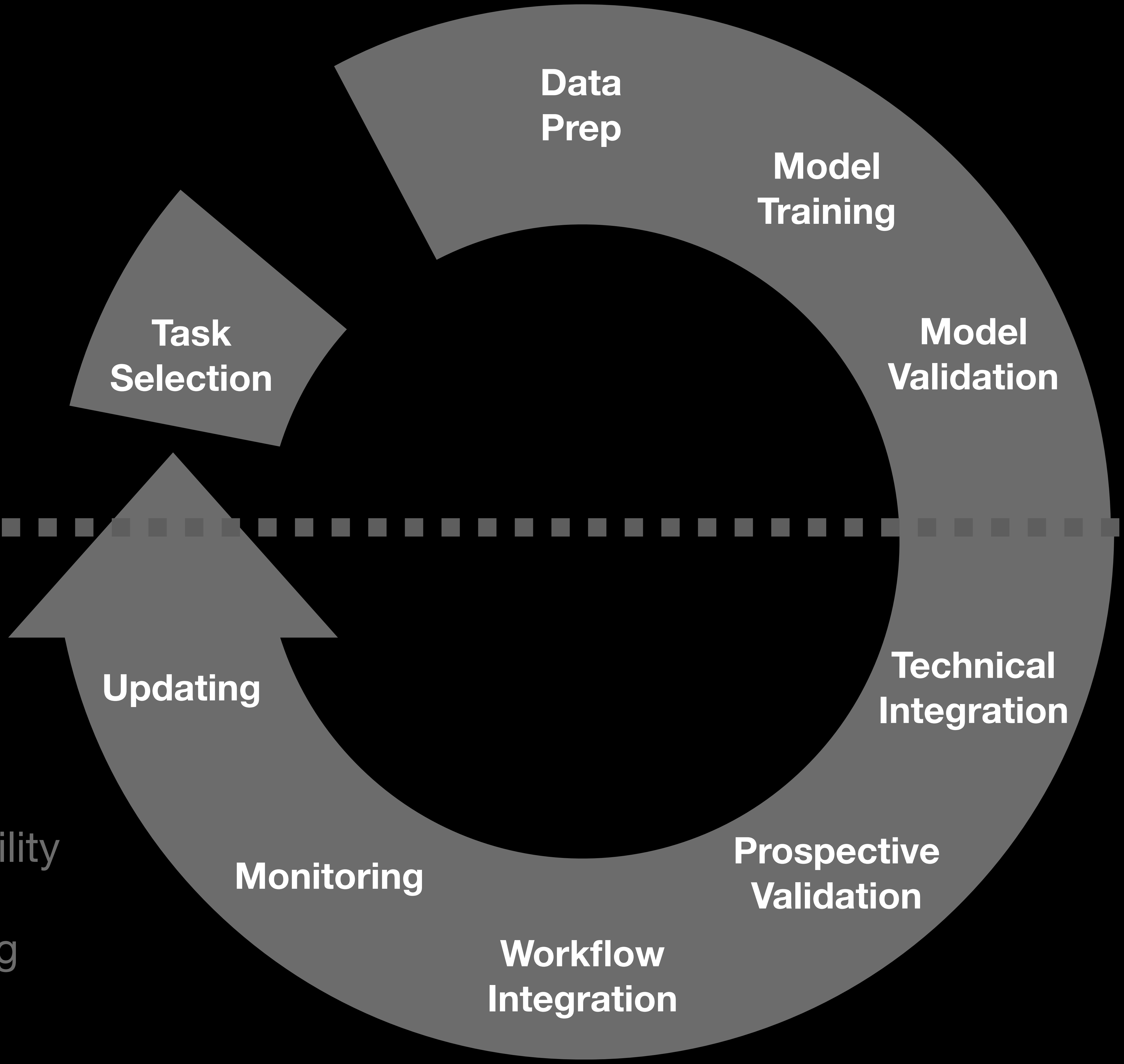

RTW Prediction

Assess value of longitudinal observations for return to work prediction

Ötleş *et al.*, JAMIA ‘22

Updating Models

Develop rank-based compatibility measurement & optimization approaches for model updating

Ötleş *et al.*, MLHC '23

Performance Gap

Characterize changes to prospective performance after model implementation

Ötleş *et al.*, MLHC ‘21

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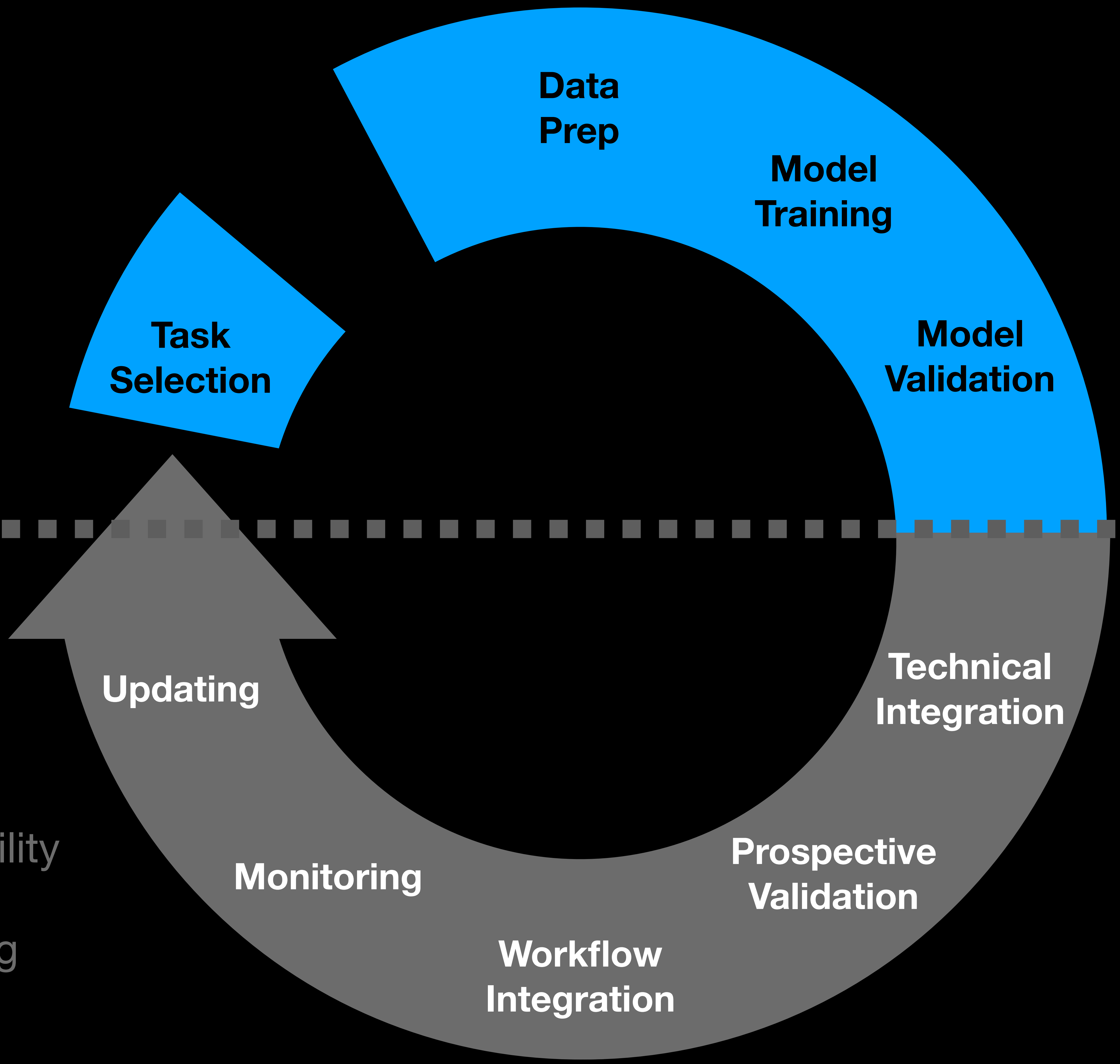

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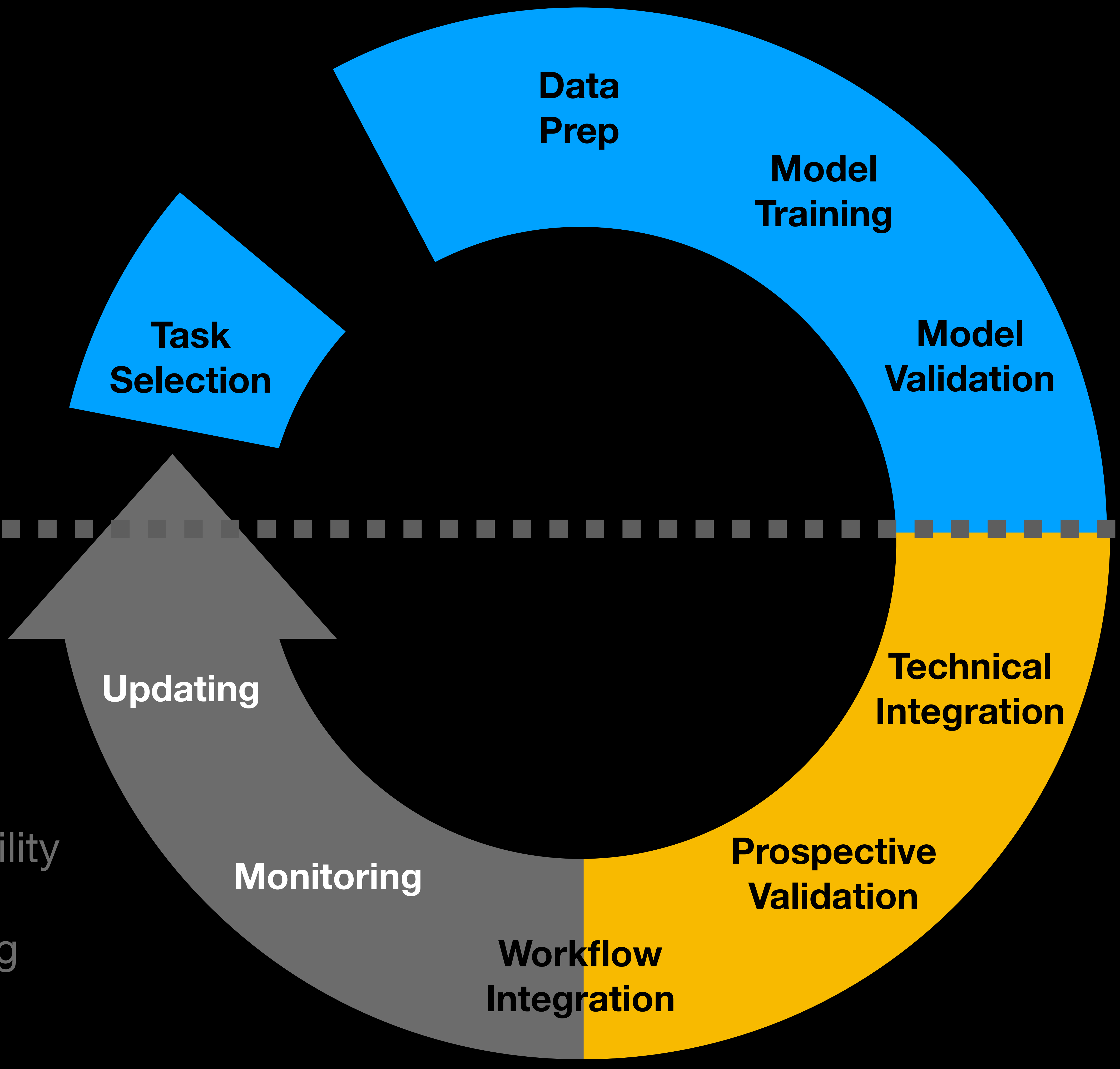

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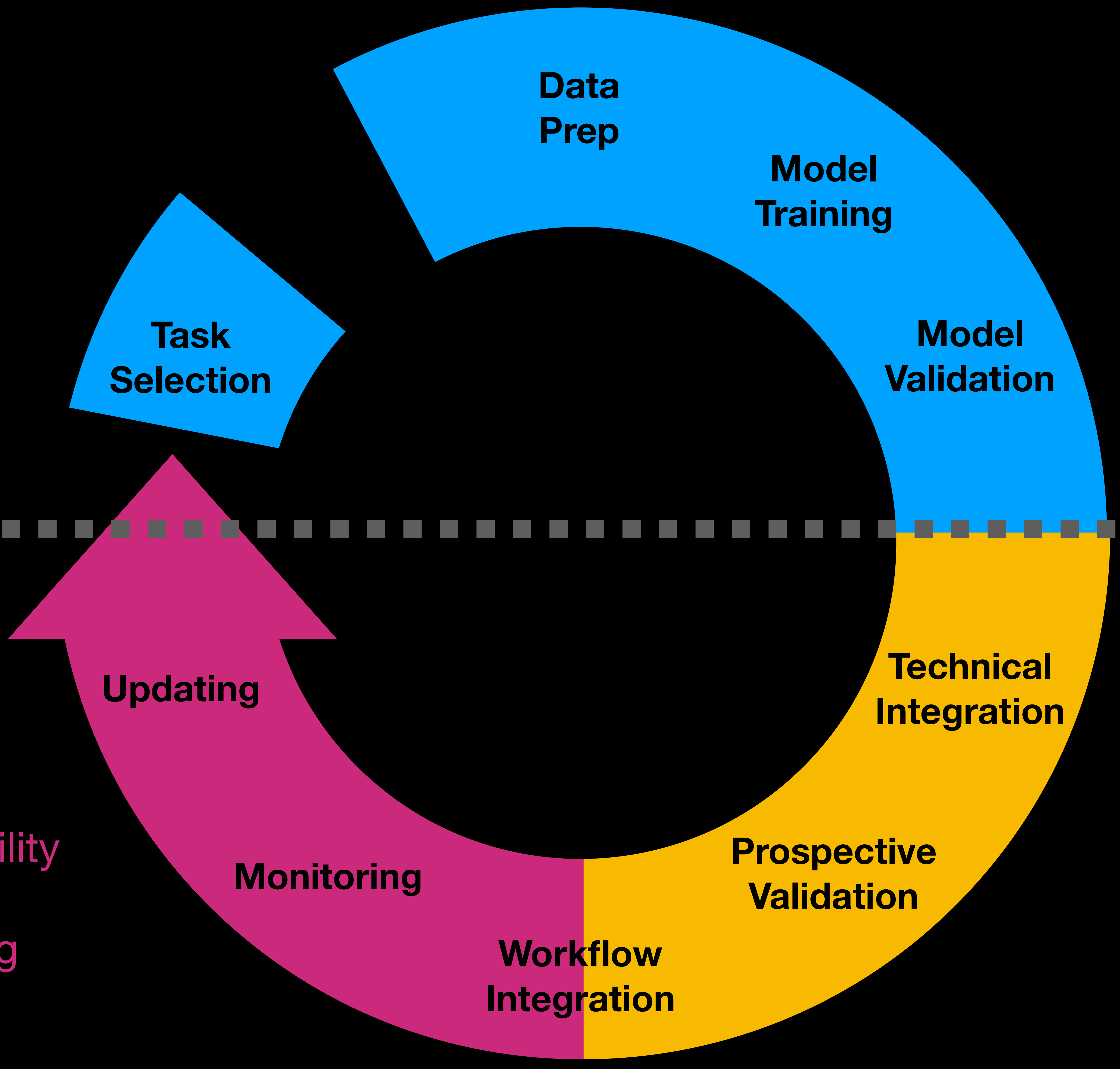

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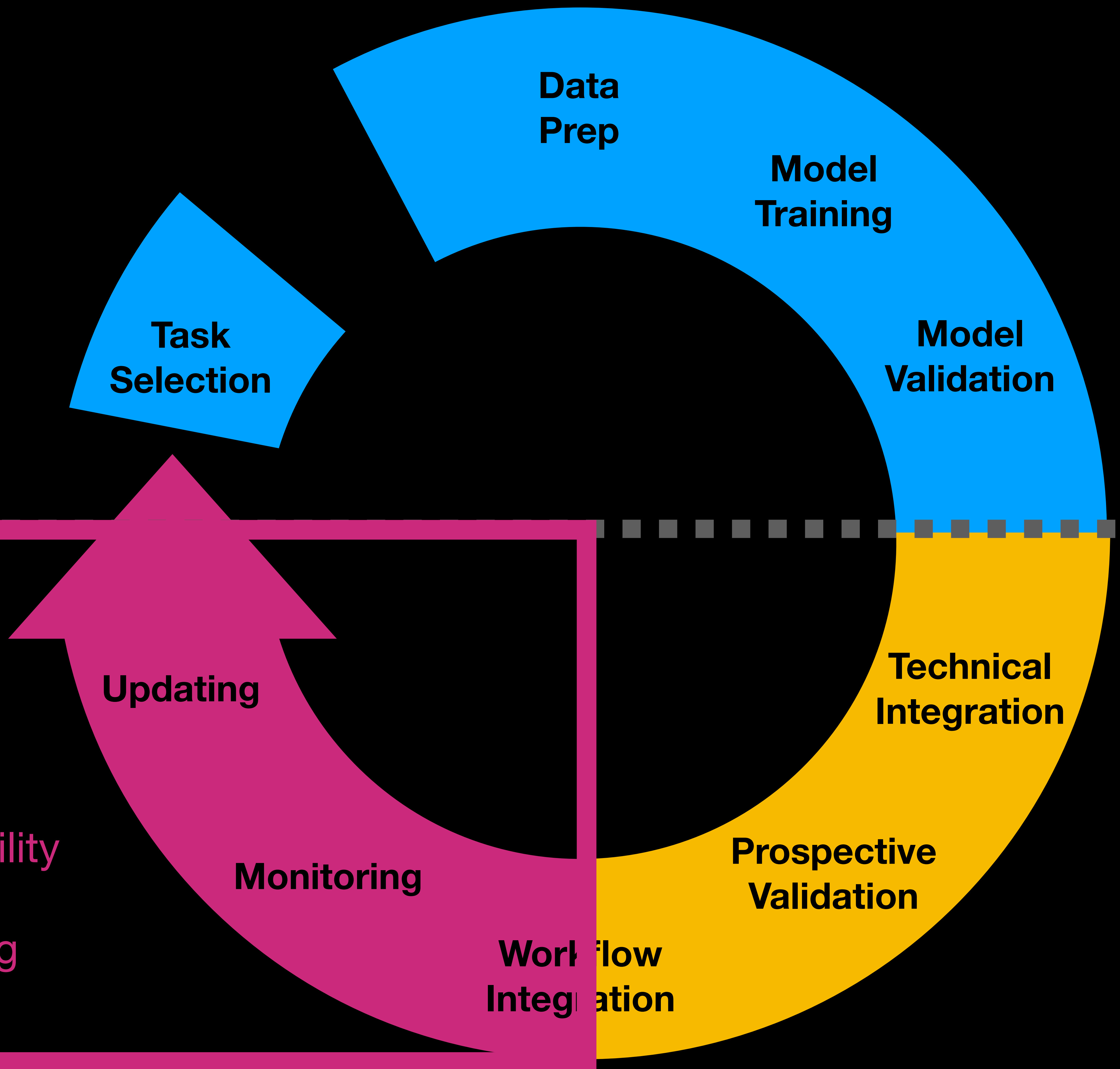
What are we going to talk about?



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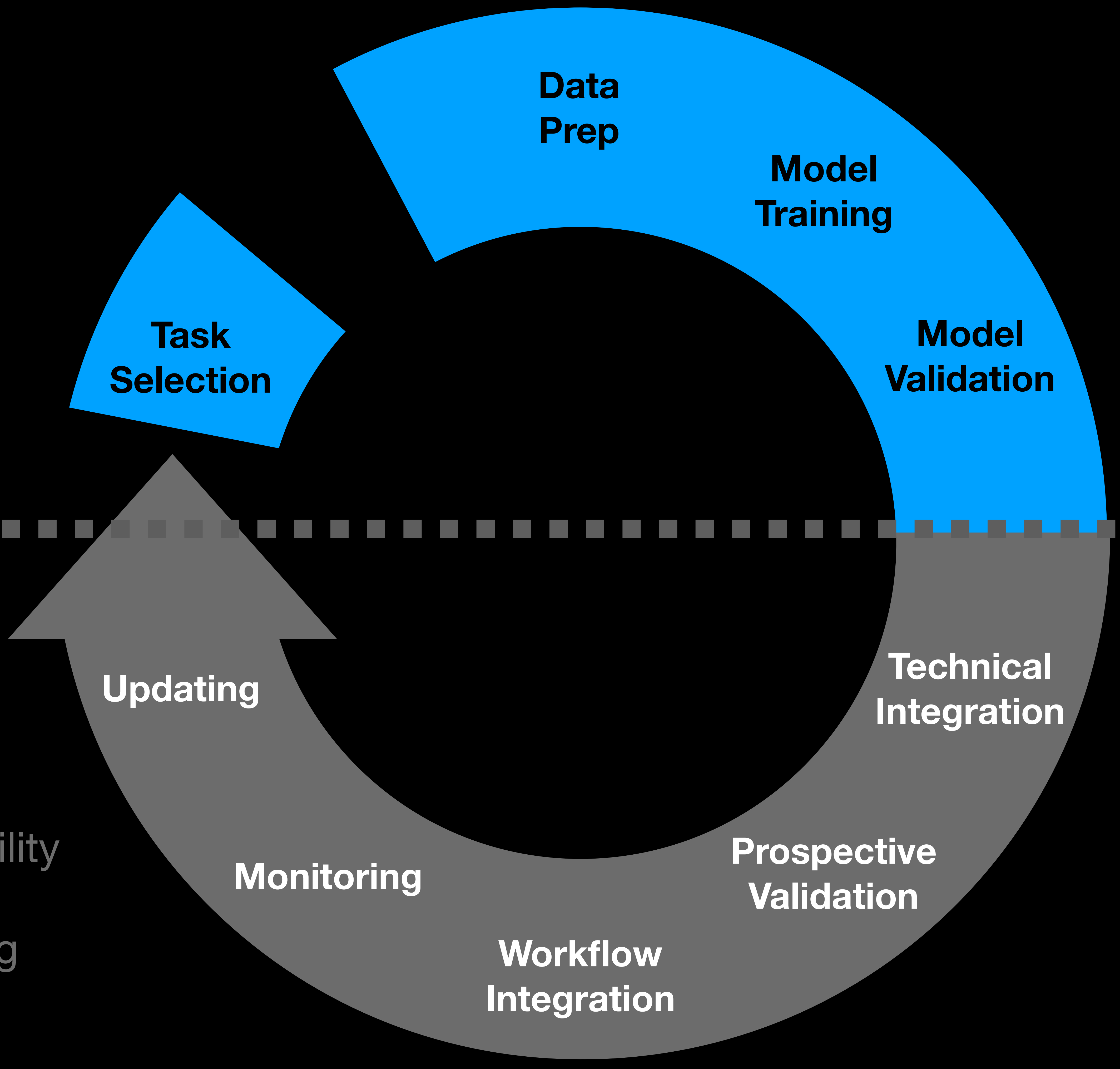
Let's dive in.



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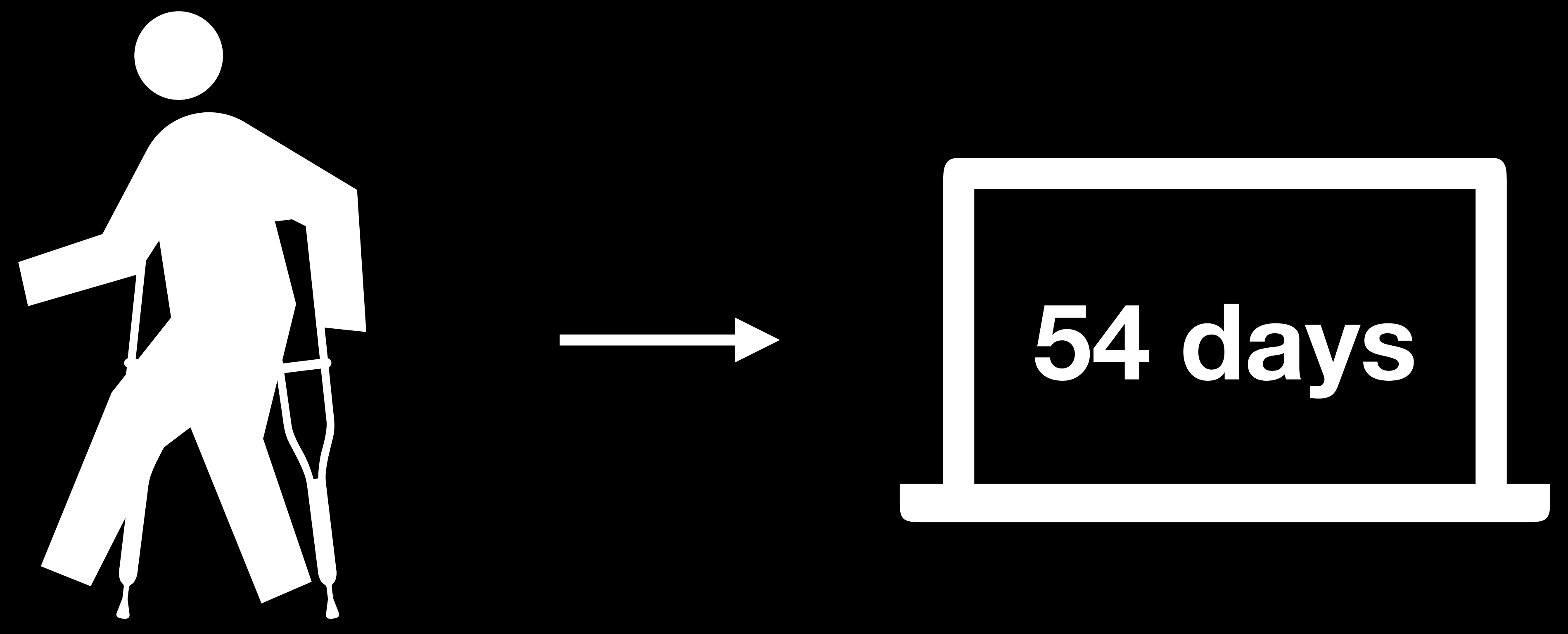
Existing return to work models ignore longitudinal observations.

55 y.o. male
postal worker

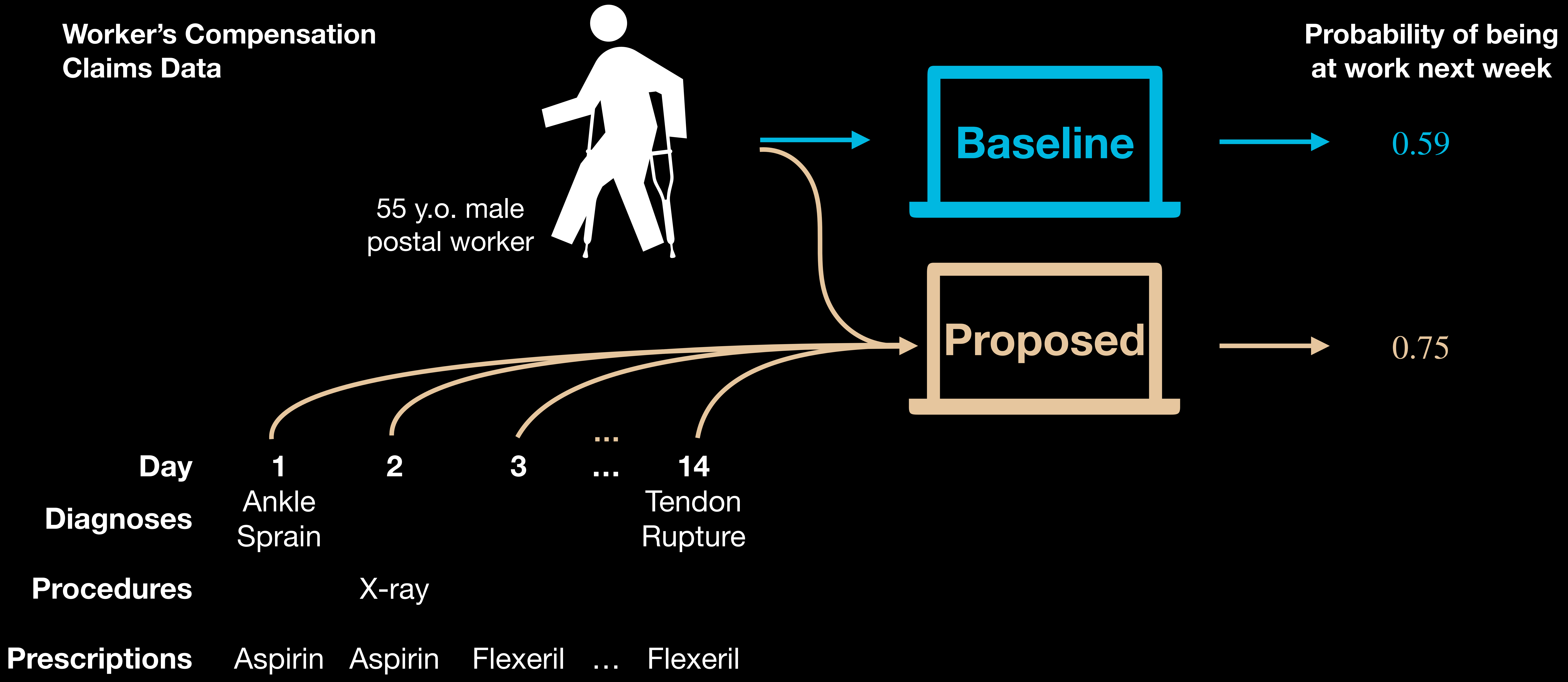


Q: *What is the value of longitudinal observations in return to work prediction?*

More specifically: when predicting future work-status do we observe a performance improvement when using longitudinal observations collected beyond the time of injury?

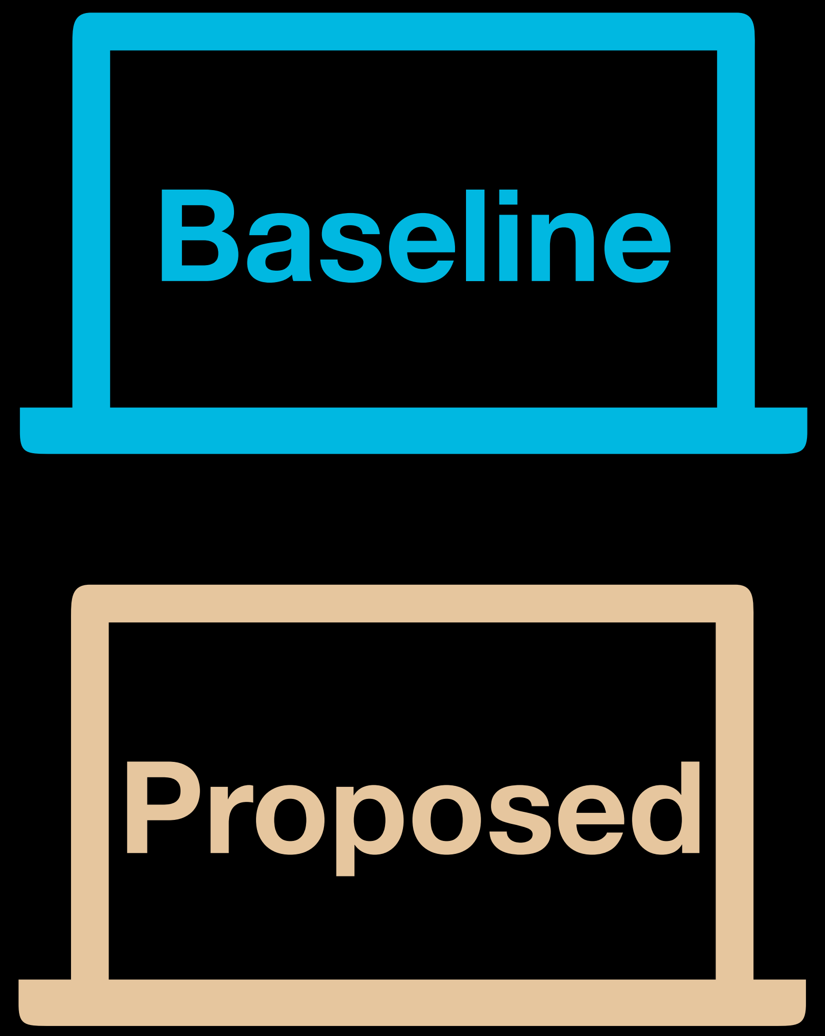
Hypothesis: Yes. Longitudinal observations improve predictions in other healthcare task.

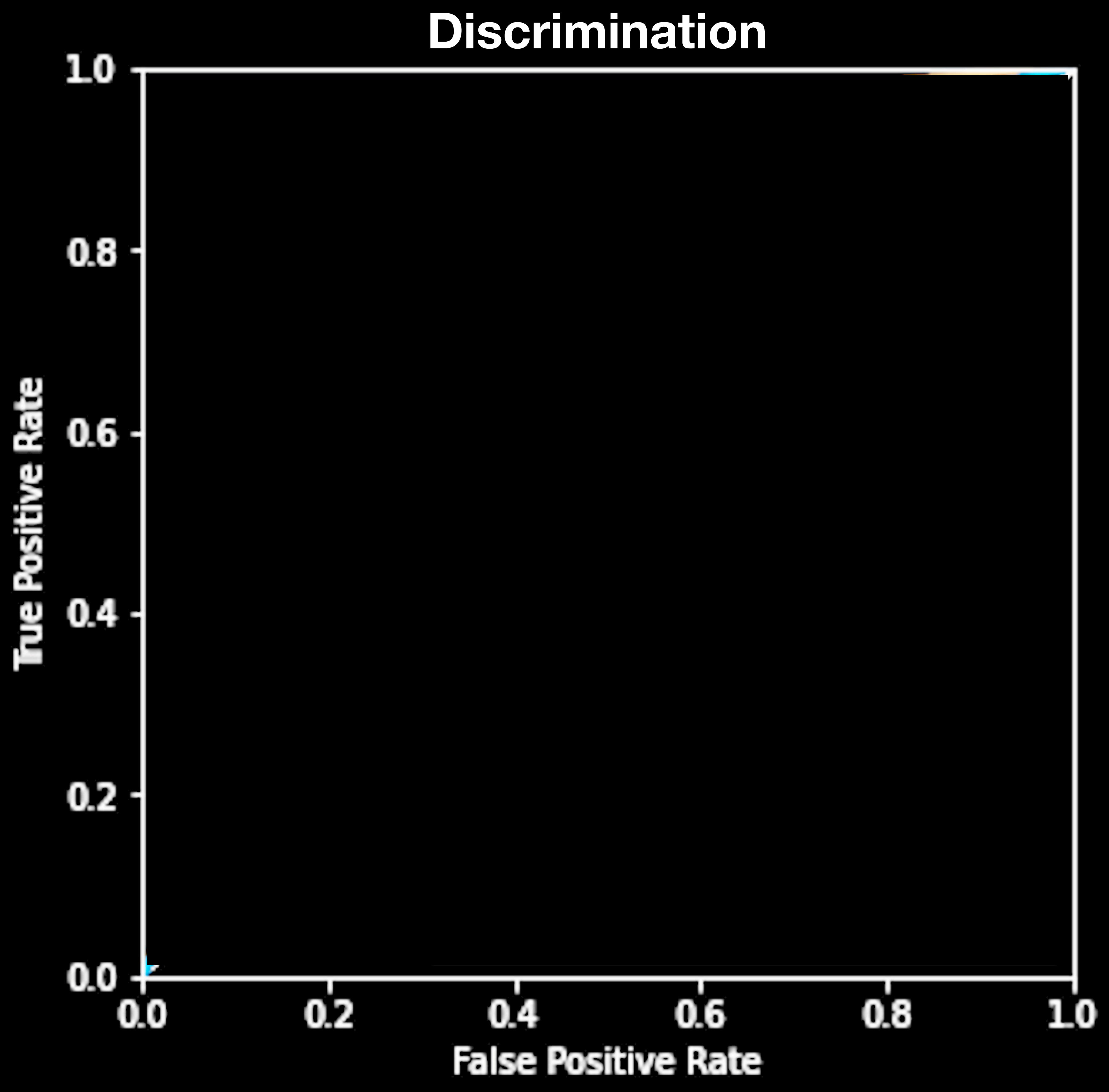
Experimental Setup

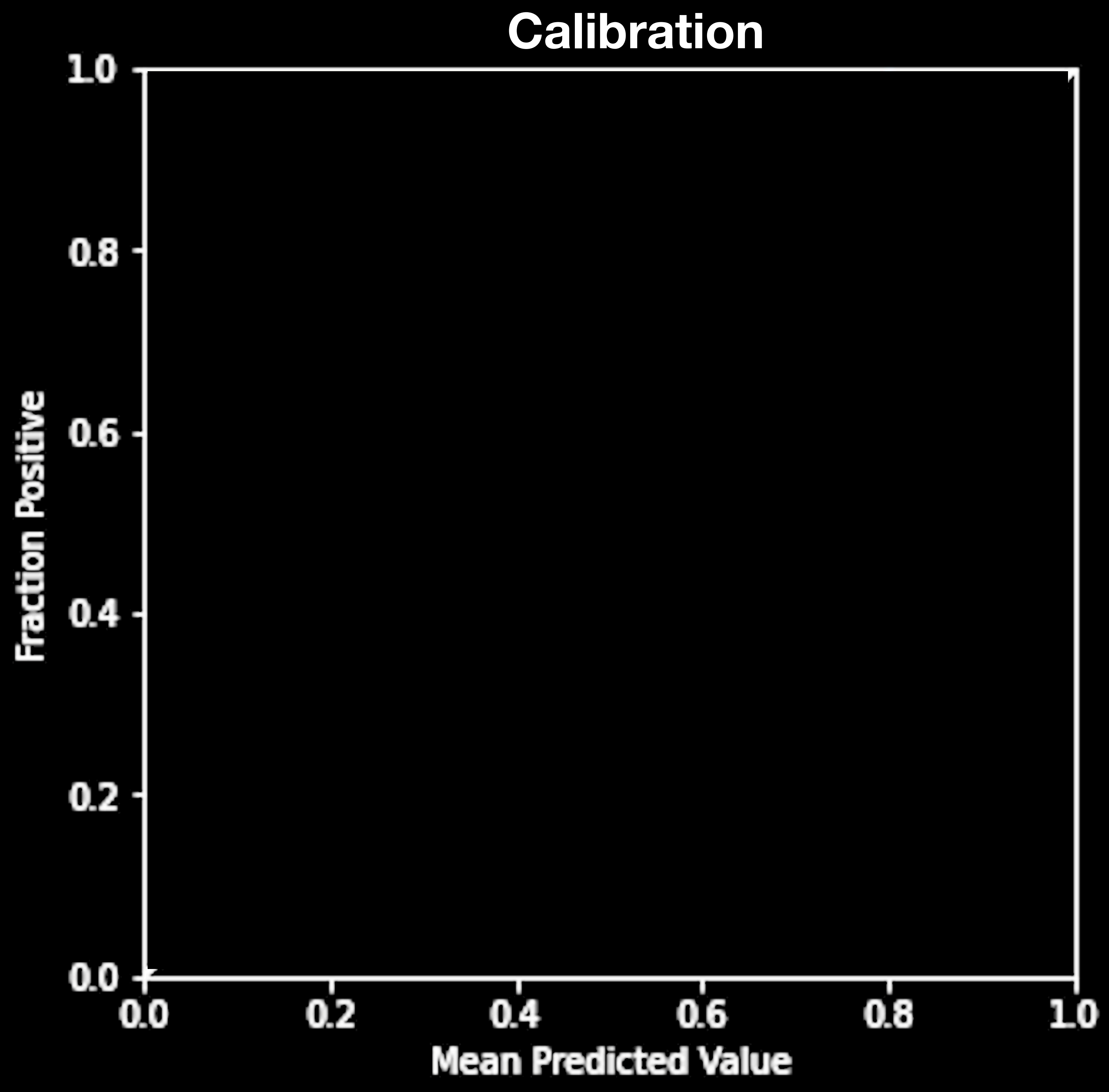


Ötleş, Seymour, Wang, Denton. Dynamic prediction of work status for workers with occupational injuries: assessing the value of longitudinal observations. *Journal of the American Medical Informatics Association.* 2022 [In Press]

Results







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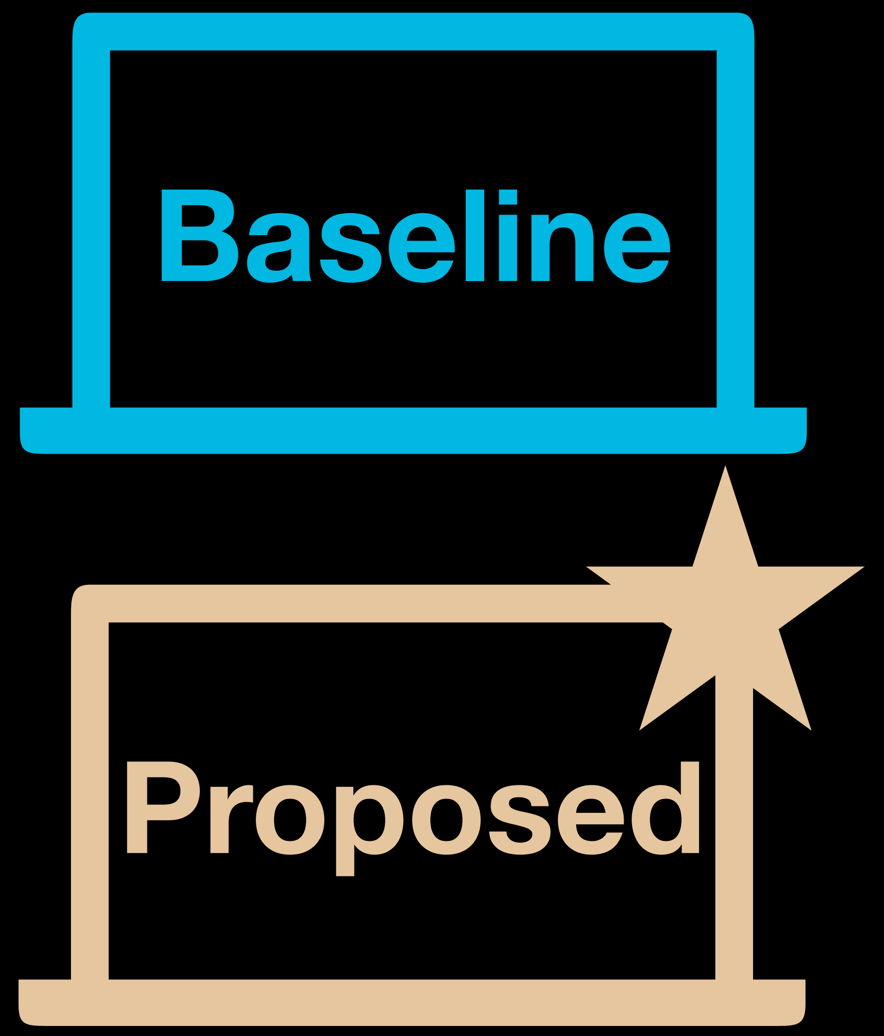

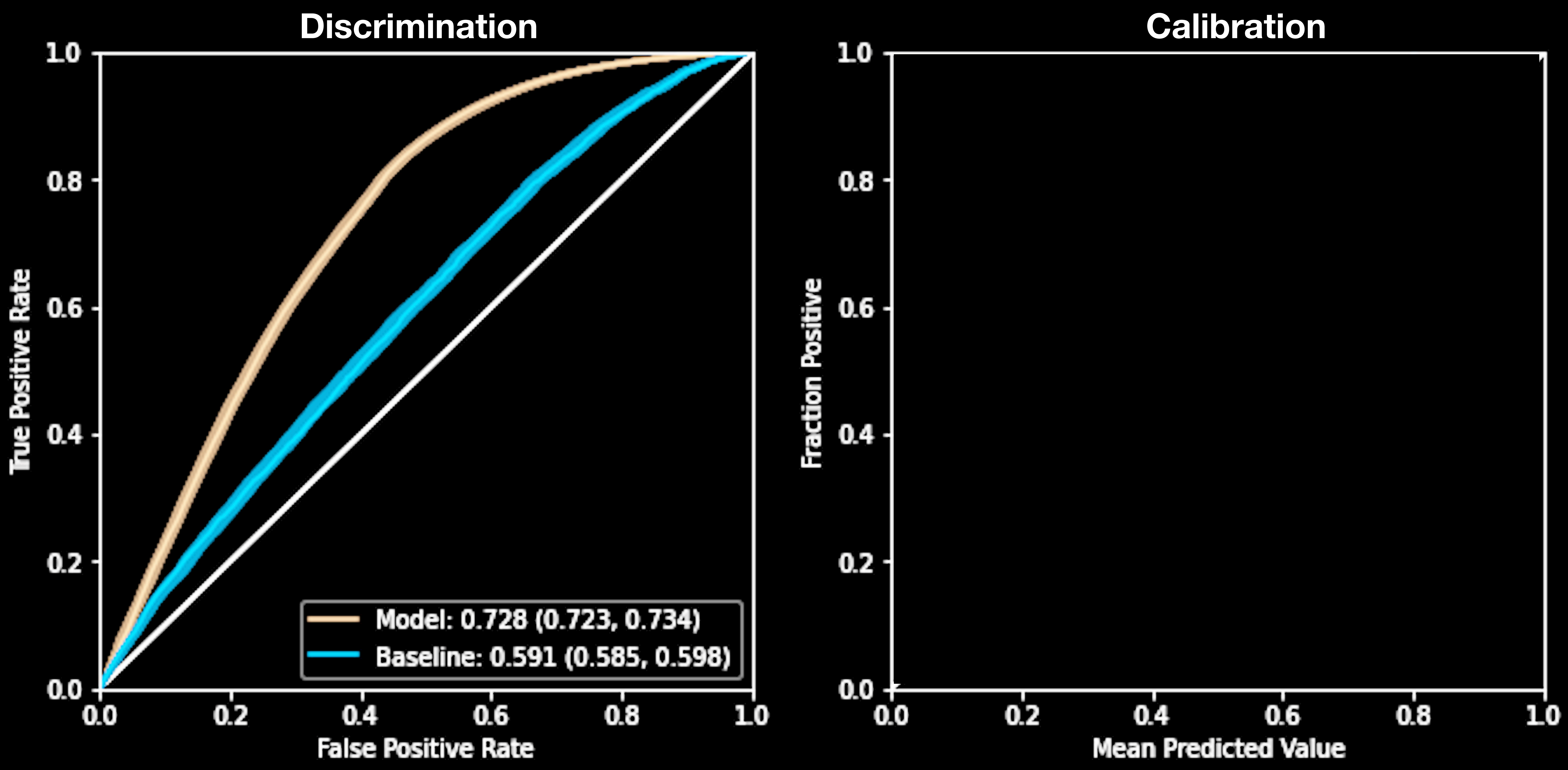

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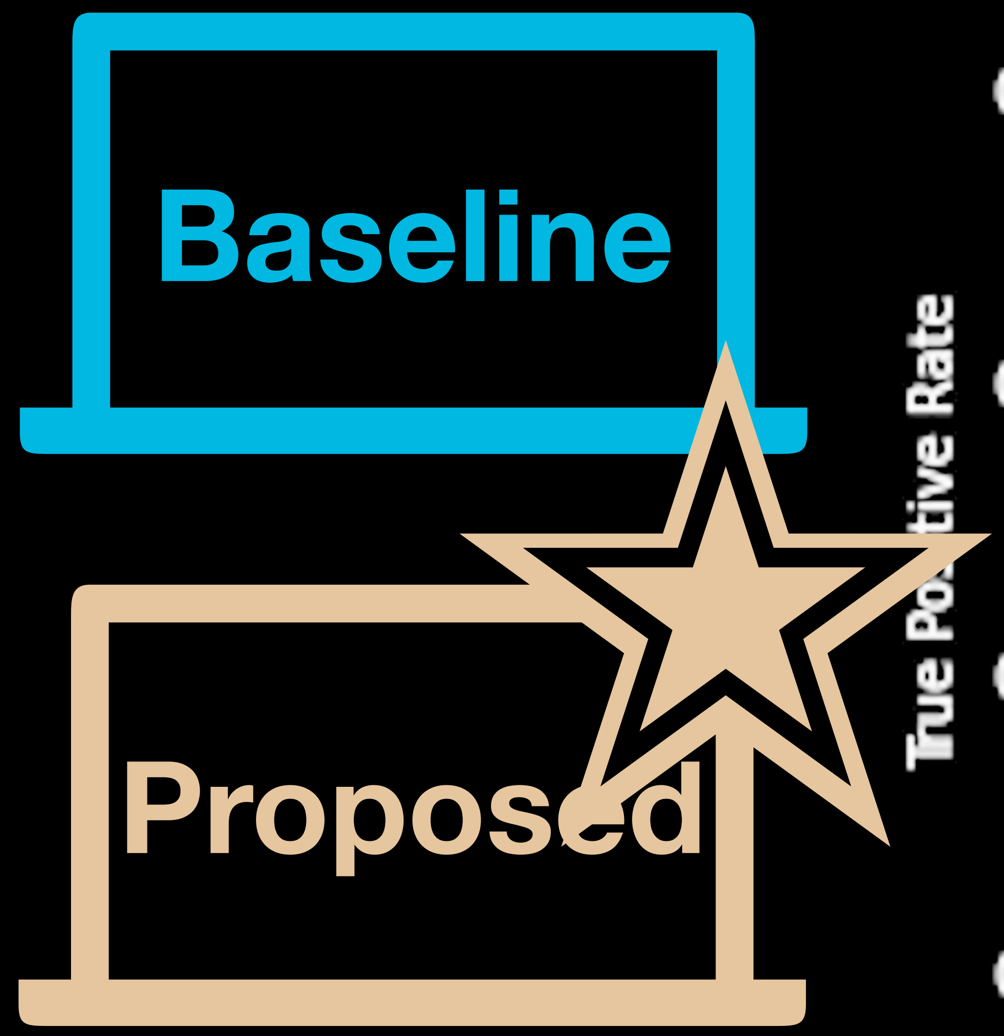

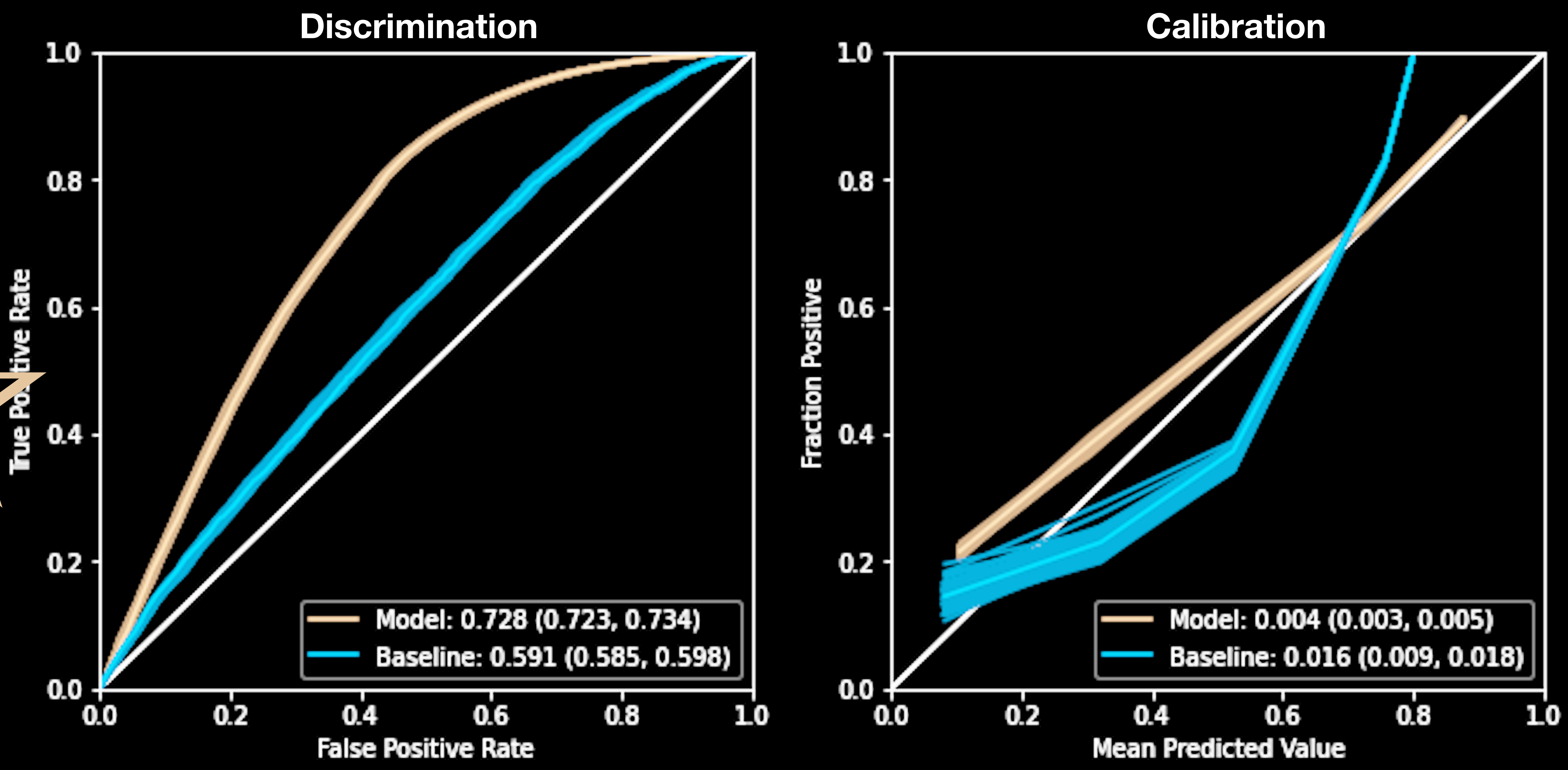

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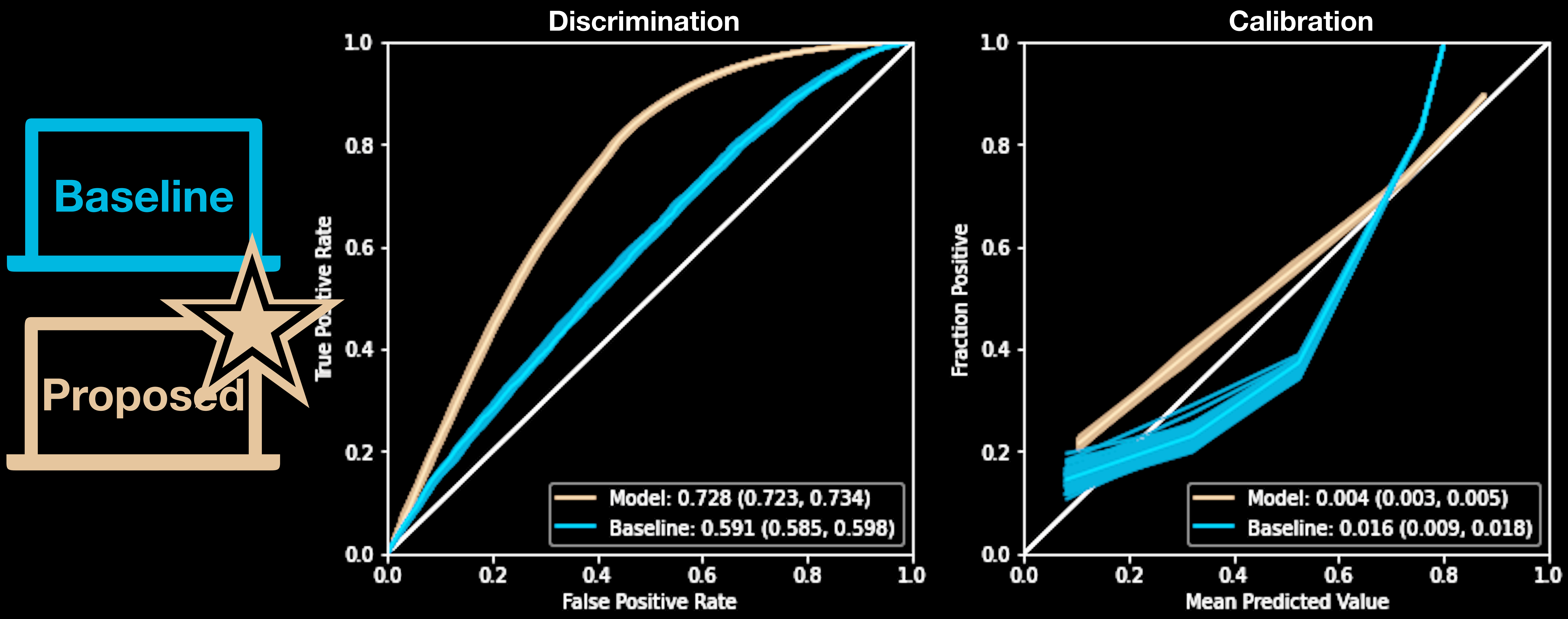
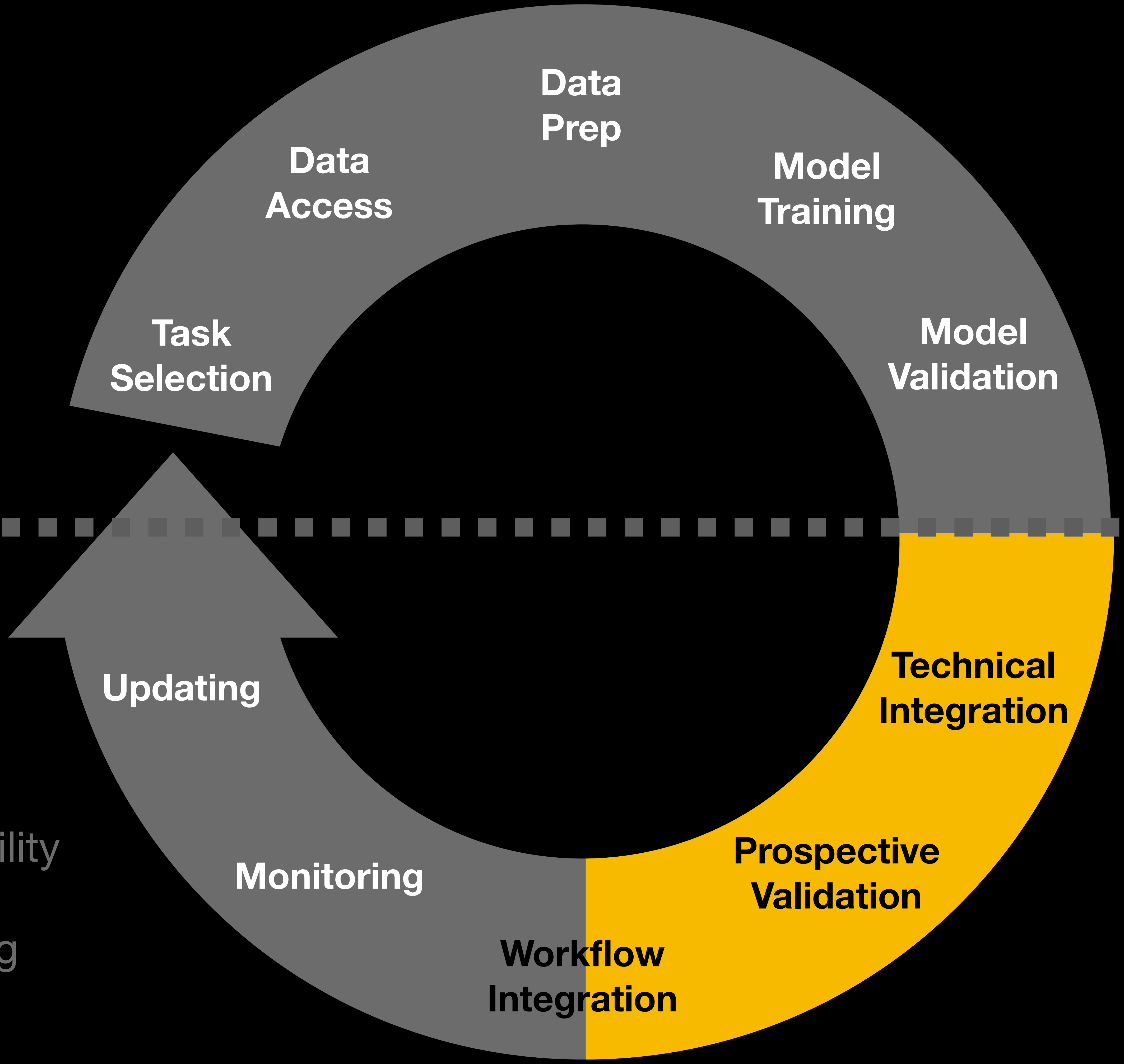
Main Takeaway from RTW Prediction.



Return to work prediction benefits from longitudinal observations.

On to the next one.



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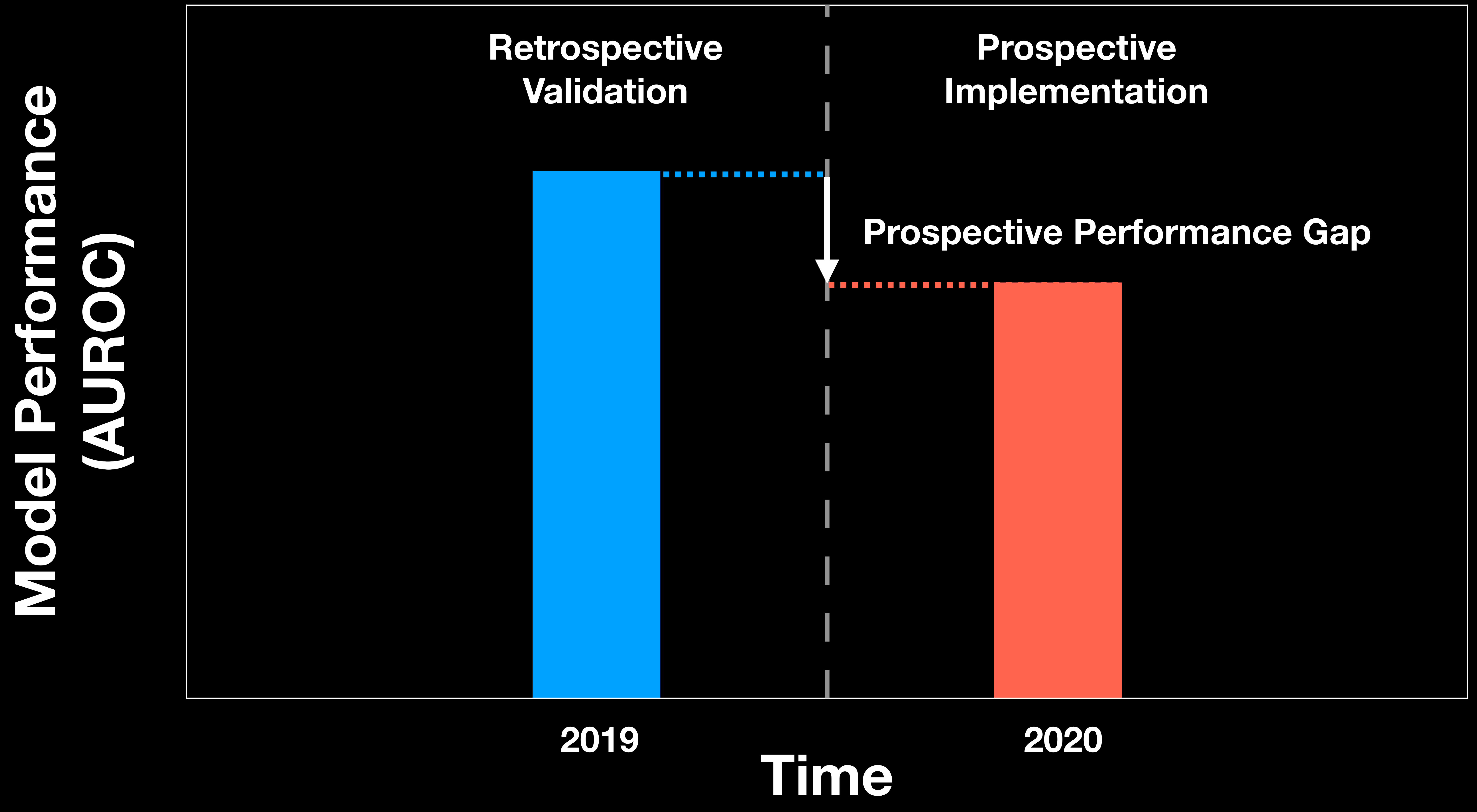
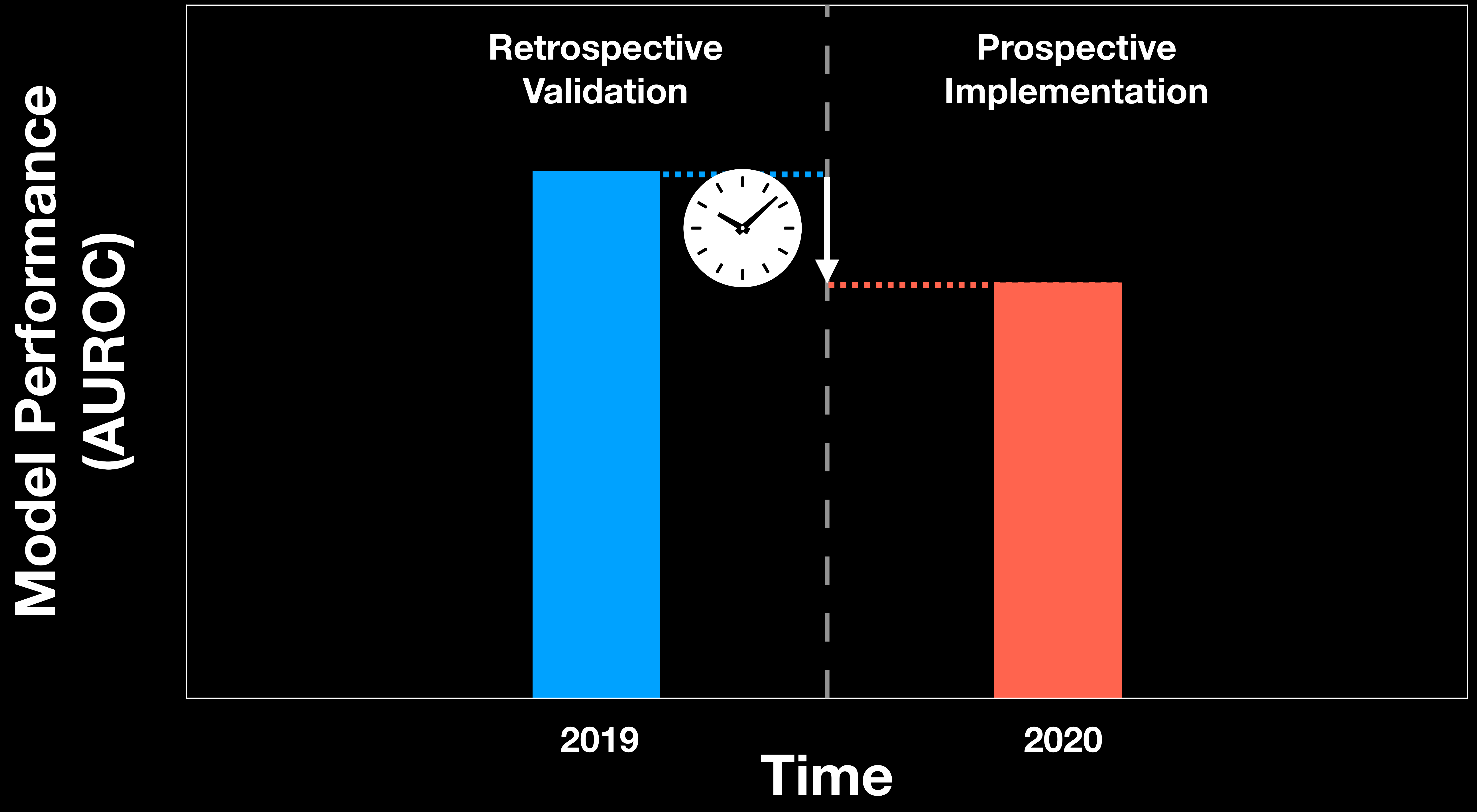
Model performance may degrade after implementation.



Davis 2017, Hickey 2013, Minne 2012

This degradation is often attributed to changes in populations & practice that occurs over time.



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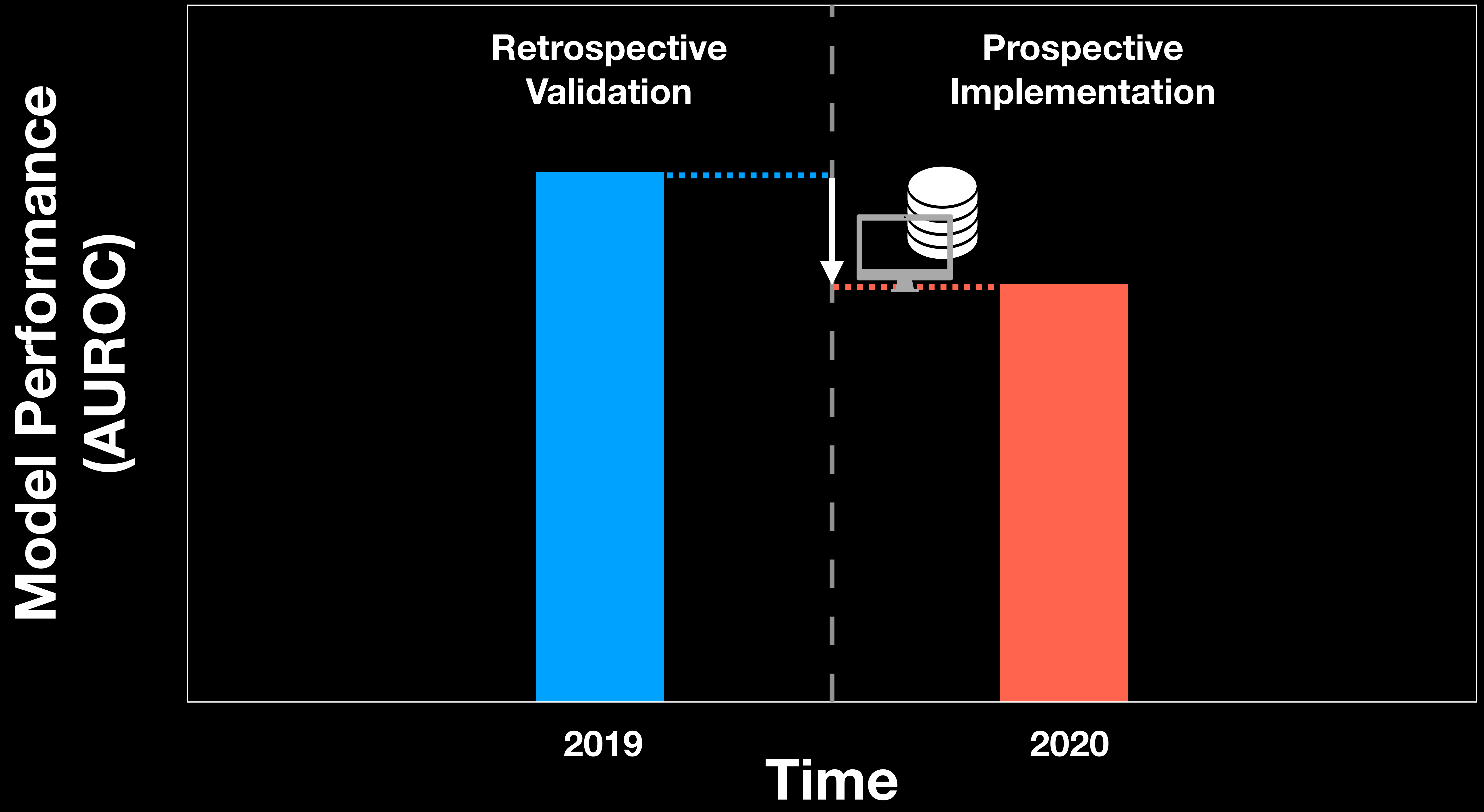
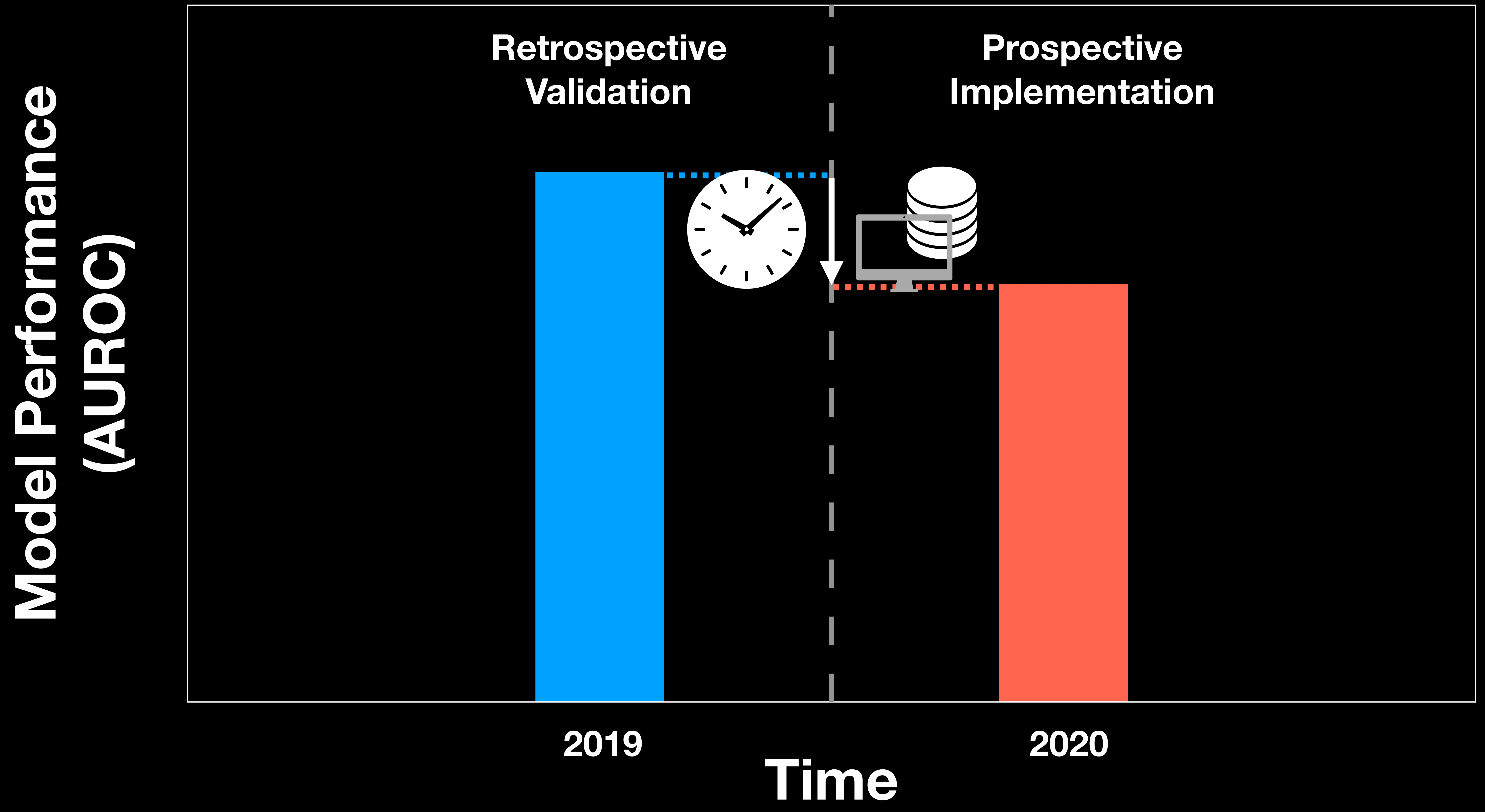
However, changes in IT infrastructure may also affect the prospective performance gap.



Degradation due to temporal & infrastructure shift.

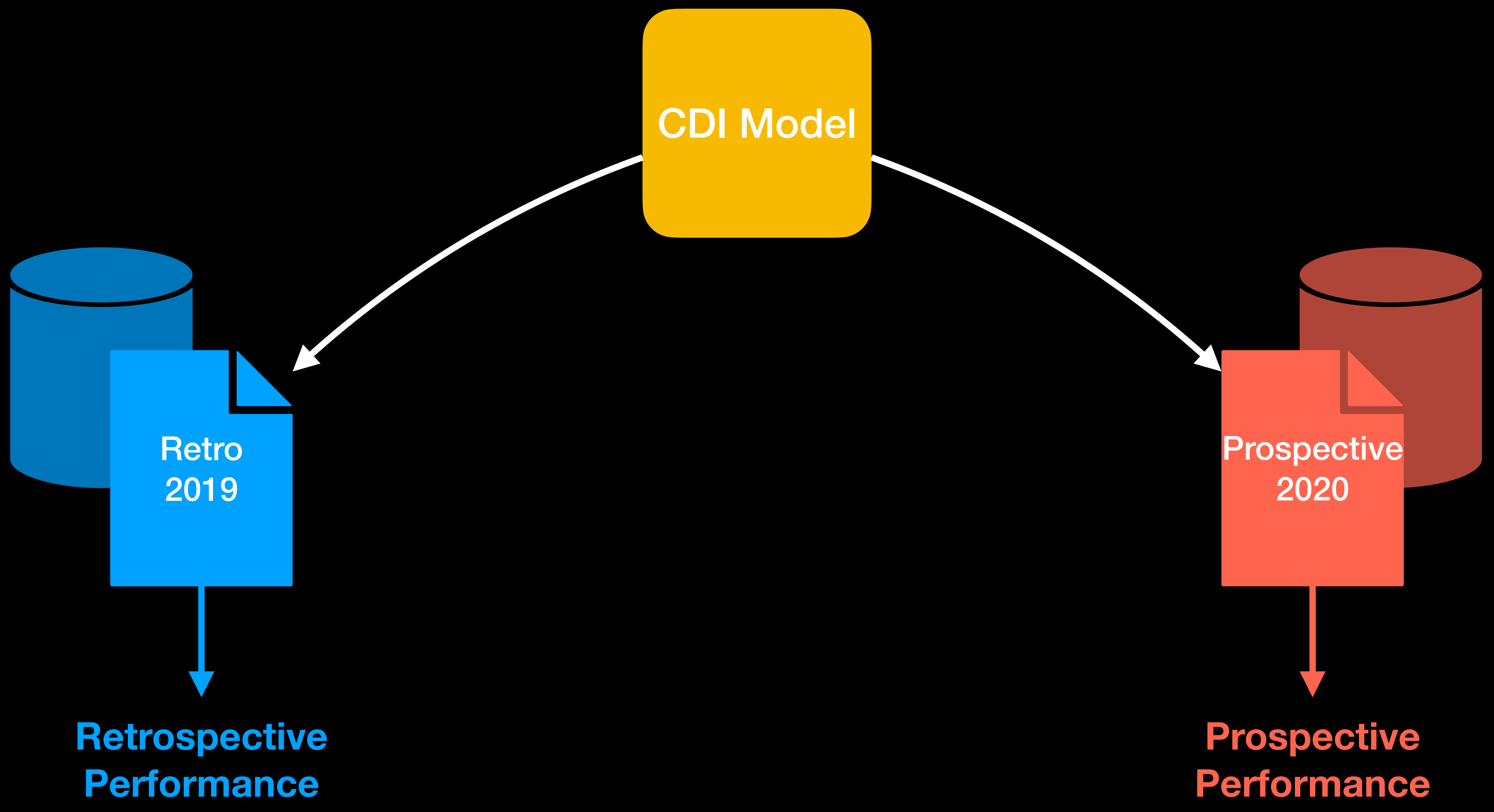


Q: *What are the causes of the prospective performance gap?*

More specifically: what are the temporal and infrastructure shift contributions to the prospective performance gap of a prospectively implemented model?

Hypothesis: Infrastructure will be an important component of the prospective performance gap.

Experimental Setup



Ötleş, Oh, Li, Bochinski, Joo, Ortwine, Shenoy, Washer, Young, Rao, Wiens.
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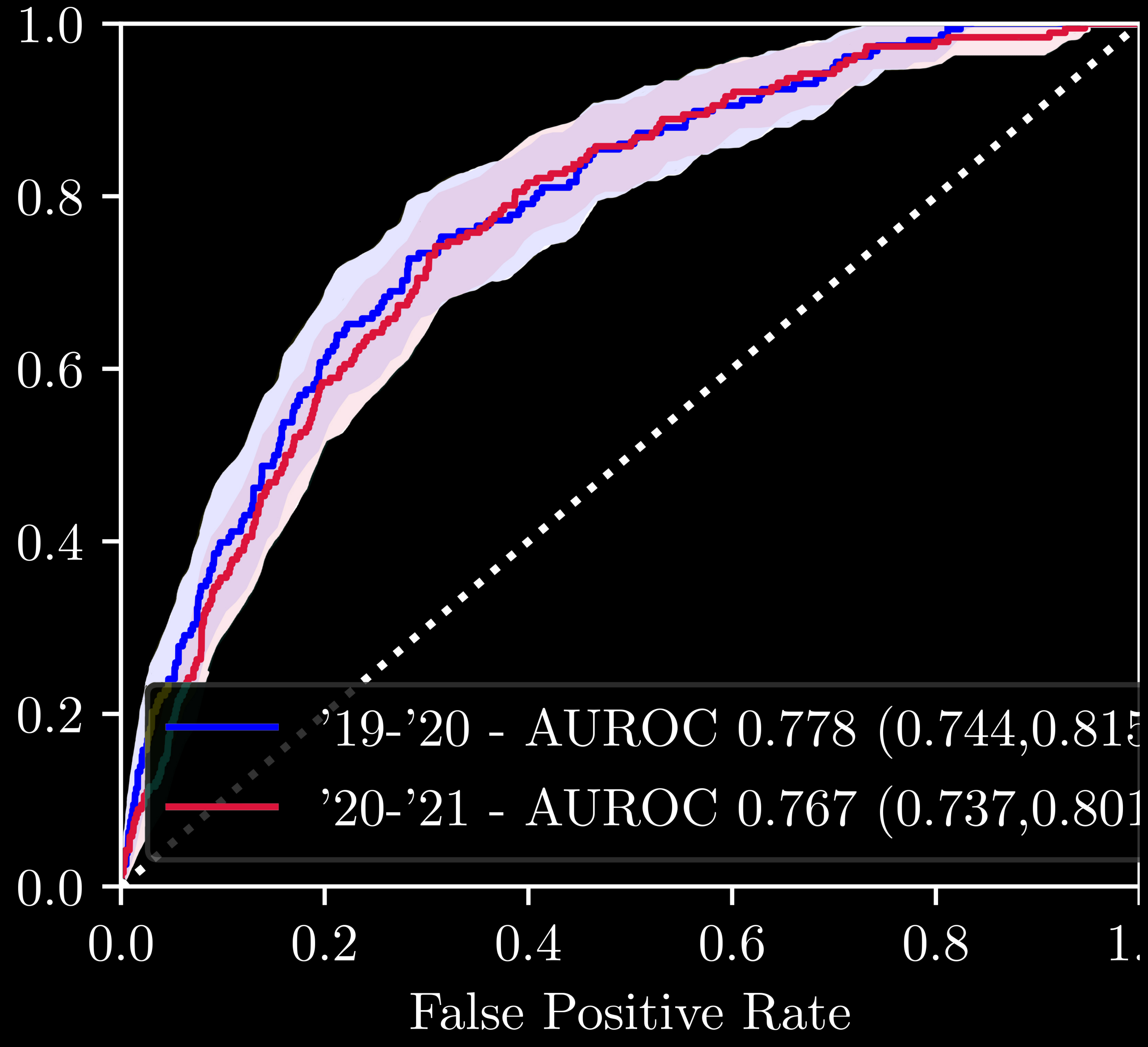

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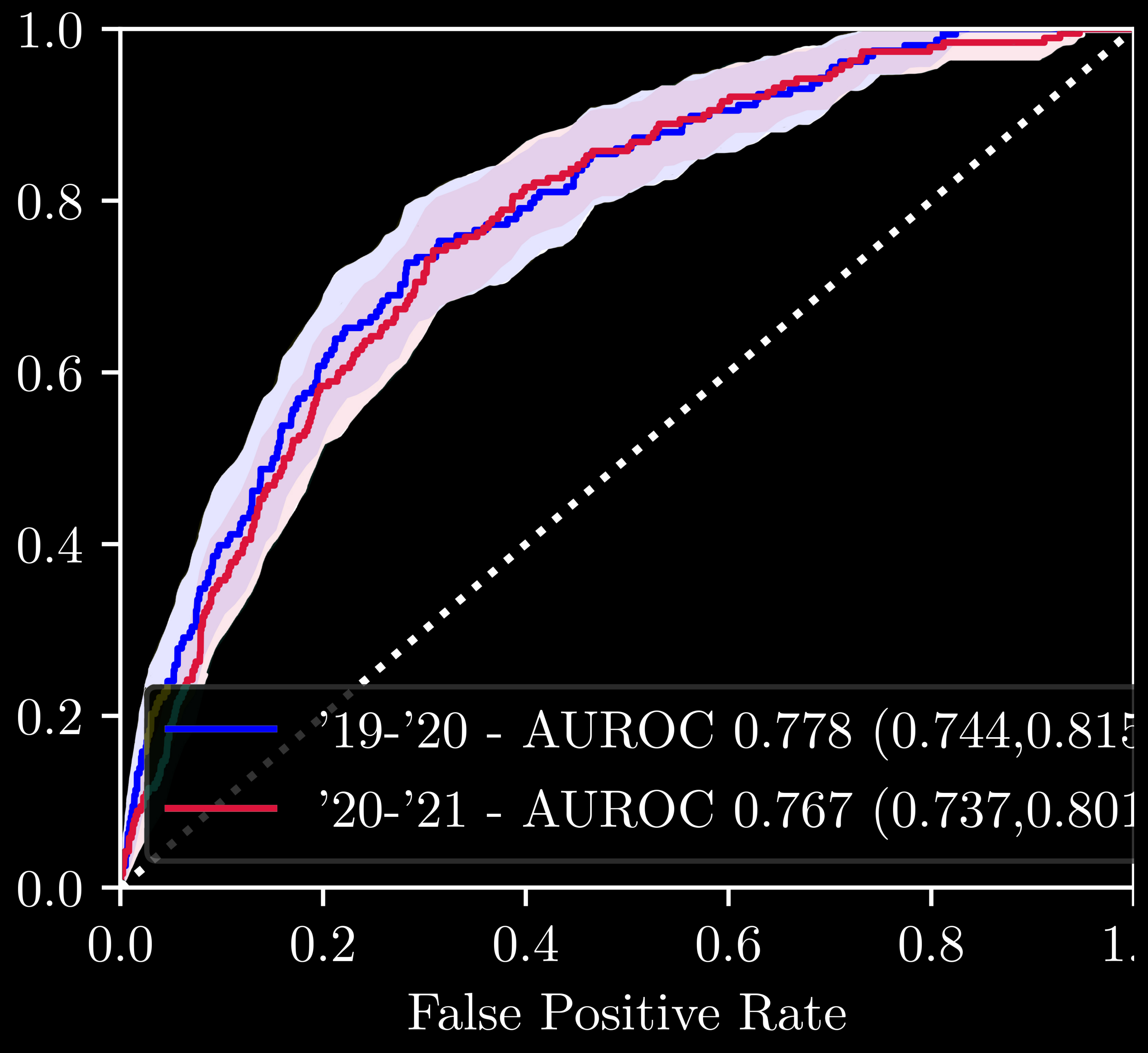
Performance Gap: 0.011



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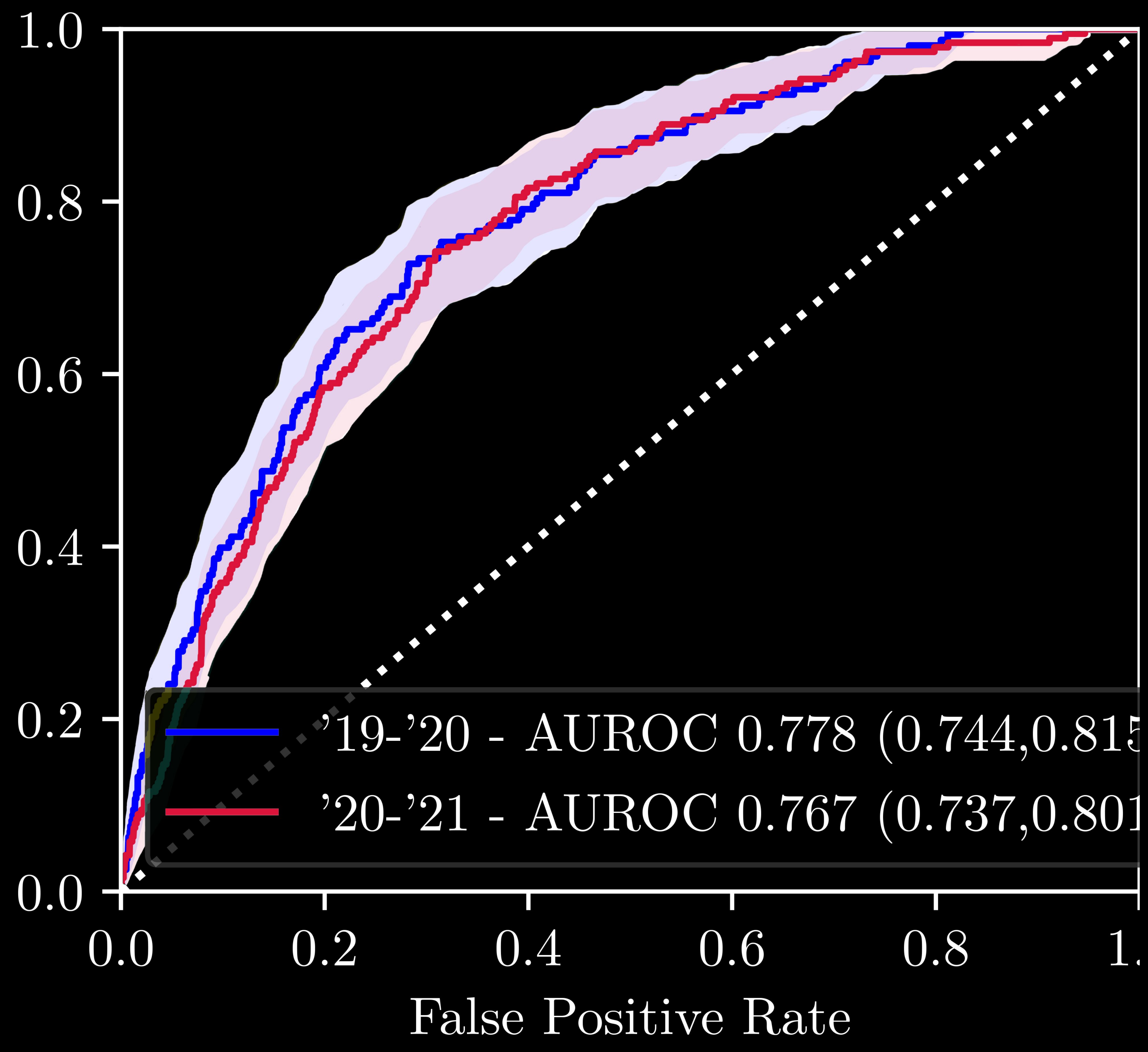
Results

Performance Gap: 0.011

Temporal Shift: -0.005



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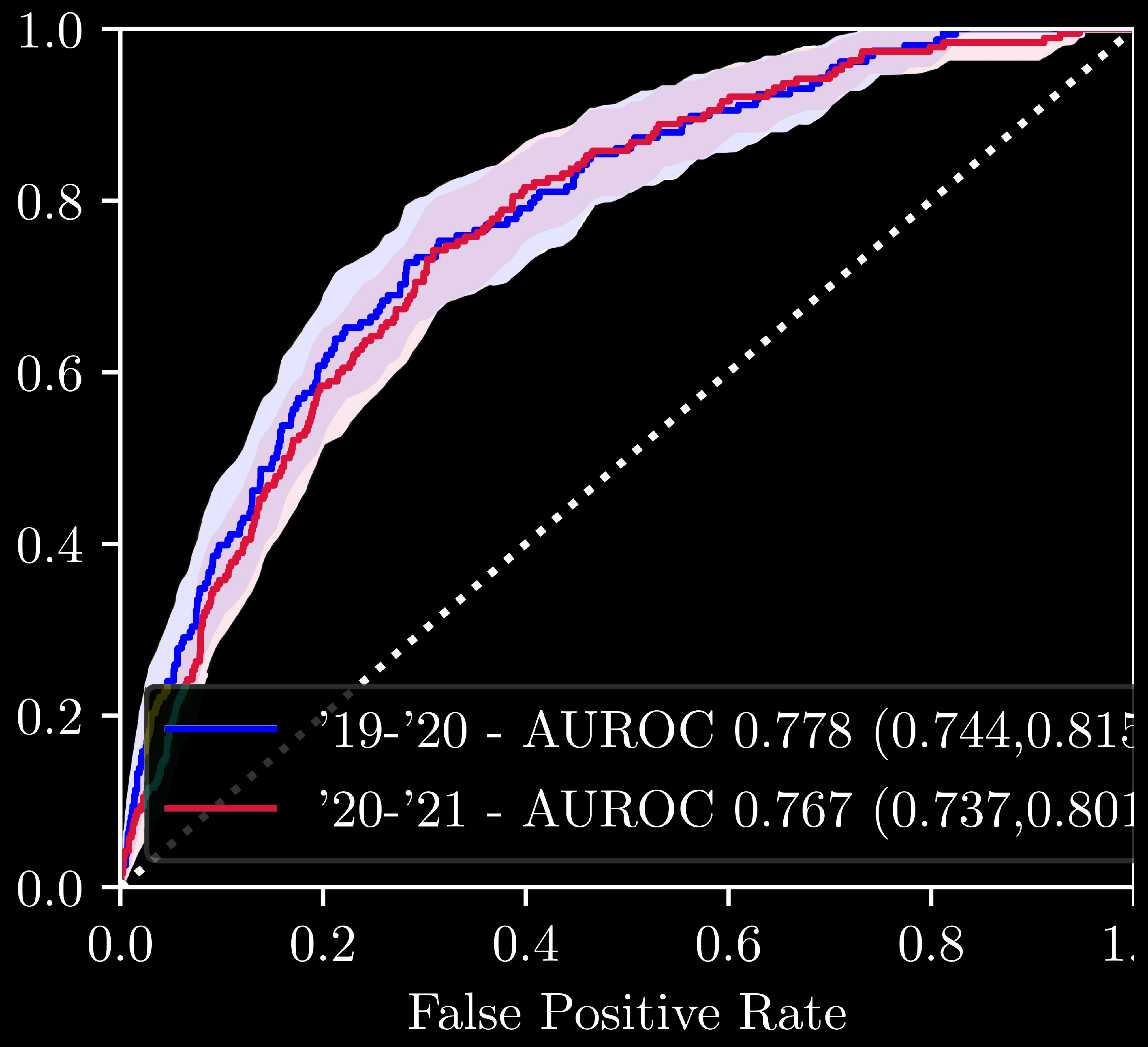
Performance Gap: 0.011

Temporal Shift: -0.005

Infrastructure Shift: 0.016



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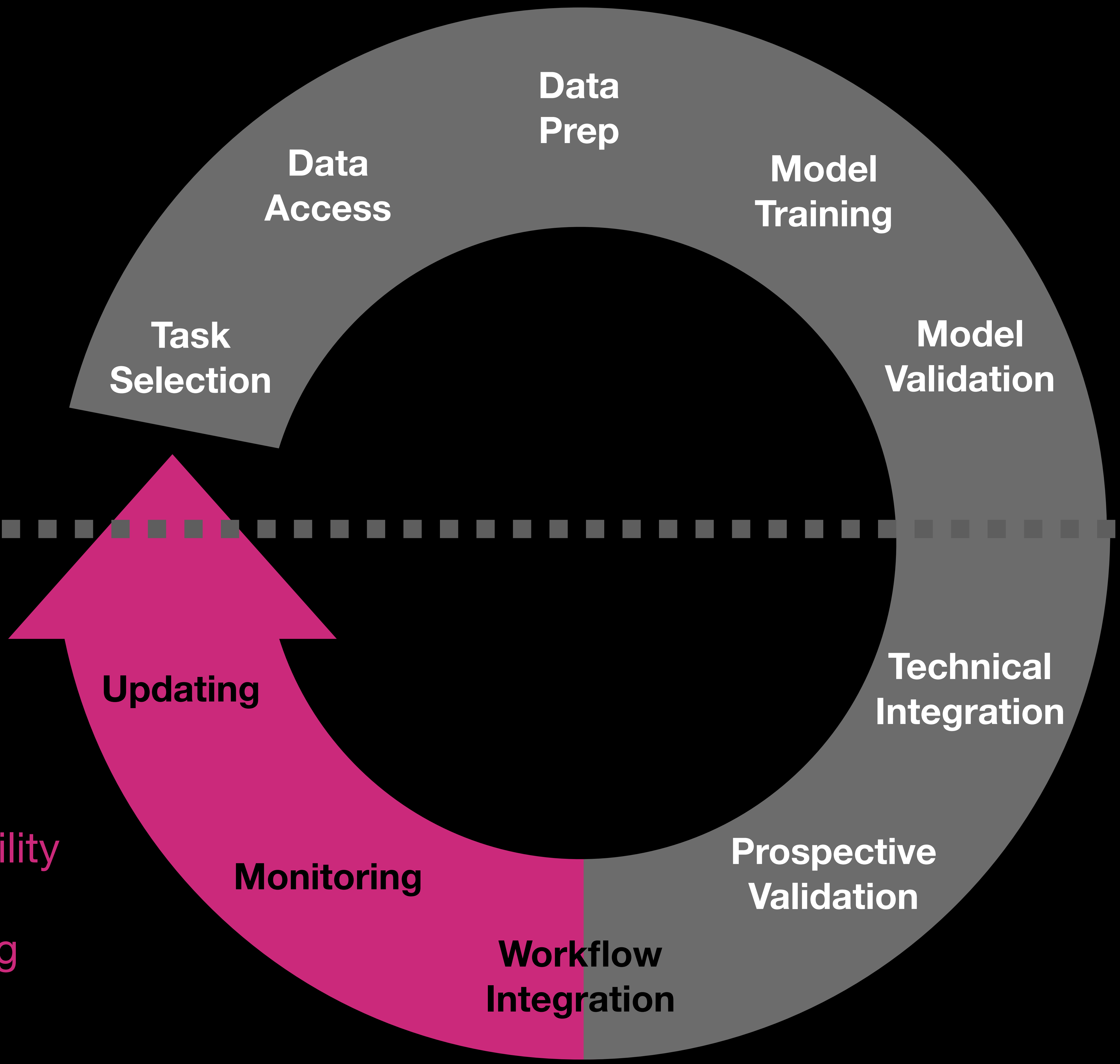
Infrastructure Matters.

Observed prospective performance gap primarily driven by infrastructure shift:

- source & processing differ, requires infrastructure updates
- timing of access differs, *when* you access the data affects *what* you access

Infrastructure shift can be mitigated, but first it must be recognized!

Last but not least.



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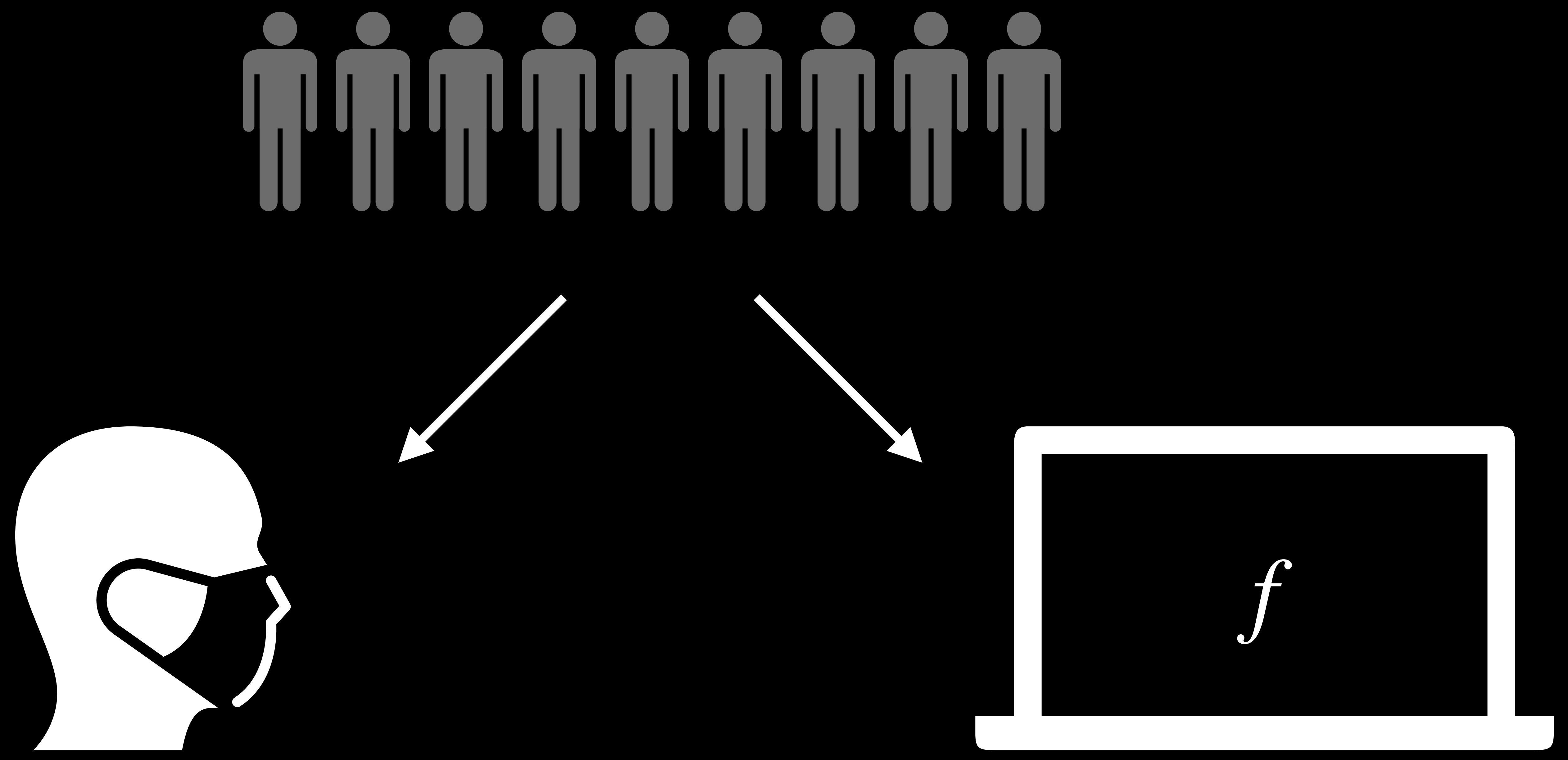
Physicians and models function as a team in healthcare settings.



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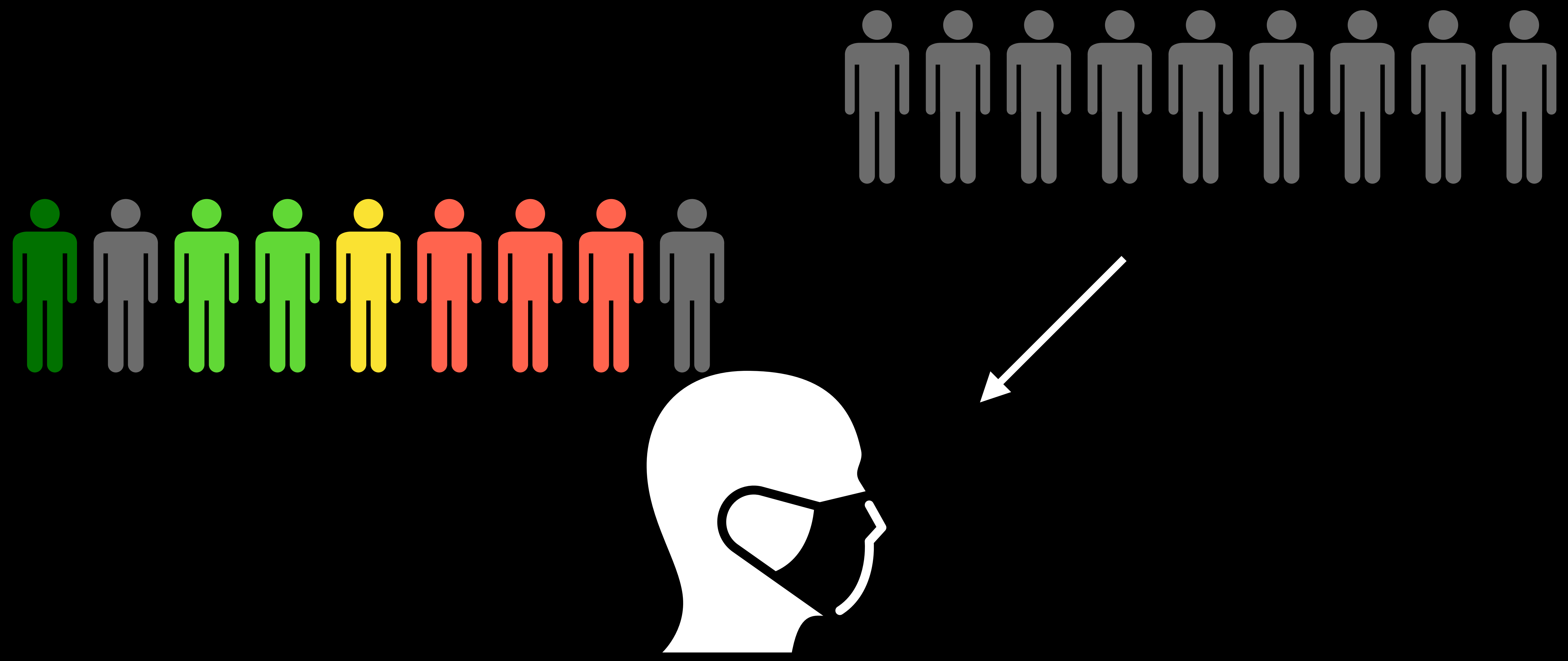

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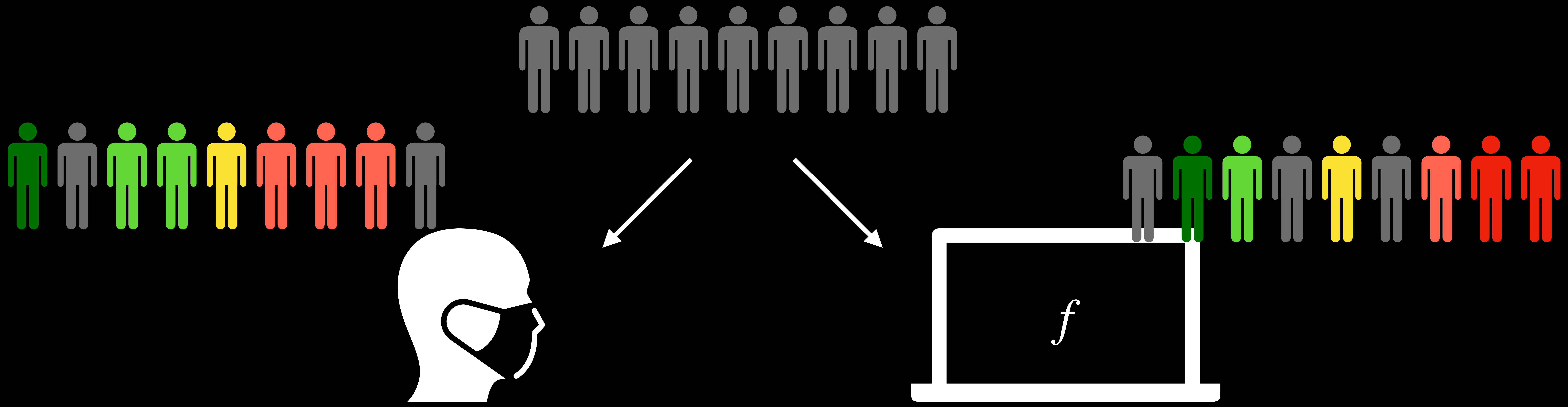

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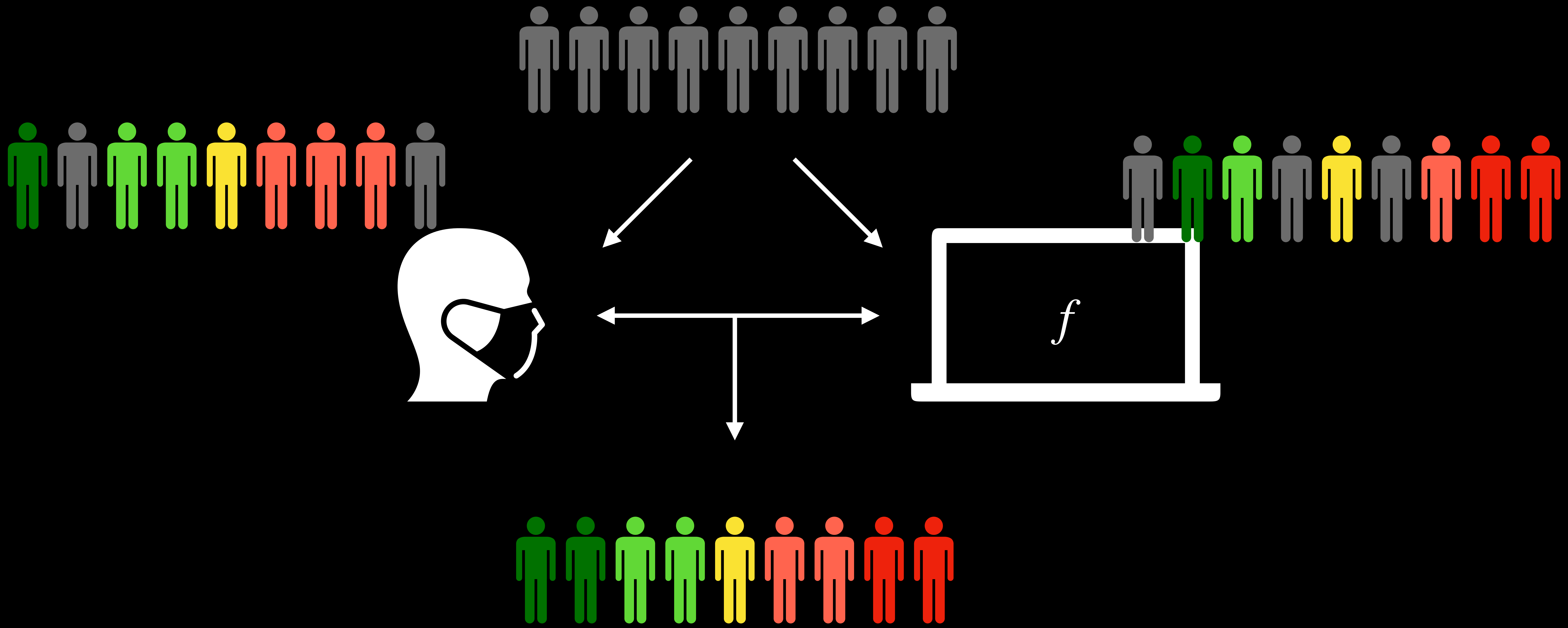

This is complicated because we need to update models over time.

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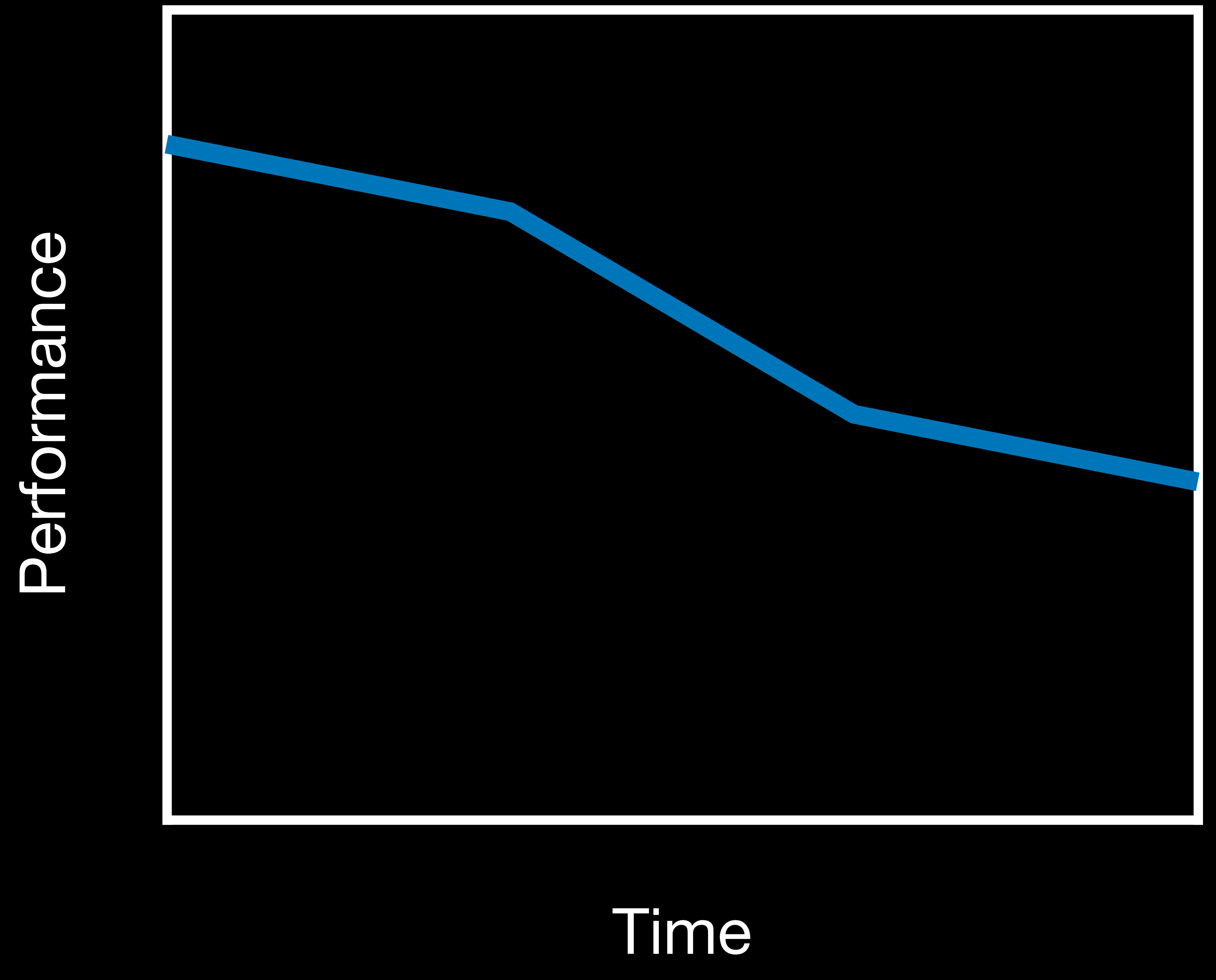
Counter performance degradation



Finlayson 2021, David 2017, Hickey 2012, Minne 2012, Bansal 2019

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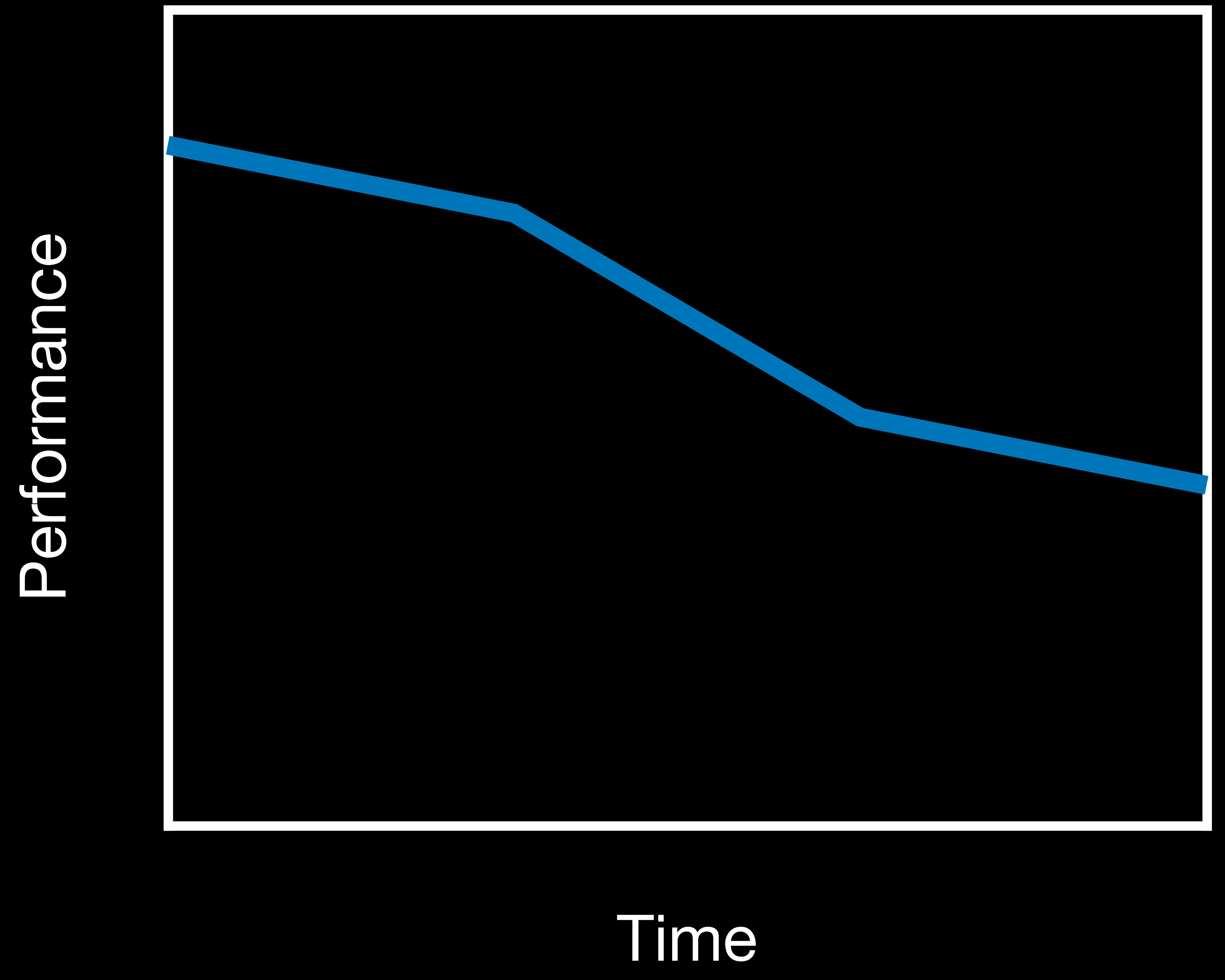
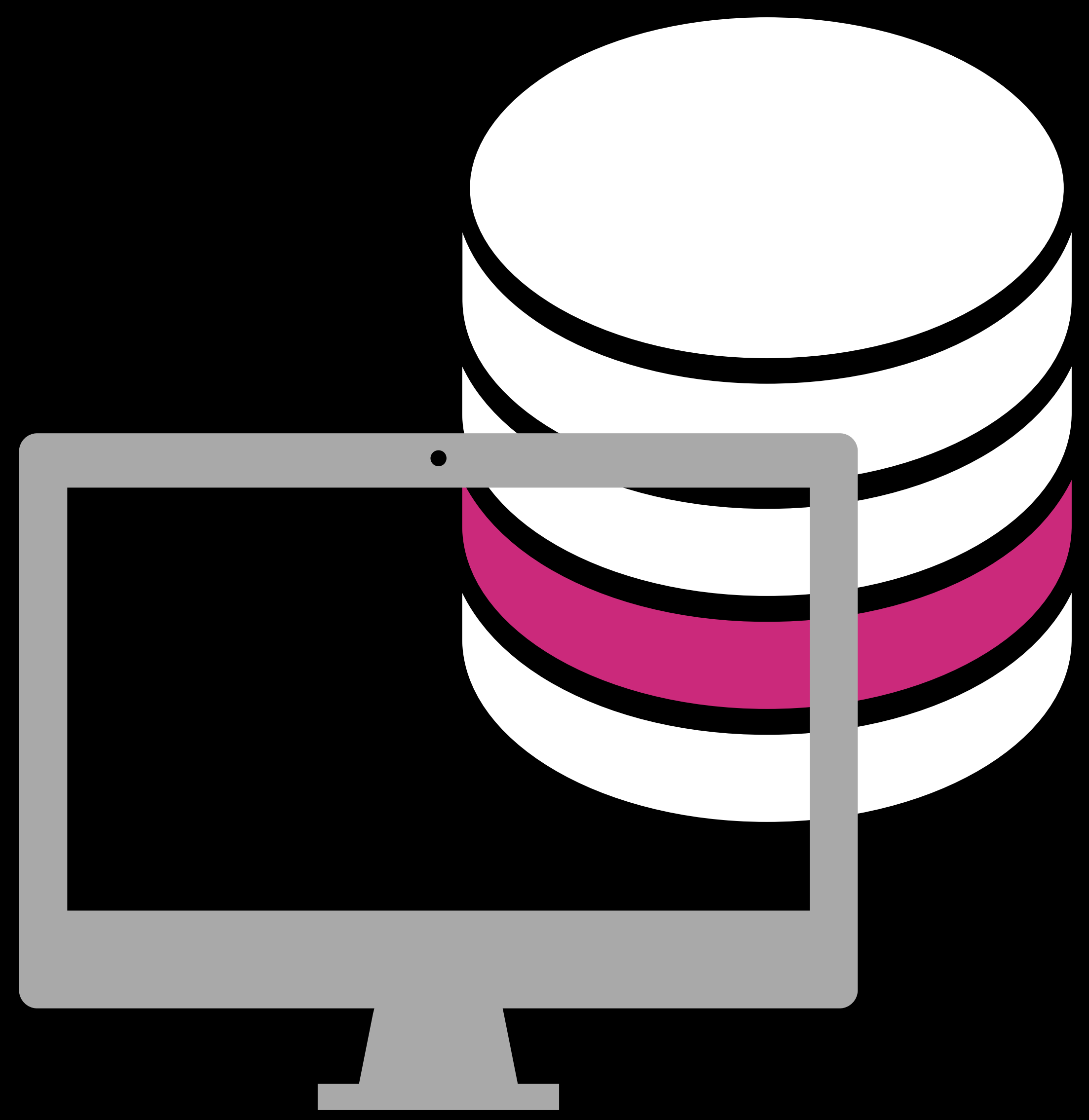


Adapt to infrastructure changes



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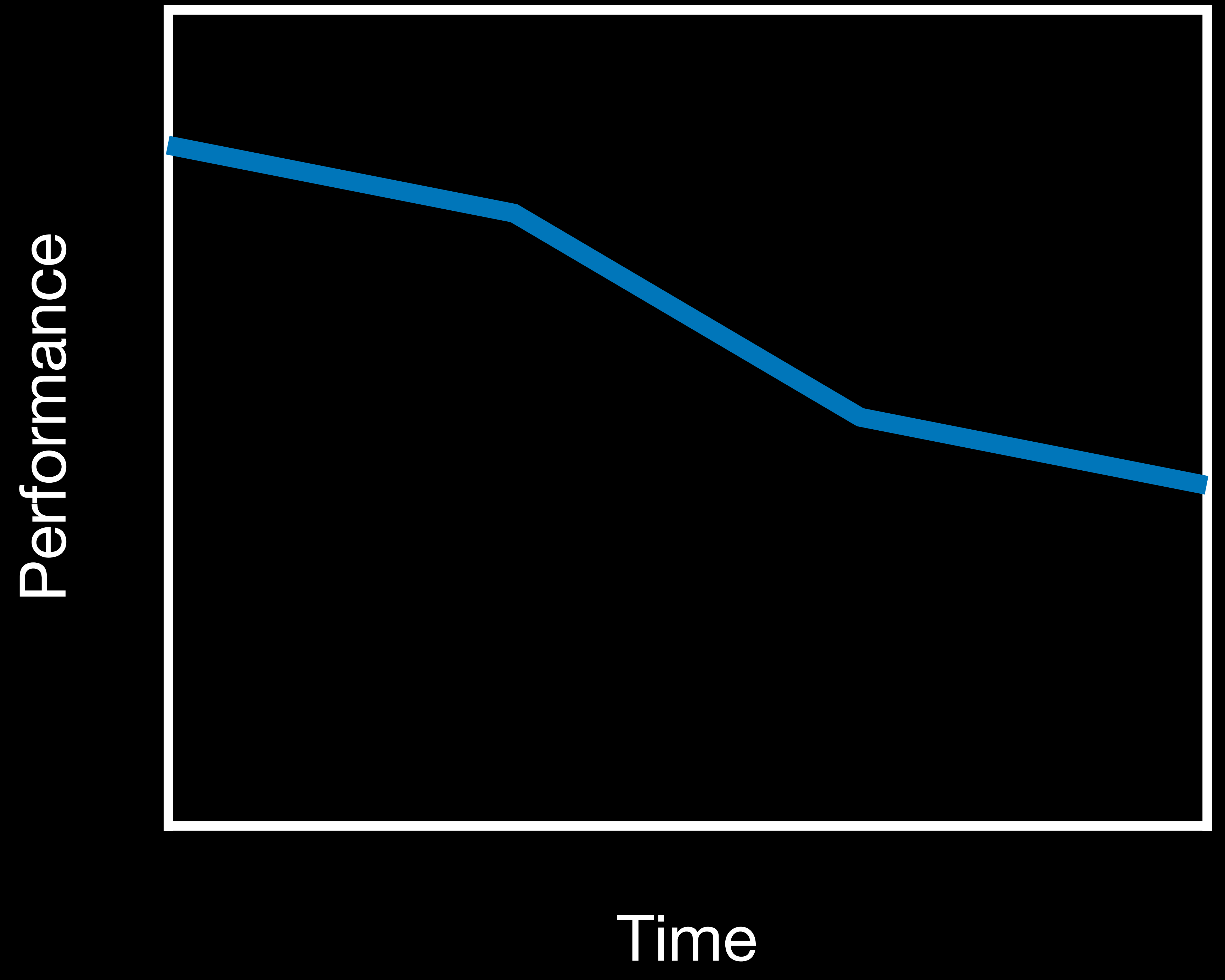

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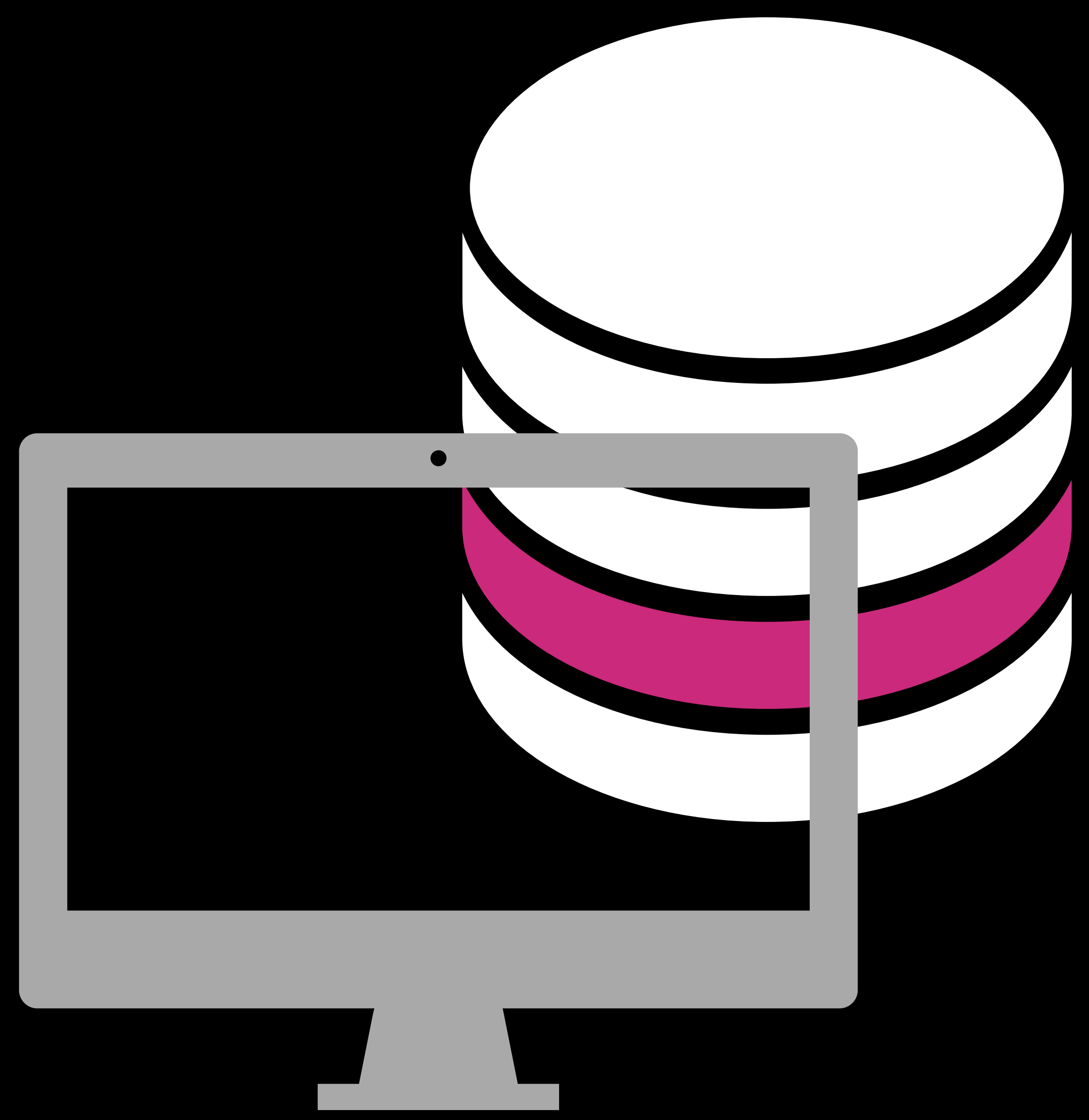
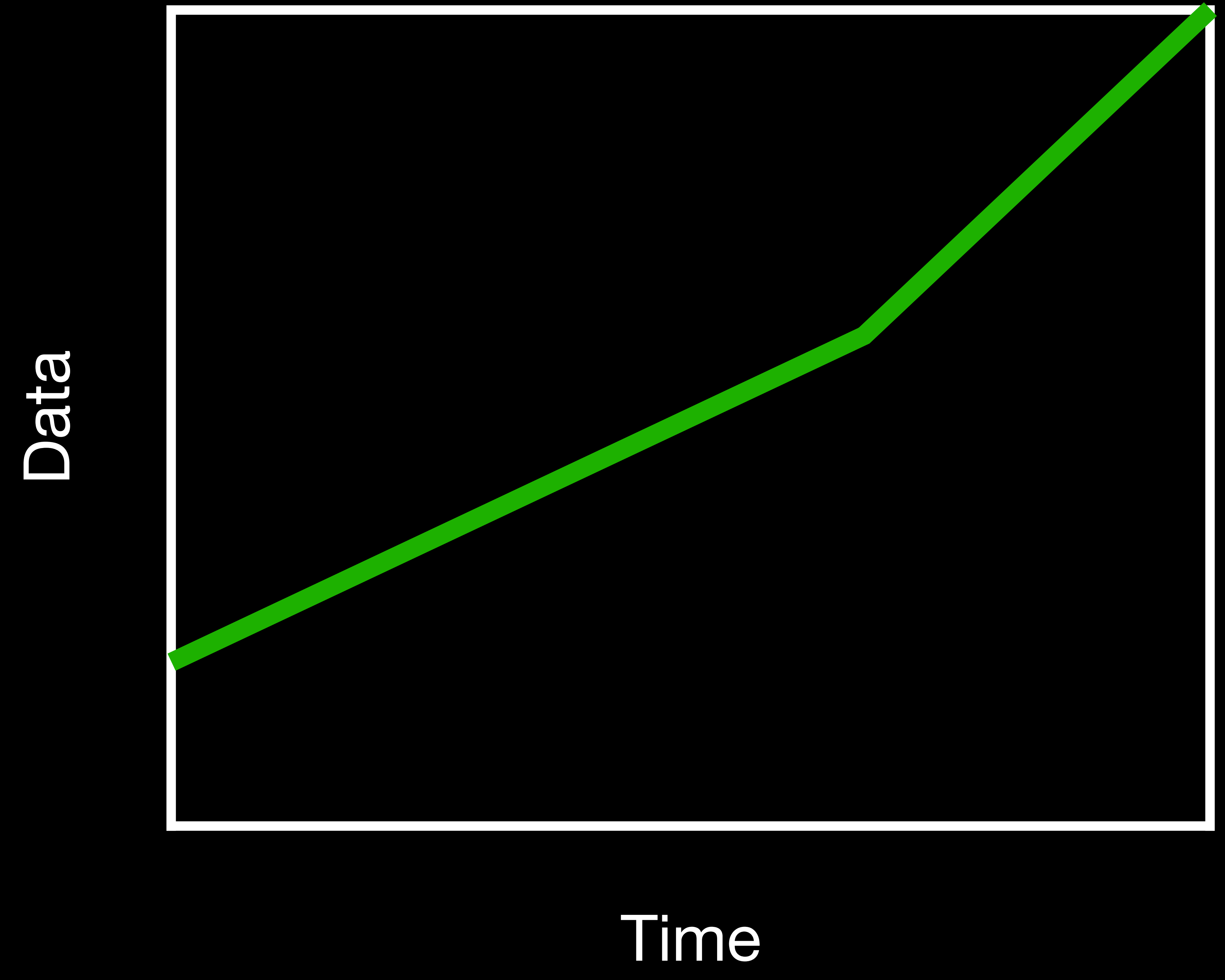


Incorporate new data



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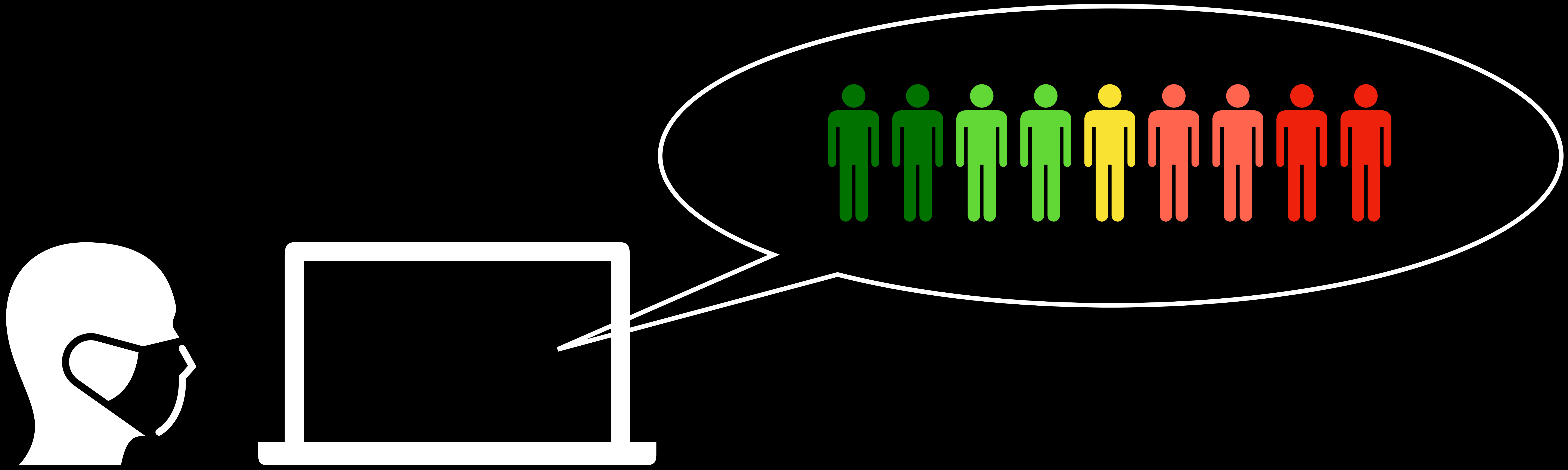
Updates can mess with user expectations.



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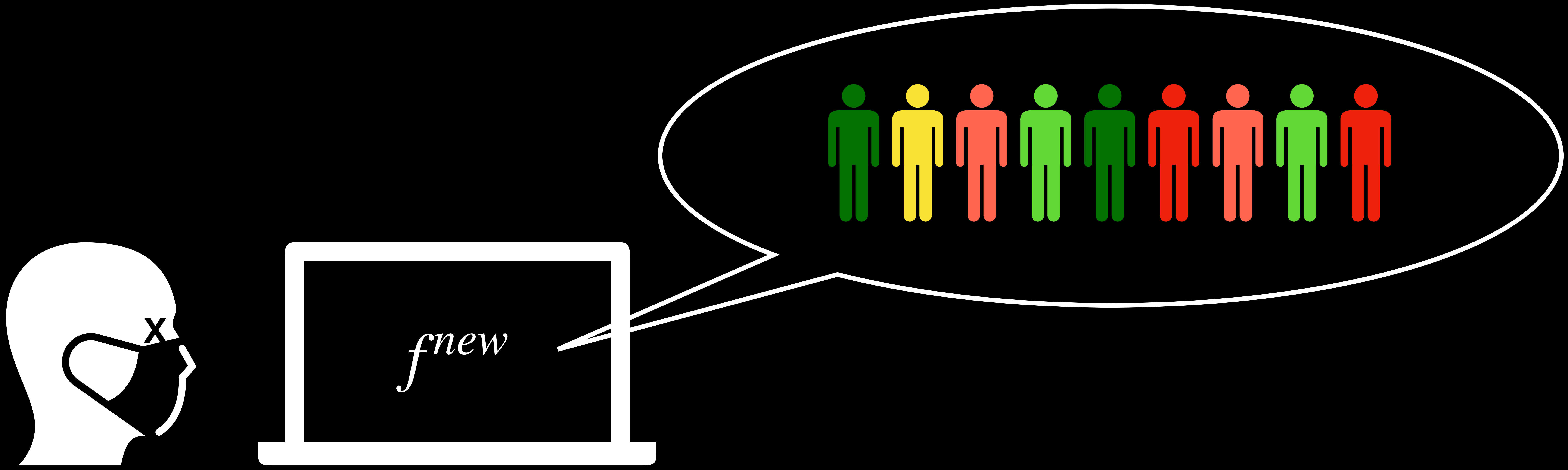
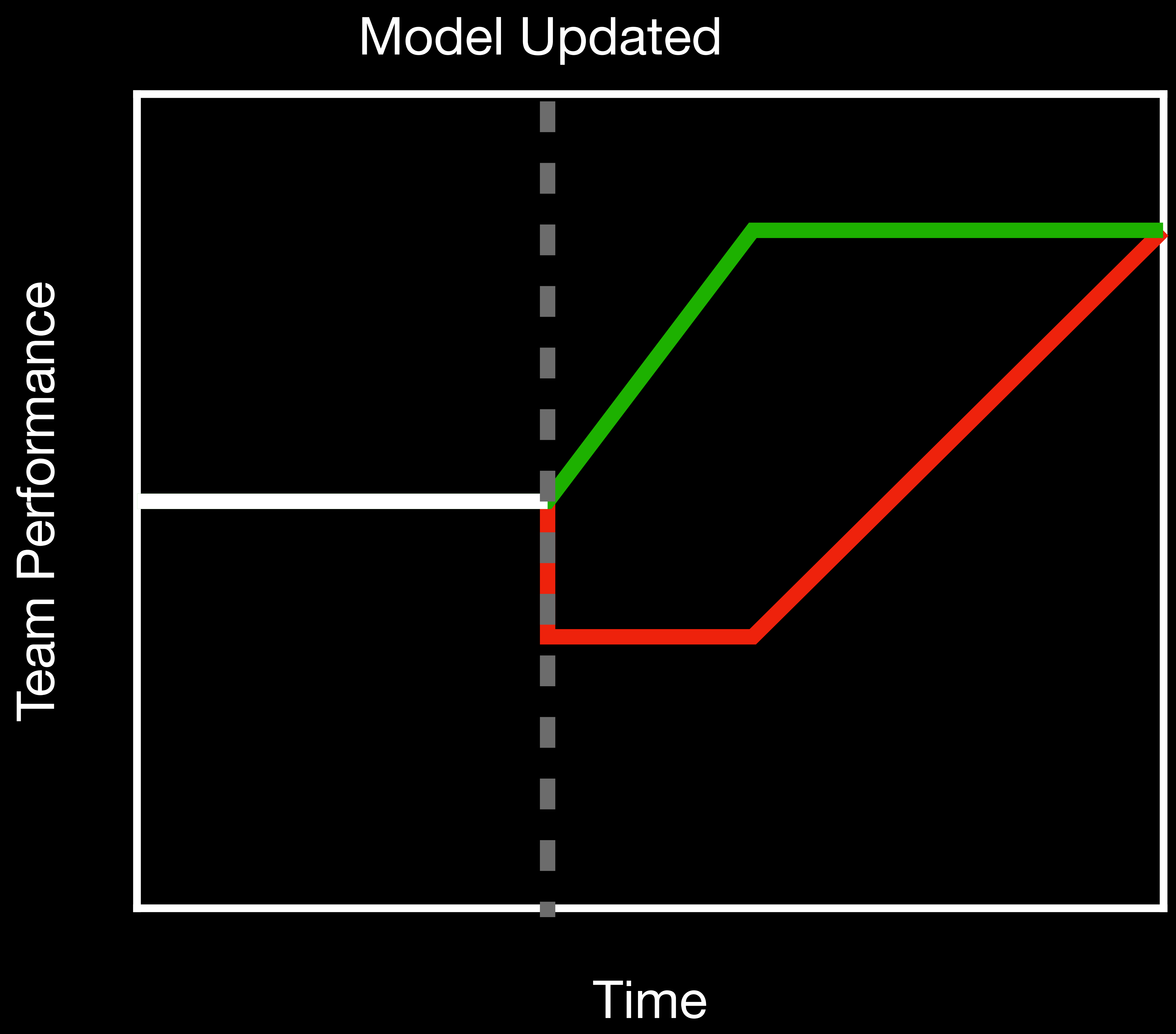


Team performance may suffer if models don't meet user expectations.



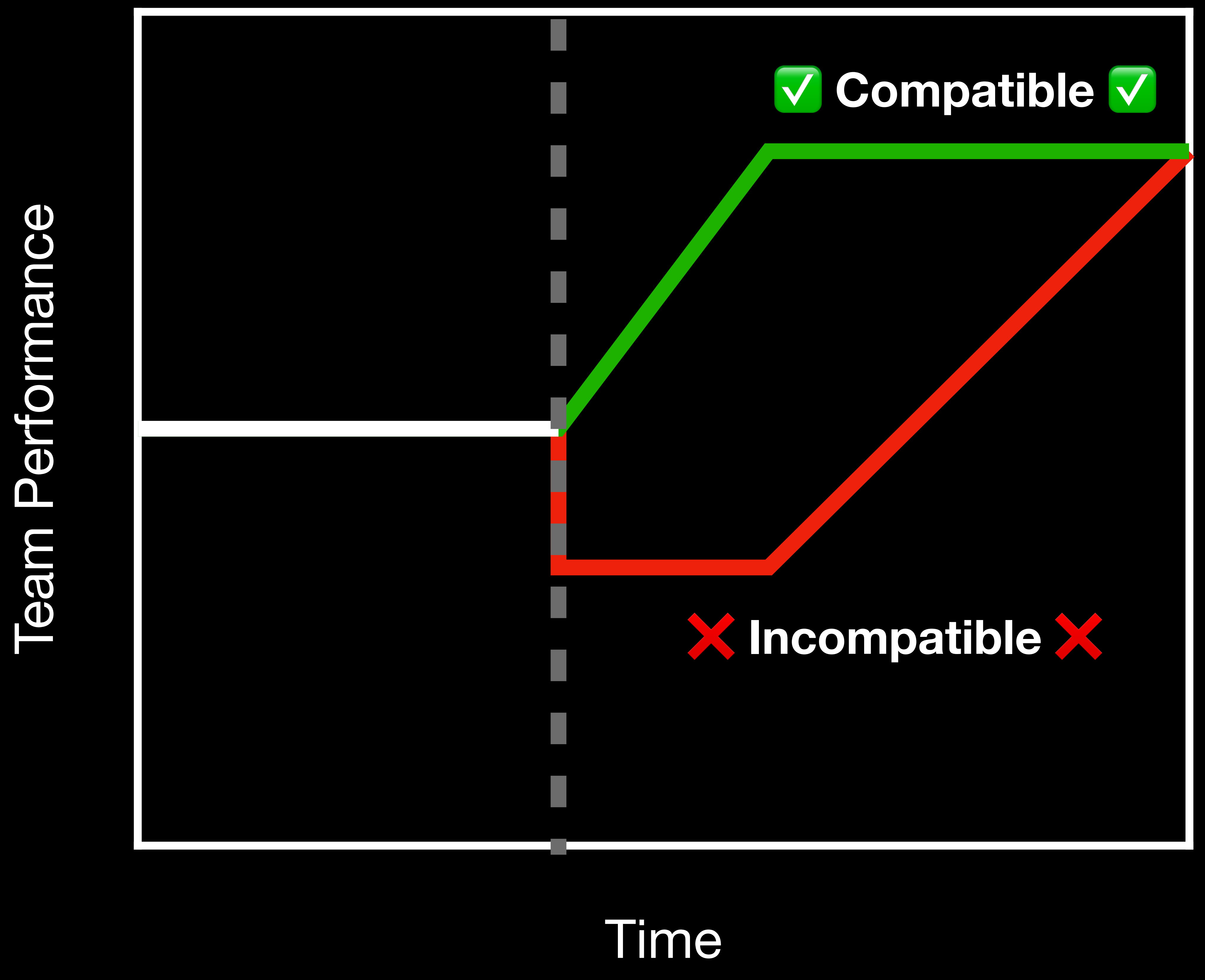
Adapted from Bansal 2019

Ideally updated models meet the expectations of users

Compatibility: the amount an updated model continues the correct behavior of an original model

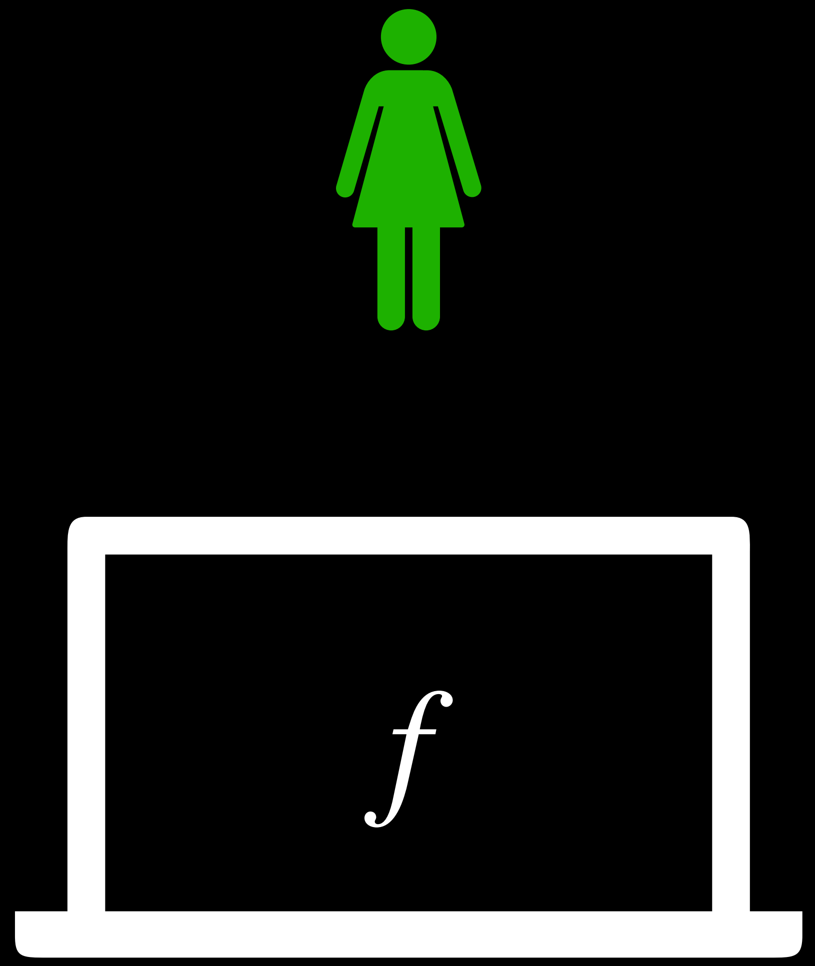
Way to measure user expectations

Goal: updated models should have high compatibility



Compatibility can be assessed by using the original and updated models for the same predictive task.

Original



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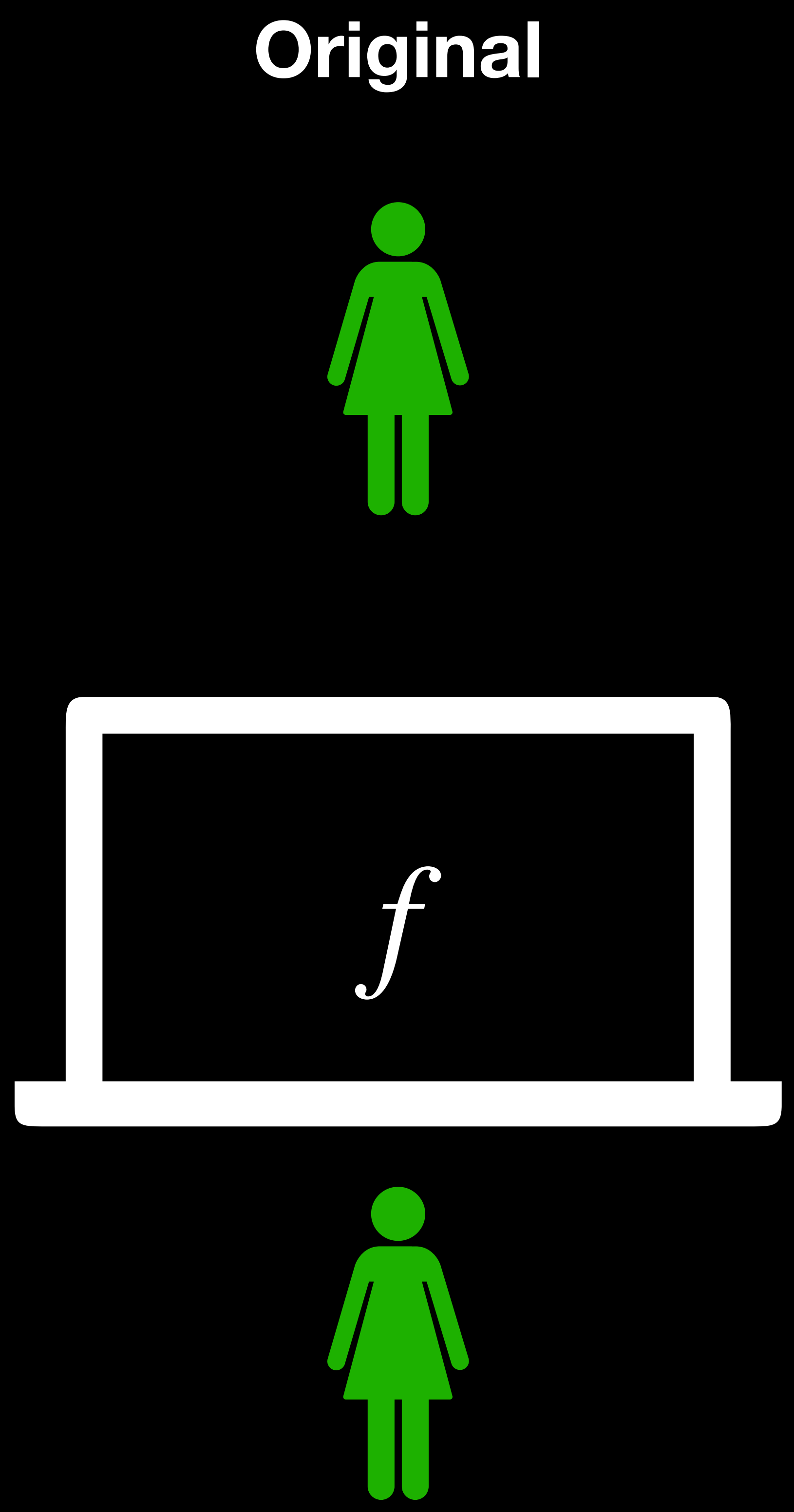

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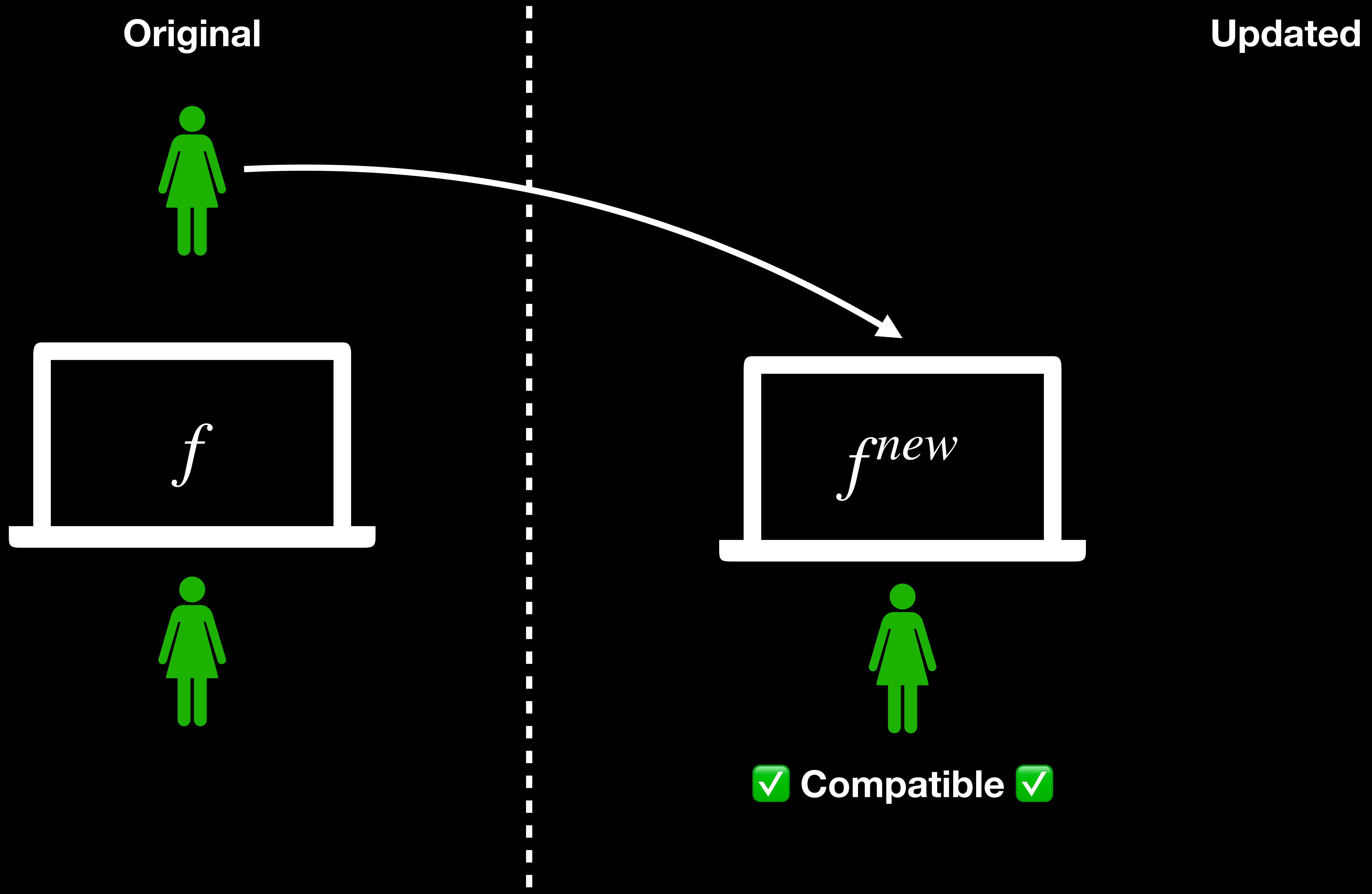

Bansal 2019

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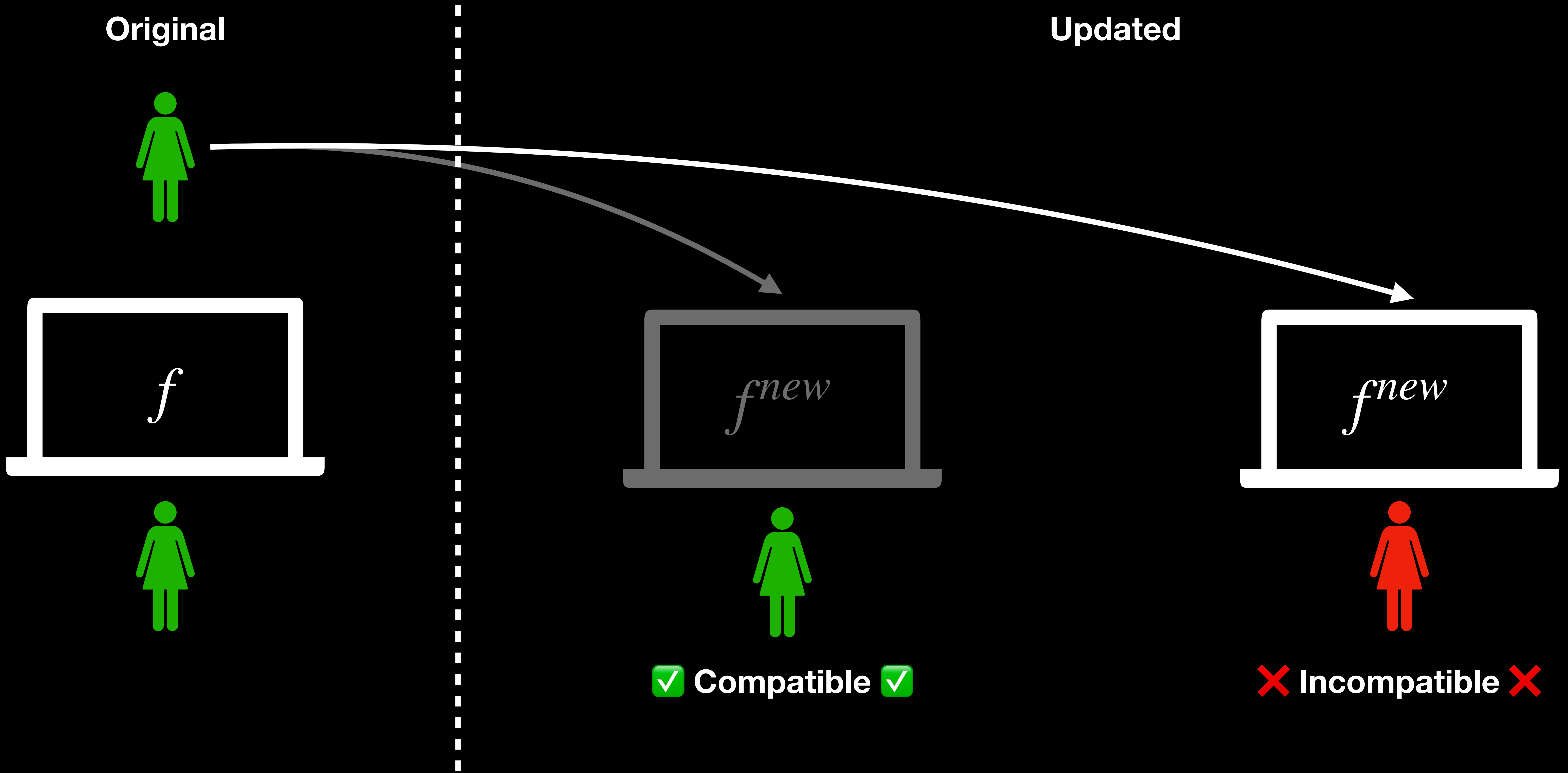

Backwards Trust Compatibility C^{BT}

The chance that the updated model's labels are correct, given that the original model's labels were correct.

$$C^{BT}(f^o, f^u) = \frac{\text{\# patients both models label correctly}}{\text{\# patients original model labels correctly}}$$

Bansal 2019

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1 → perfect compatibility, 0 → perfect incompatibility

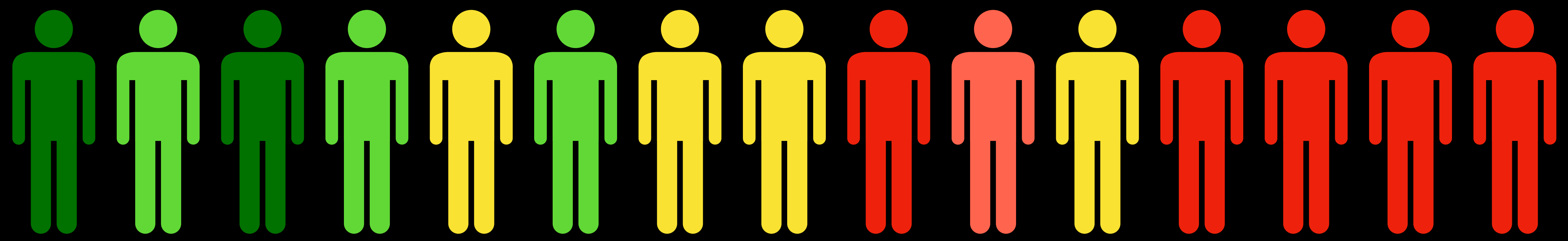
Bansal 2019

Problems with existing compatibility measures.

Existing measure depends on equality comparison

Problematic for use in risk stratification model & healthcare settings

- Depends on setting a single decision threshold



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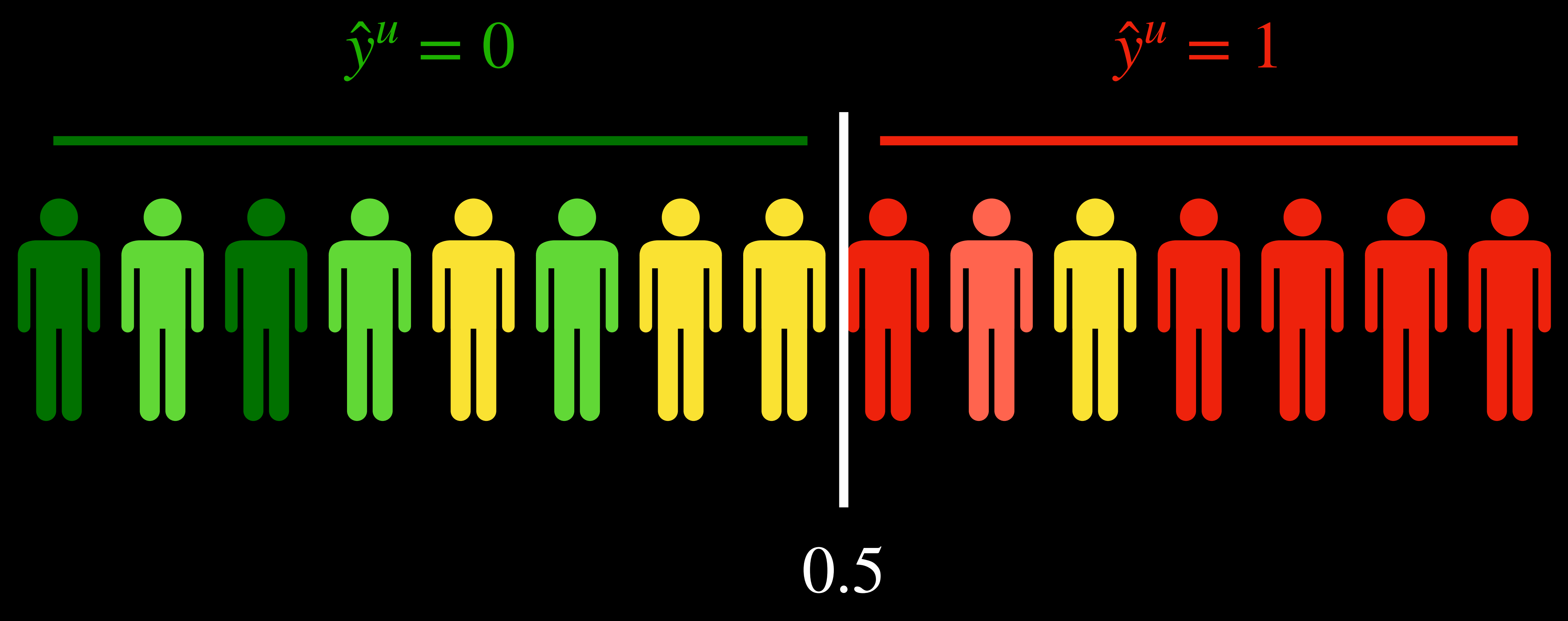

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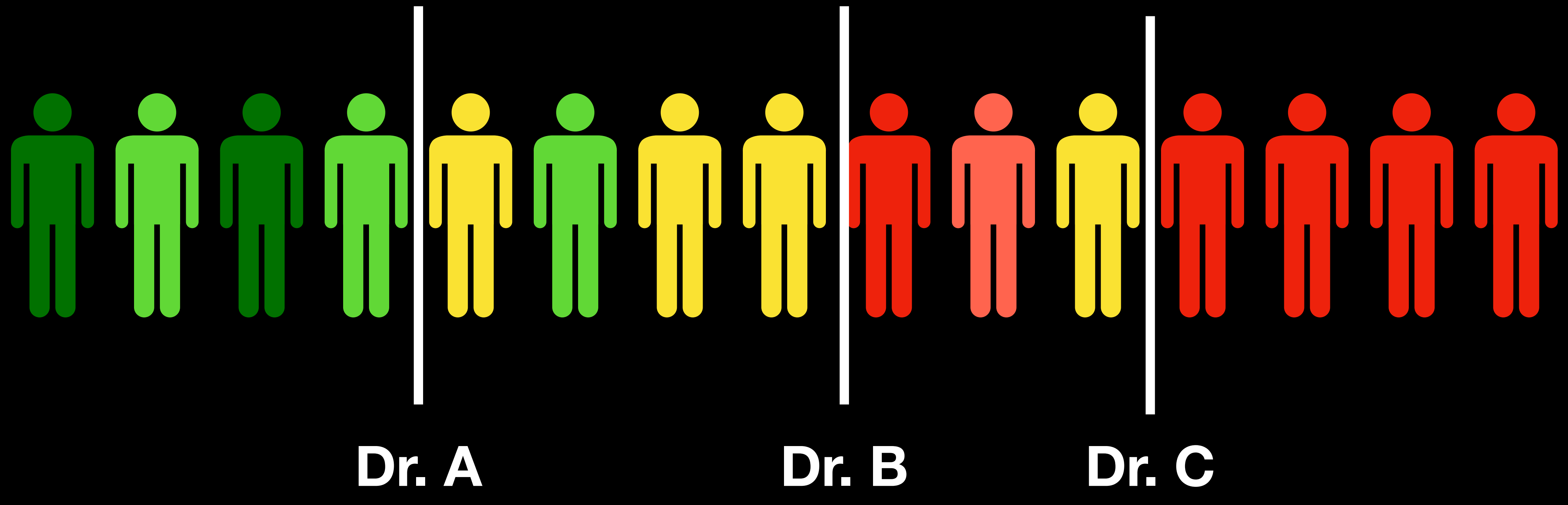
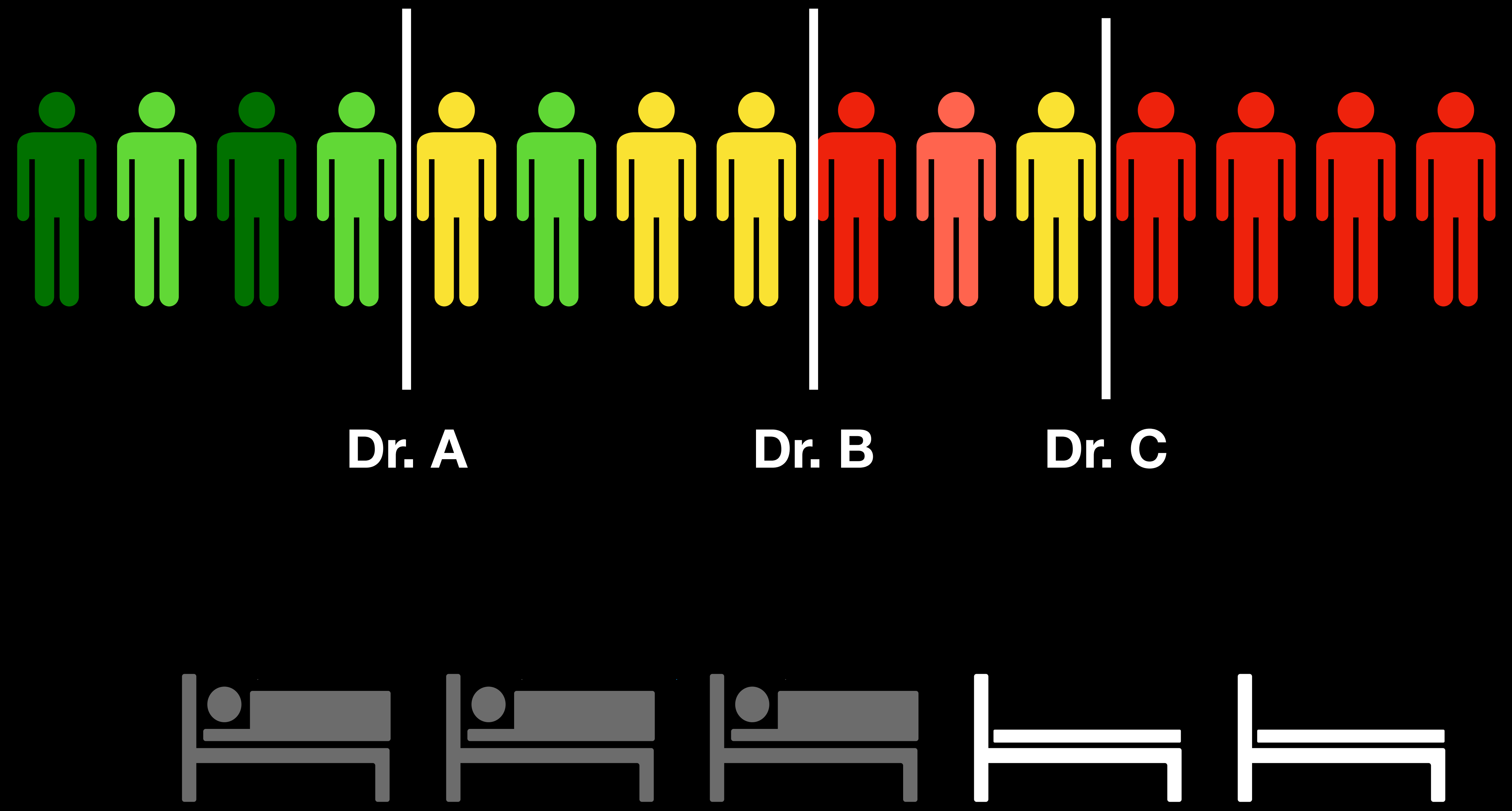


Problems with existing compatibility measures.

Existing measure depends on equality comparison

Problematic for use in risk stratification model & healthcare settings

- Depends on setting a single decision threshold



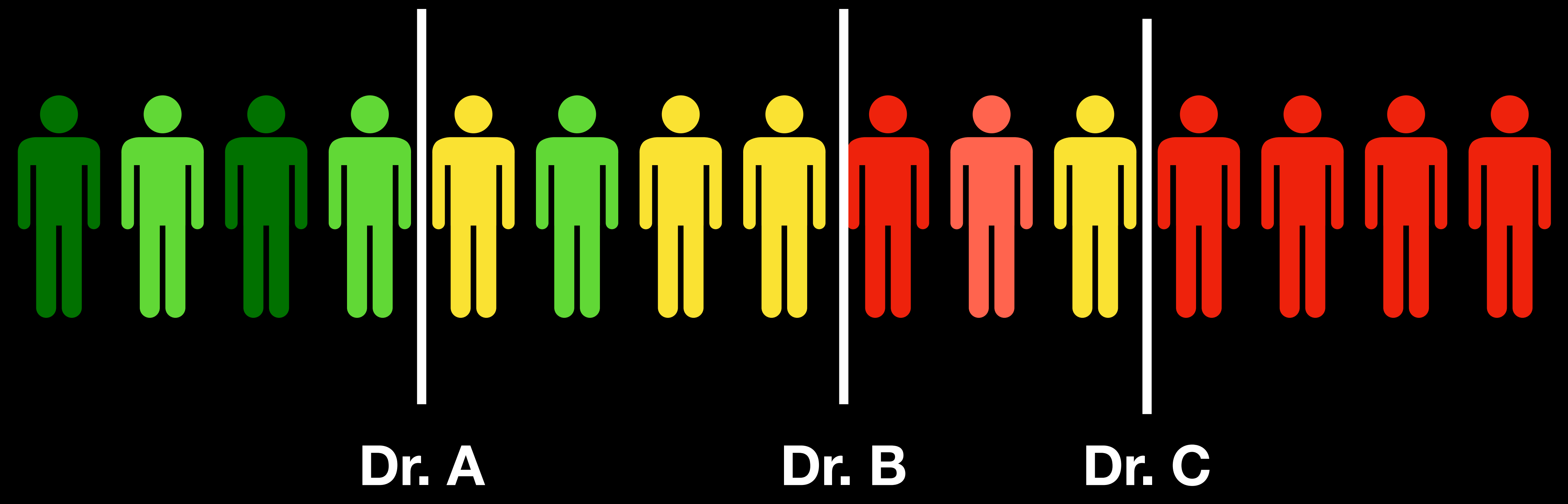
Problems with existing compatibility measures.

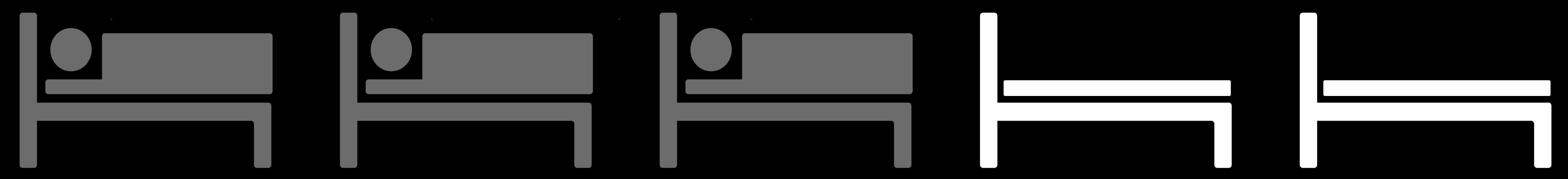
Existing measure depends on equality comparison

Problematic for use in risk stratification model & healthcare settings

- Depends on setting a single decision threshold

- No direct relationship with AUROC





Our contributions

Define a new rank-based compatibility measure (C^R)

Characterize C^R and its relationship with AUROC

Custom loss function to engineer model updates with improved C^R

Intuition: C^R should inherit from both C^{BT} & AUROC

$$C^{BT}(f^o, f^u) = \frac{\text{\# patients both models label correctly}}{\text{\# patients original model labels correctly}}$$

$$AUROC(f^o) = \frac{\sum_{i \in I^0} \sum_{j \in I^1} \mathbf{1}(\hat{p}_i^o < \hat{p}_j^o)}{m}$$

Evaluate correct behavior of both models
Normalized based on original model's behavior

"Correctness" based on risk estimate ordering

Rank-based compatibility C^R

Agreement of risk estimate rankings produced by original & updated models given original ranked correctly:

$$C^R(f^o, f^u) = \frac{\sum_{i \in I^0} \sum_{j \in I^1} \mathbf{1}(\hat{p}_i^o < \hat{p}_j^o) \cdot \mathbf{1}(\hat{p}_i^u < \hat{p}_j^u)}{\sum_{i \in I^0} \sum_{j \in I^1} \mathbf{1}(\hat{p}_i^o < \hat{p}_j^o)}$$

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Agreement of risk estimate rankings produced by original & updated models given original ranked correctly:

$$C^R(\boxed{f^o},\boxed{f^u}) = \frac{\sum_{i \in I^0} \sum_{j \in I^1} \mathbf{1}(\hat{p}_i^o < \hat{p}_j^o) \cdot \mathbf{1}(\hat{p}_i^u < \hat{p}_j^u)}{\sum_{i \in I^0} \sum_{j \in I^1} \mathbf{1}(\hat{p}_i^o < \hat{p}_j^o)}$$

original model **updated model**

Rank-based compatibility C^R

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original model ranks correctly

Rank-based compatibility C^R

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updated model ranks correctly

original model ranks correctly

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1 → perfect compatibility, 0 → perfect incompatibility

C^R is a new compatibility measure inspired by AUROC

Not threshold dependent.

Has a direct relationship with AUROC which we can use to assess trade-offs.

Lower bound of C^R expected to increase as model performance increases.

Q1: *Do we get C^R for free when we make updated models targeting AUROC?*

More specifically: do we observe $C^R = 1$ (or very close) when we train updated models using binary cross entropy loss?

Hypothesis: No, analytically we'd expect that C^R is centered at a region away from the upper and lower bounds.

Q1: Experimental Setup

Original Model
$n = 1{,}000$

- Original Model Development
  $n = 500$
- Original Model Validation
  $n = 500$

Updated Model Dataset
$n = 5{,}000$

- Updated Model Development
  $n = 2{,}500$
- Updated Model Validation
  $n = 2{,}500$

Evaluation Dataset
$n = 2{,}577$

MIMIC-III Mortality Dataset

Alistair 2016, Bansal 2019, Tang 2020

Q1: Experimental Setup

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$n = 1{,}000$

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Original Model Validation
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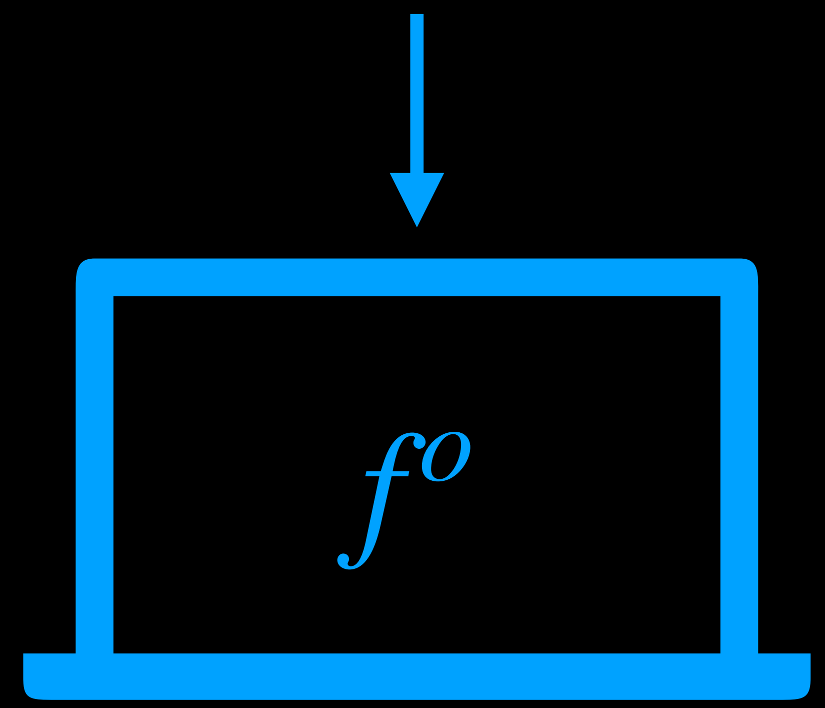

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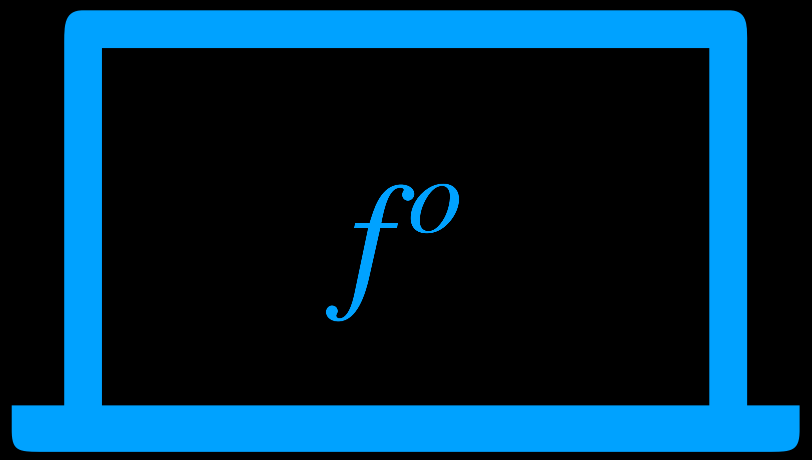


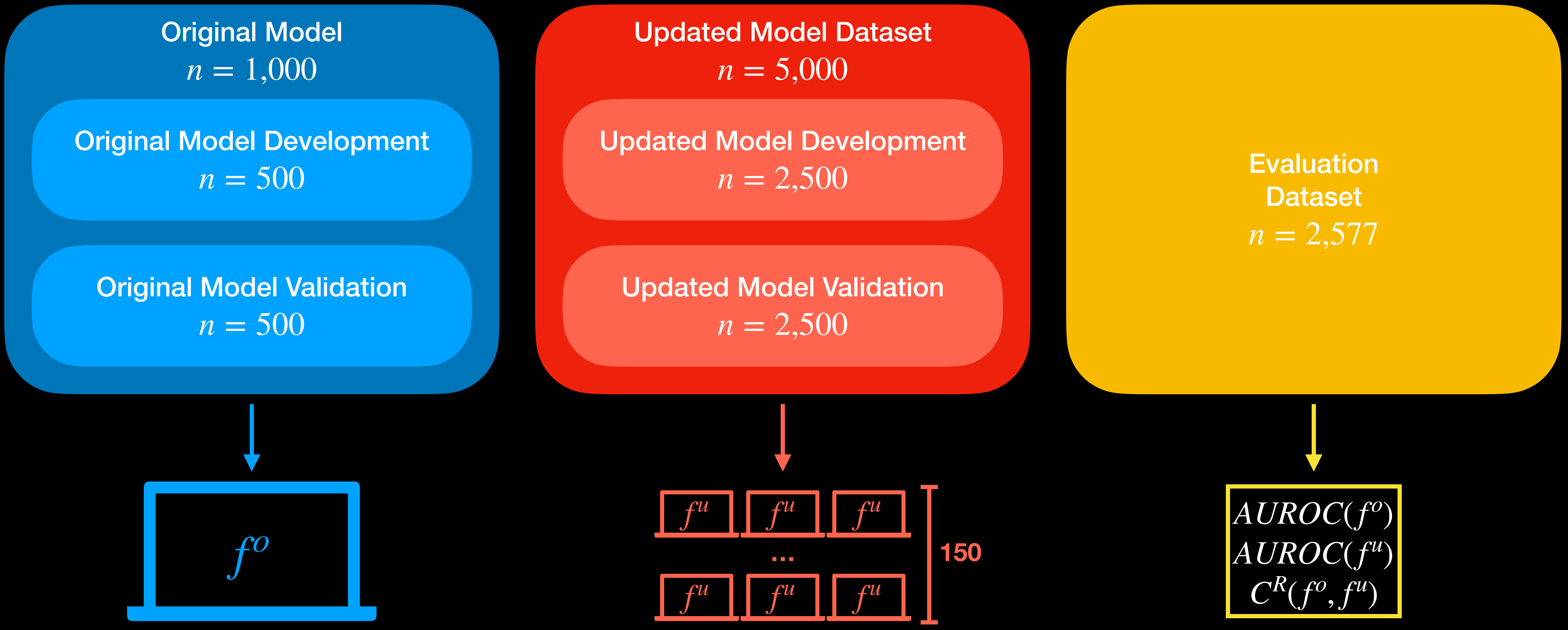
f^u f^u f^u

...

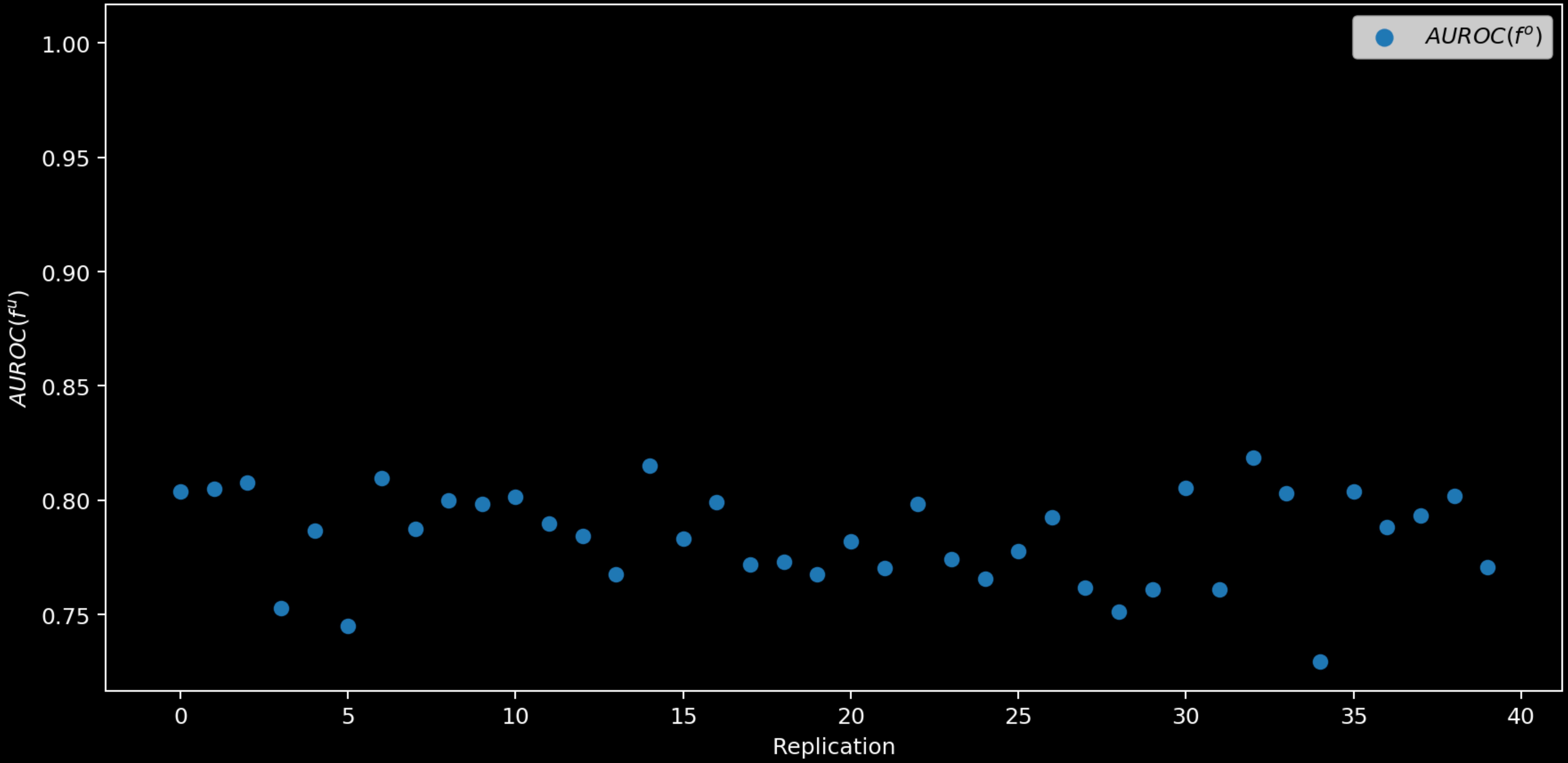
f^u f^u f^u

150

Q1: Experimental Setup

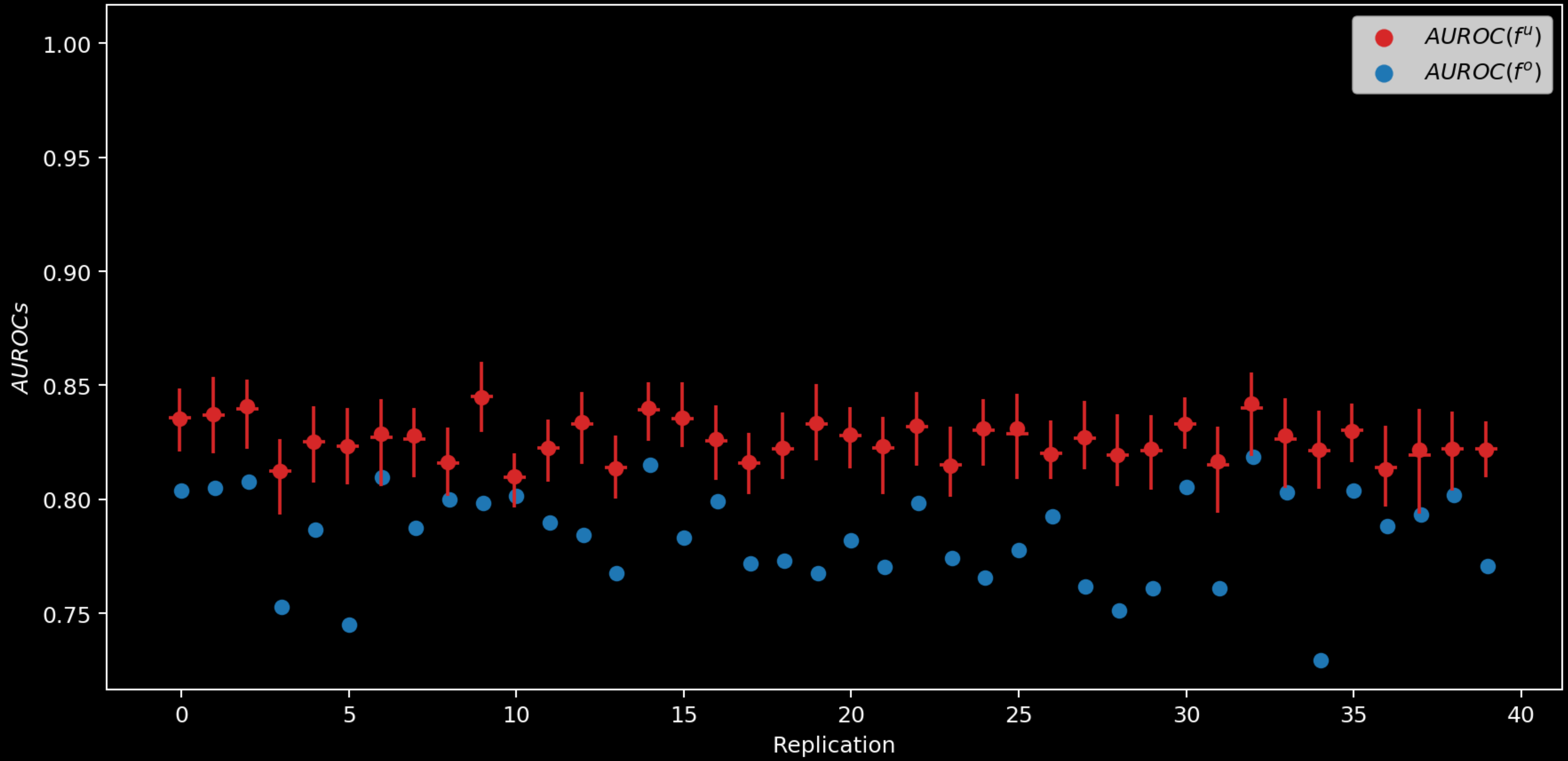


Results



$AUROC(f^o)$
$AUROC(f^u)$
1.00
0.95
0.90
0.85
0.80
0.75
0
5
10
15
20
25
30
35
40
Replication

Results



$AUROC(f^u)$
$AUROC(f^o)$
1.00
0.95
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$AUROCs$
0
5
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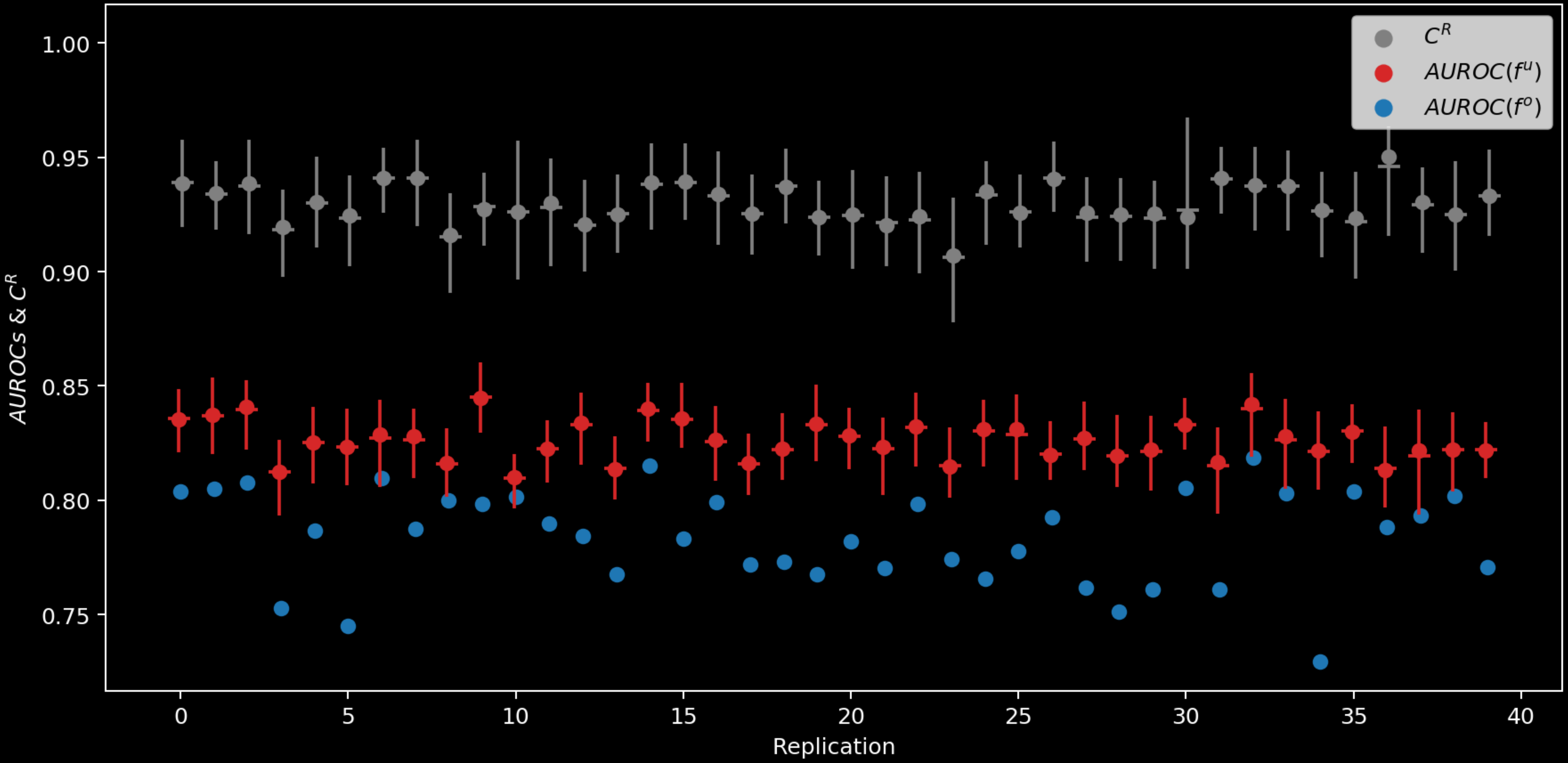
35
40
Replication

Results



C^R
$AUROC(f^u)$
$AUROC(f^o)$
1.00
0.95
0.90
0.85
0.80
0.75
AUROCs & C^R
0
5
10
15
20
25
30
35
40
Replication

Q1: *Do we get C^R for free when we make updated models targeting AUROC?*

No.

We observe updated models have a limited range in C^R.

Analytical results suggest that there’s a large search space .

Motivates techniques to search for updated models that have higher C^R.

Risk stratification models are usually trained with binary cross entropy loss.

Binary cross entropy loss:

$$\mathscr{L}^{BCE}(f) = -\sum_{i \in I^0} \log(1 - \hat{p}_i) - \sum_{j \in I^1} \log(\hat{p}_j)$$

Minimization of $\mathscr{L}^{BCE}$ leads to higher AUROC because risk estimates tend to align with labels.

Risk stratification models are usually trained with binary cross entropy loss.

Binary cross entropy loss:

Make 0-labeled patients have low risk estimates

$$\mathscr{L}^{BCE}(f) = \boxed{-\sum_{i \in I^0} \log(1 - \hat{p}_i)} - \sum_{j \in I^1} \log(\hat{p}_j)$$

Minimization of $\mathscr{L}^{BCE}$ leads to higher AUROC because risk estimates tend to align with labels.

Risk stratification models are usually trained with binary cross entropy loss.

Binary cross entropy loss:

Make 0-labeled patients have low risk estimates

Make 1-labeled patients have high risk estimates

$$\mathscr{L}^{BCE}(f) = \boxed{-\sum_{i \in I^0} \log(1 - \hat{p}_i)} \boxed{-\sum_{j \in I^1} \log(\hat{p}_j)}$$

Minimization of $\mathscr{L}^{BCE}$ leads to higher AUROC because risk estimates tend to align with labels.

Risk stratification models are usually trained with binary cross entropy loss.

Binary cross entropy loss:

Make 0-labeled patients have low risk estimates

Make 1-labeled patients have high risk estimates

$$\mathscr{L}^{BCE}(f) = \boxed{-\sum_{i\in I^0}\log(1-\hat{p}_i)}\ \boxed{-\sum_{j\in I^1}\log(\hat{p}_j)}$$

Minimization of $\mathscr{L}^{BCE}$ leads to higher AUROC because risk estimates tend to align with labels.

No focus on compatibility between the updated and original model.

We introduce rank-based incompatibility loss.

Rank-based incompatibility loss:

$$\mathscr{L}^R(f^o, f^u) = 1 - C^R(f^o, f^u)$$

Minimization of $\mathscr{L}^R$ will lead to higher levels of C^R.

Differentiable approximation $\widetilde{\mathscr{L}^R}$ for SGD.

Weighted loss trades-off between binary cross entropy and compatibility.

Weighted loss function:

$$\alpha \mathscr{L}^{BCE}(f^u) + (1-\alpha)\widetilde{\mathscr{L}^R}(f^o, f^u)$$

where $\alpha \in [0,1]$

When:

$\alpha = 1$ then only minimize $\mathscr{L}^{BCE}$, ↑ AUROC

$\alpha = 0$ then only minimize $\widetilde{\mathscr{L}^R}$, ↑ C^R

$\alpha = 0.5$ then balance $\mathscr{L}^{BCE}$ and $\widetilde{\mathscr{L}^R}$

Q2: *Can we make updated models with higher levels of C^R?*

Specifically: Compared to standard update model generation and selection approaches, can we use the weighted loss function to generate updates with better C^R?

Hypothesis: using weighted loss function will produce models with better C^R.

Also, can this be accomplished without a loss of AUROC?

Q2: Extends Previous Experimental Setup

Original Model
$n = 1{,}000$

Original Model Development
$n = 500$

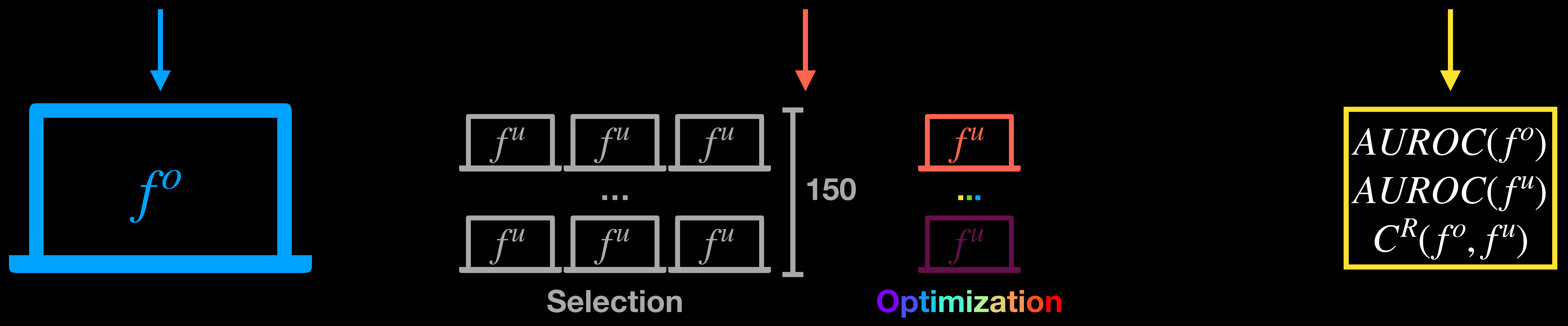
Original Model Validation
$n = 500$

Updated Model Dataset
$n = 5{,}000$

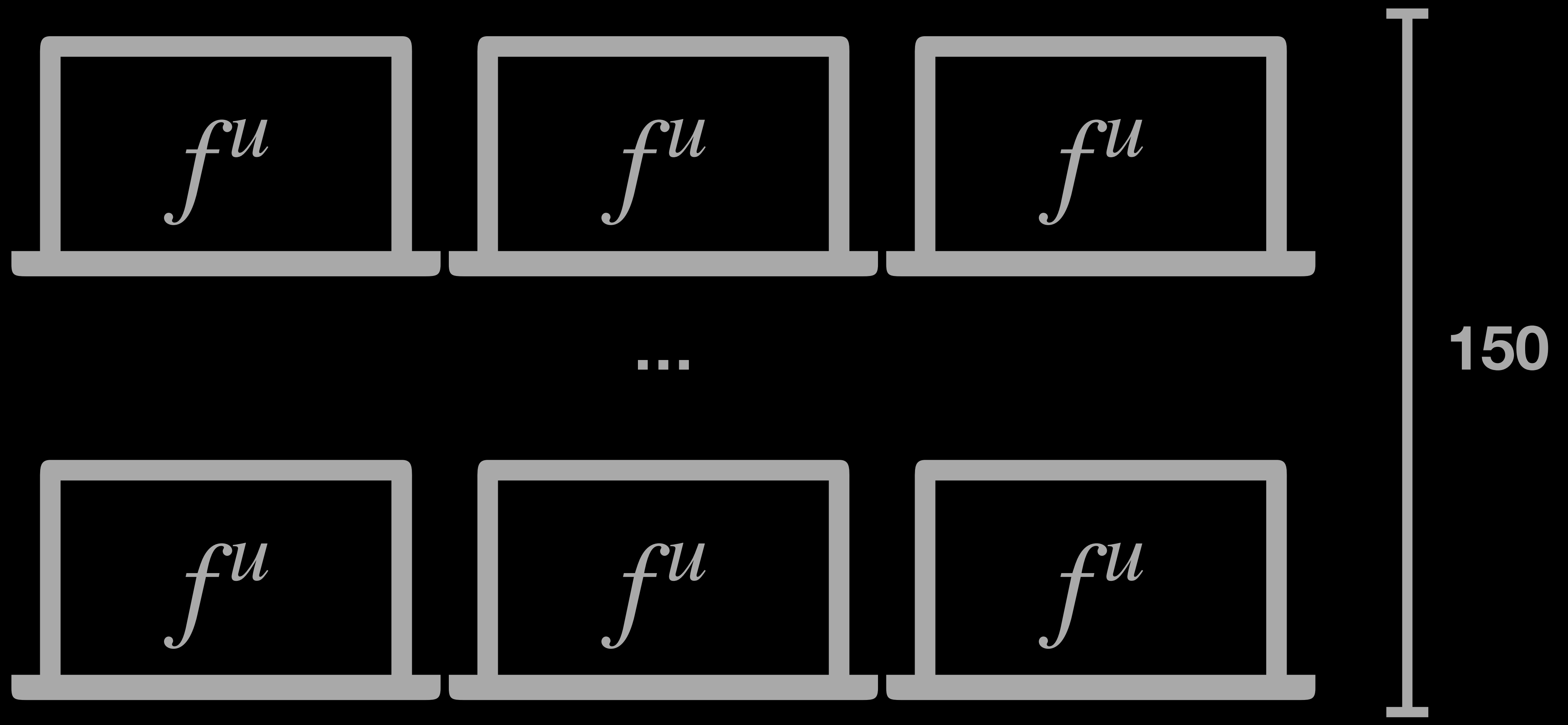
Updated Model Development
$n = 2{,}500$

Updated Model Validation
$n = 2{,}500$

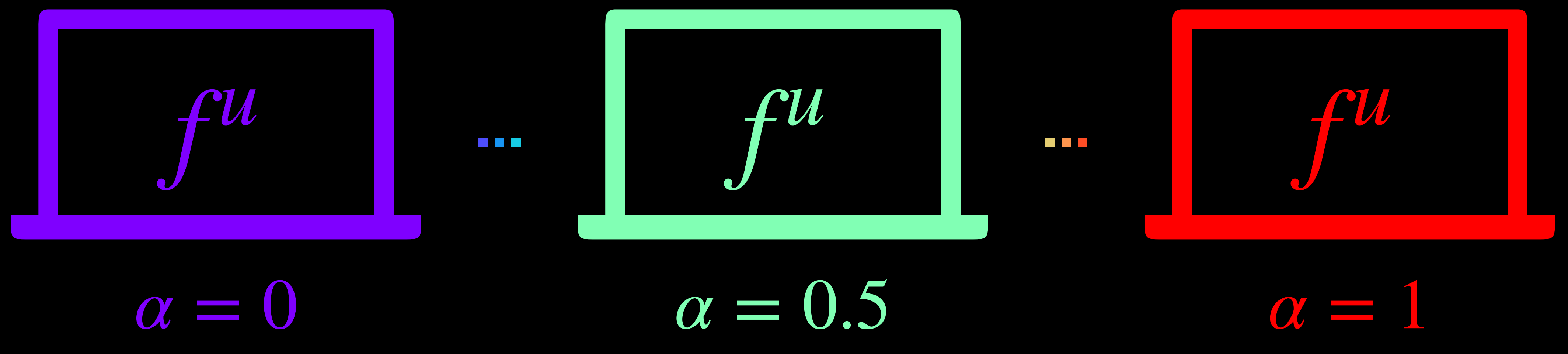
Evaluation Dataset
$n = 2{,}577$



Q2: Updated Models Selection vs. Optimization



Selection

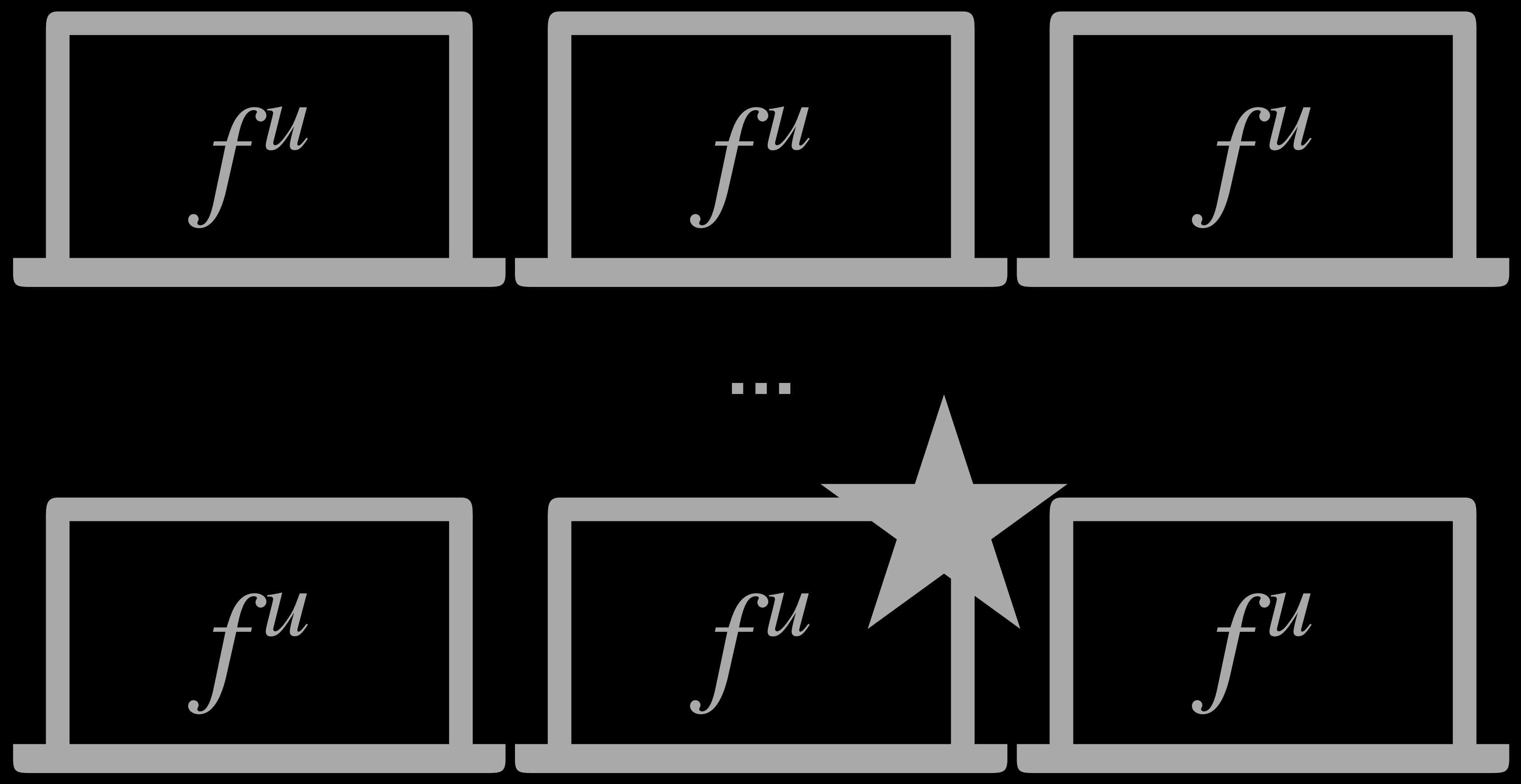


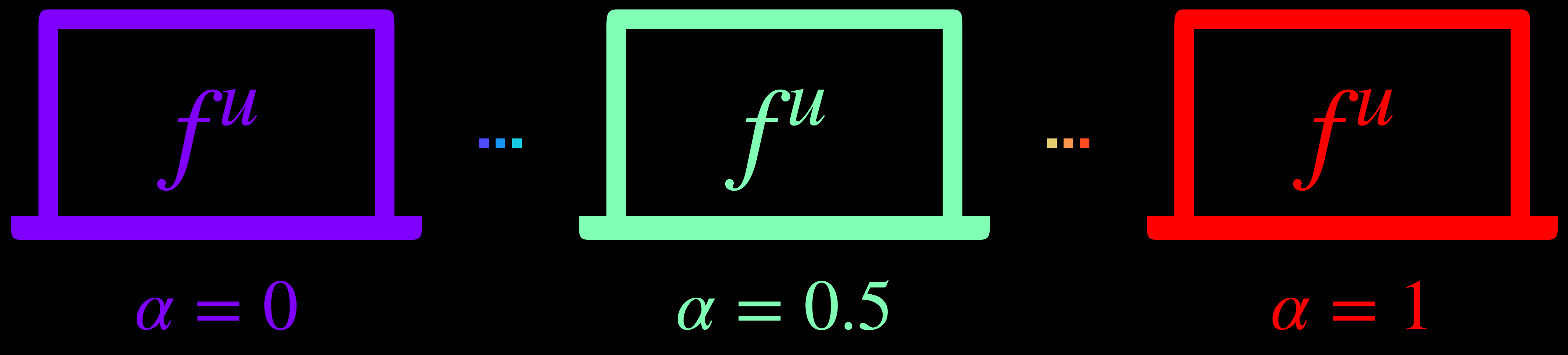
Optimization

150 "selection" models created through training with $\mathscr{L}^{BCE}$ and randomly resampling the development dataset

11 "optimization" models created through training with weighted loss with $\alpha = \{0, 0.1, \ldots, 0.9, 1\}$

Q2: Updated Models Selection vs. Optimization





Selection

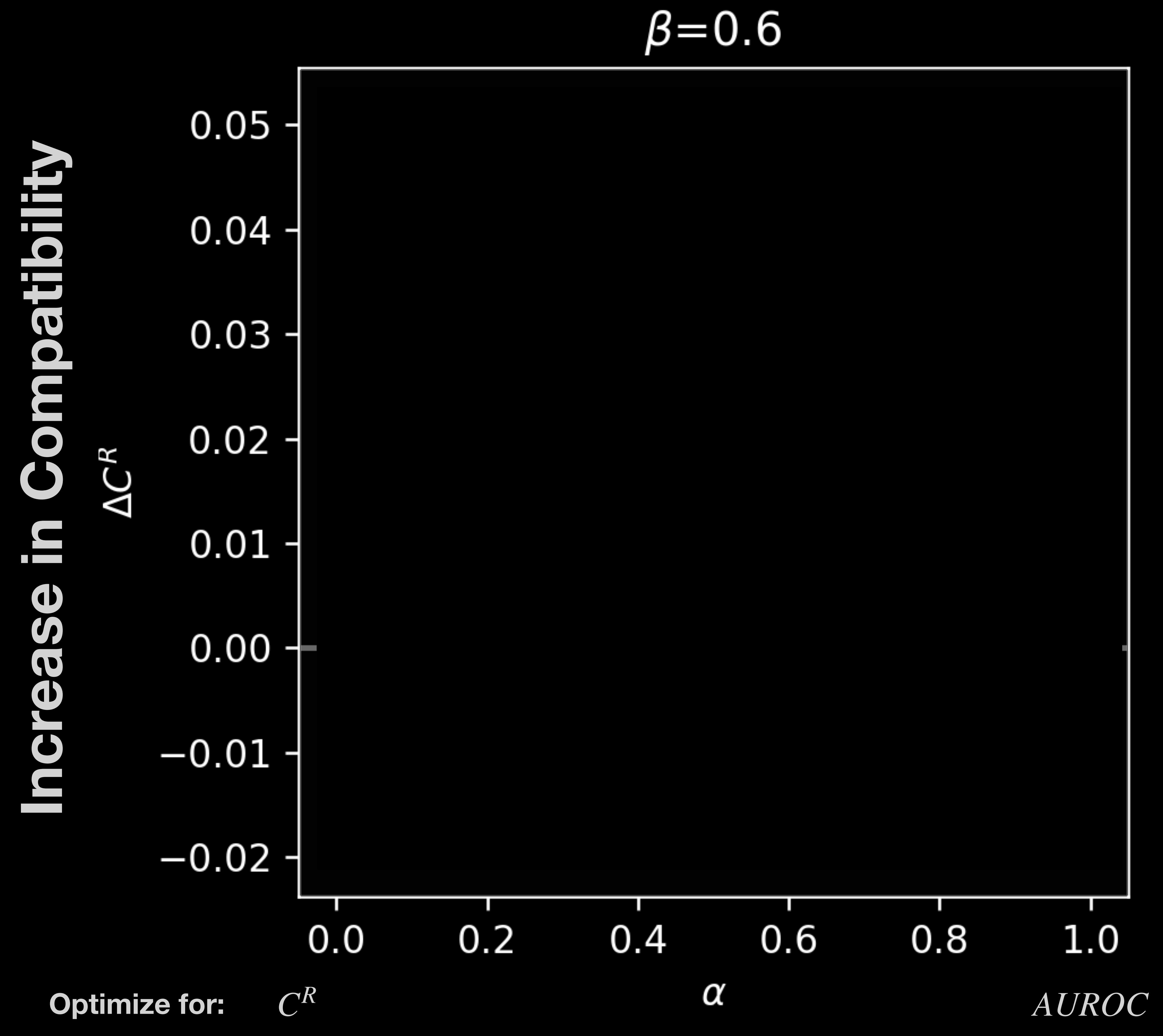
Optimization

Use a selection procedure to pick an updated model to use as a baseline

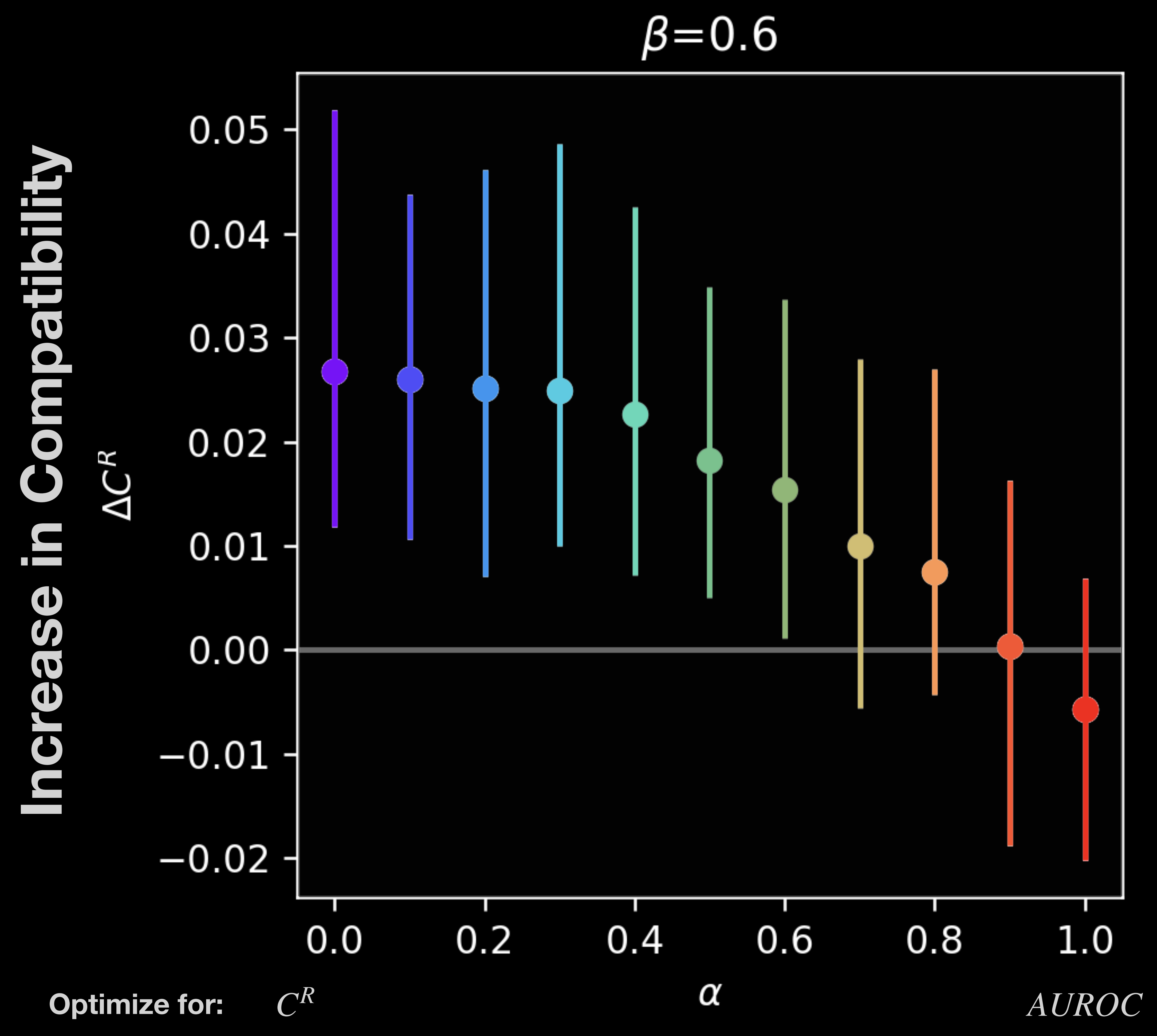
For example model with best validation AUROC

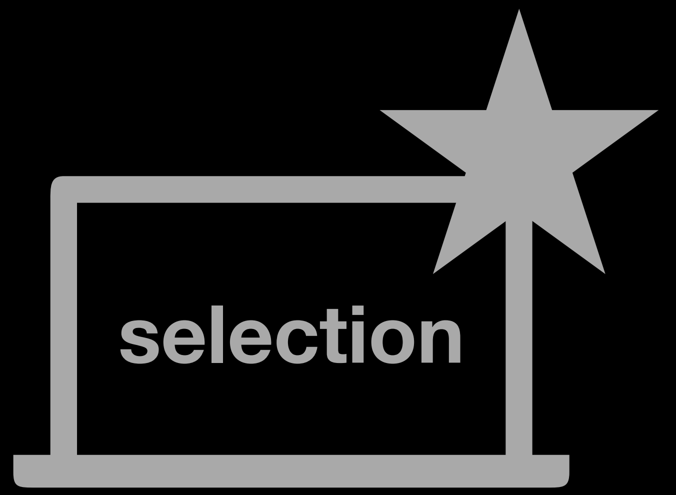
Examine difference in held out evaluation C^R and AUROC

Q2: C^R performance results

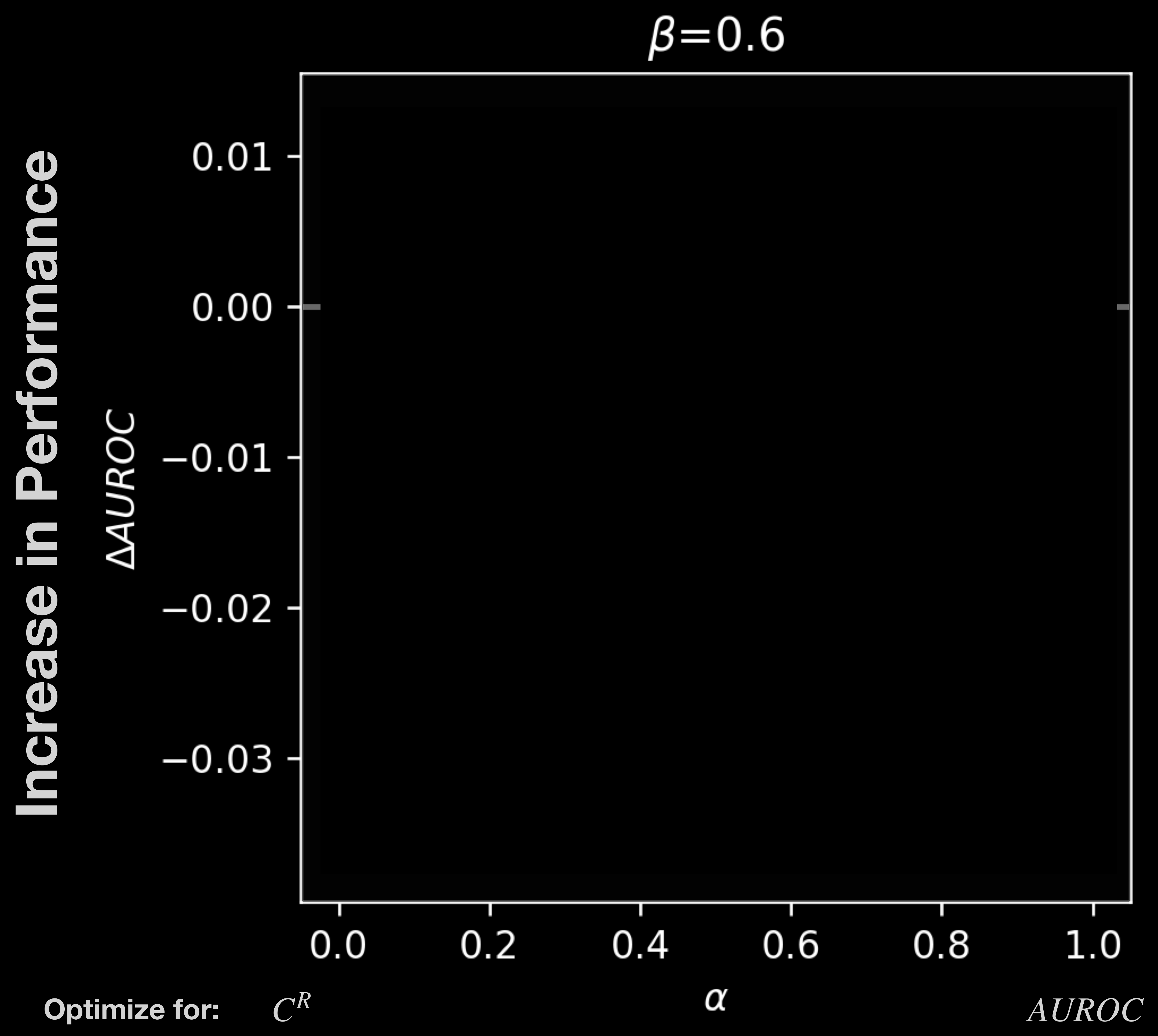


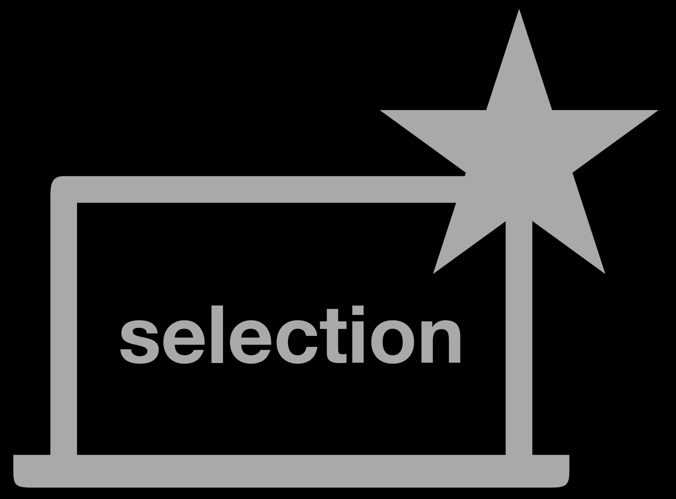
Q2: C^R performance results



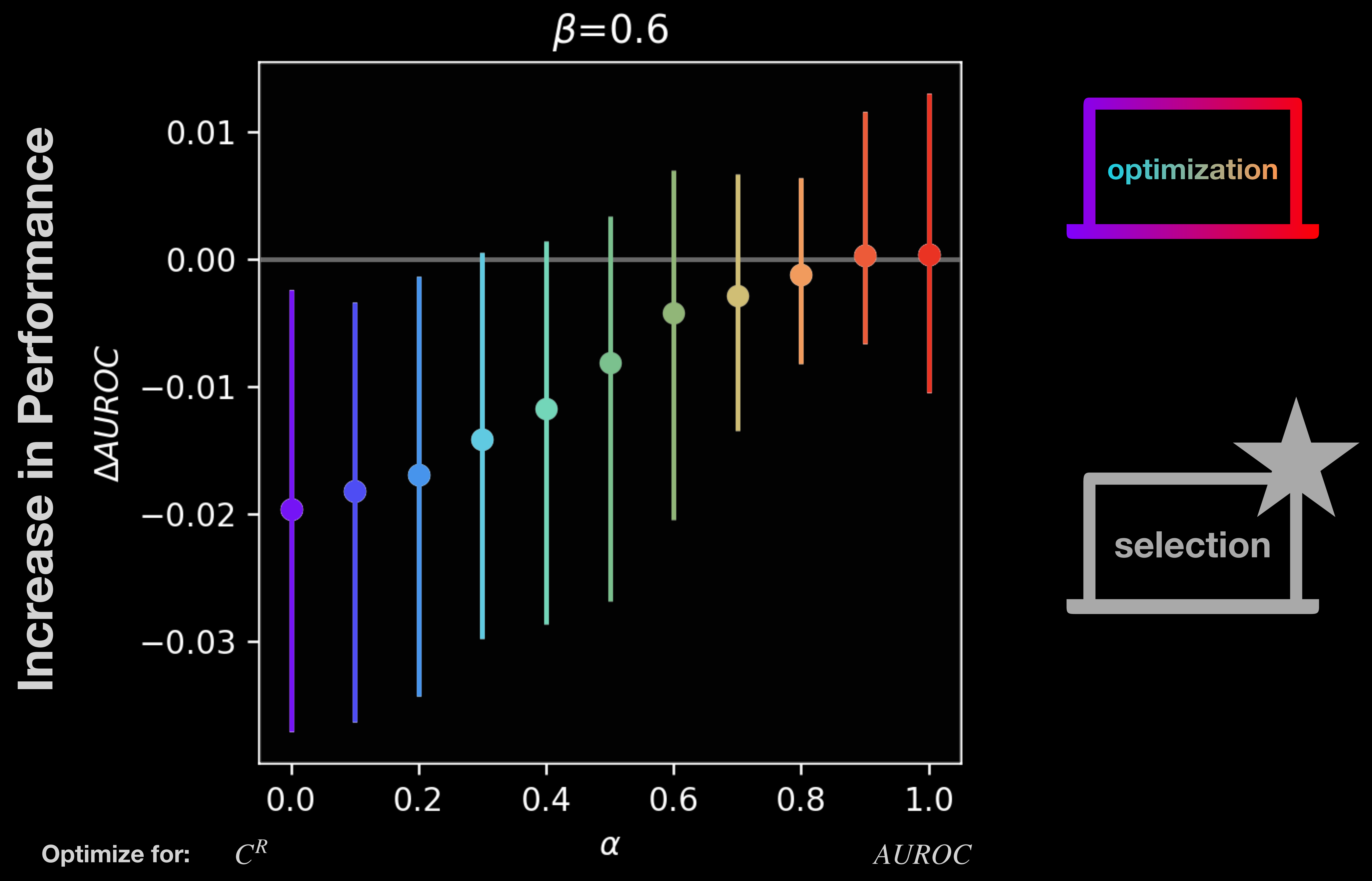


Q2: $AUROC$ performance results

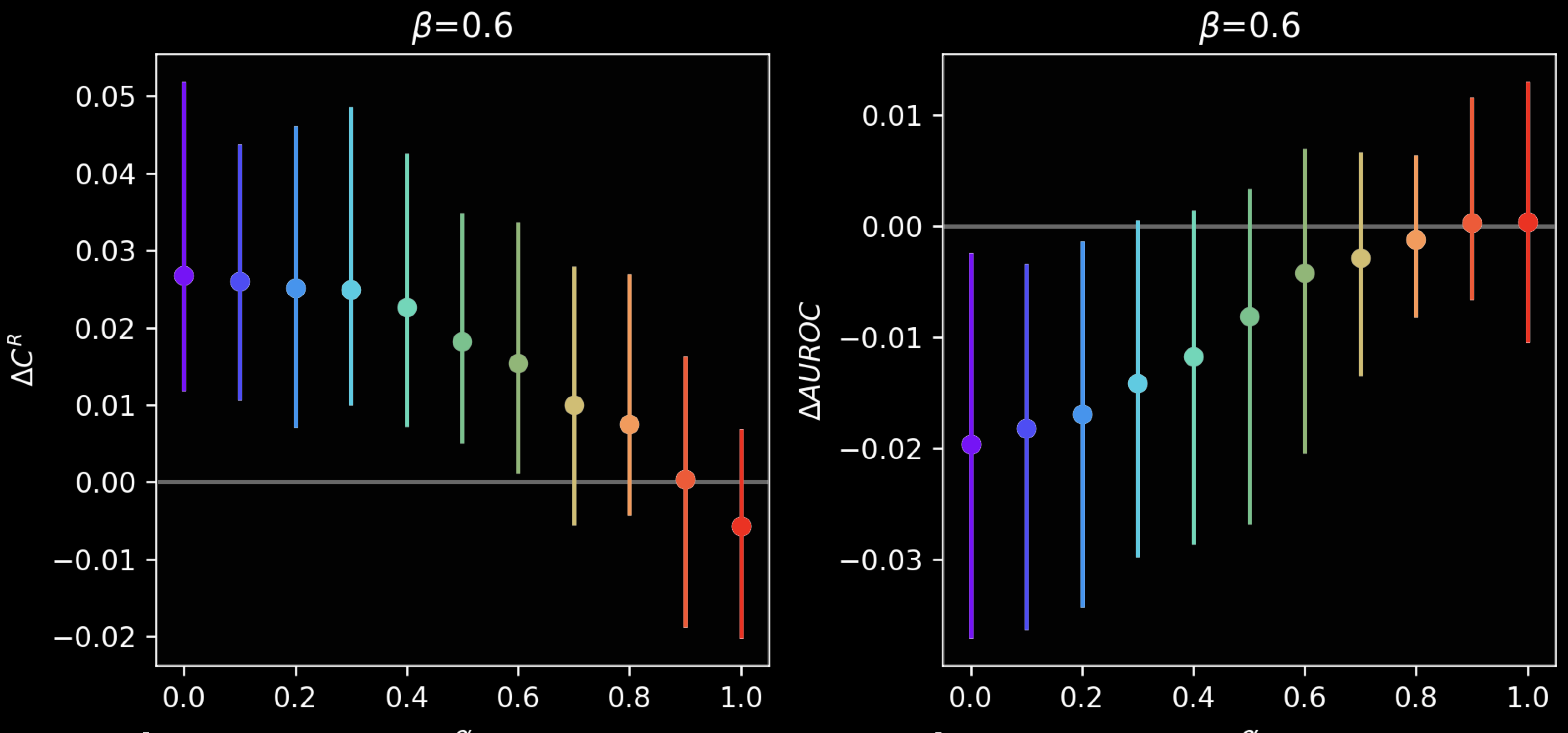




Q2: $AUROC$ performance results

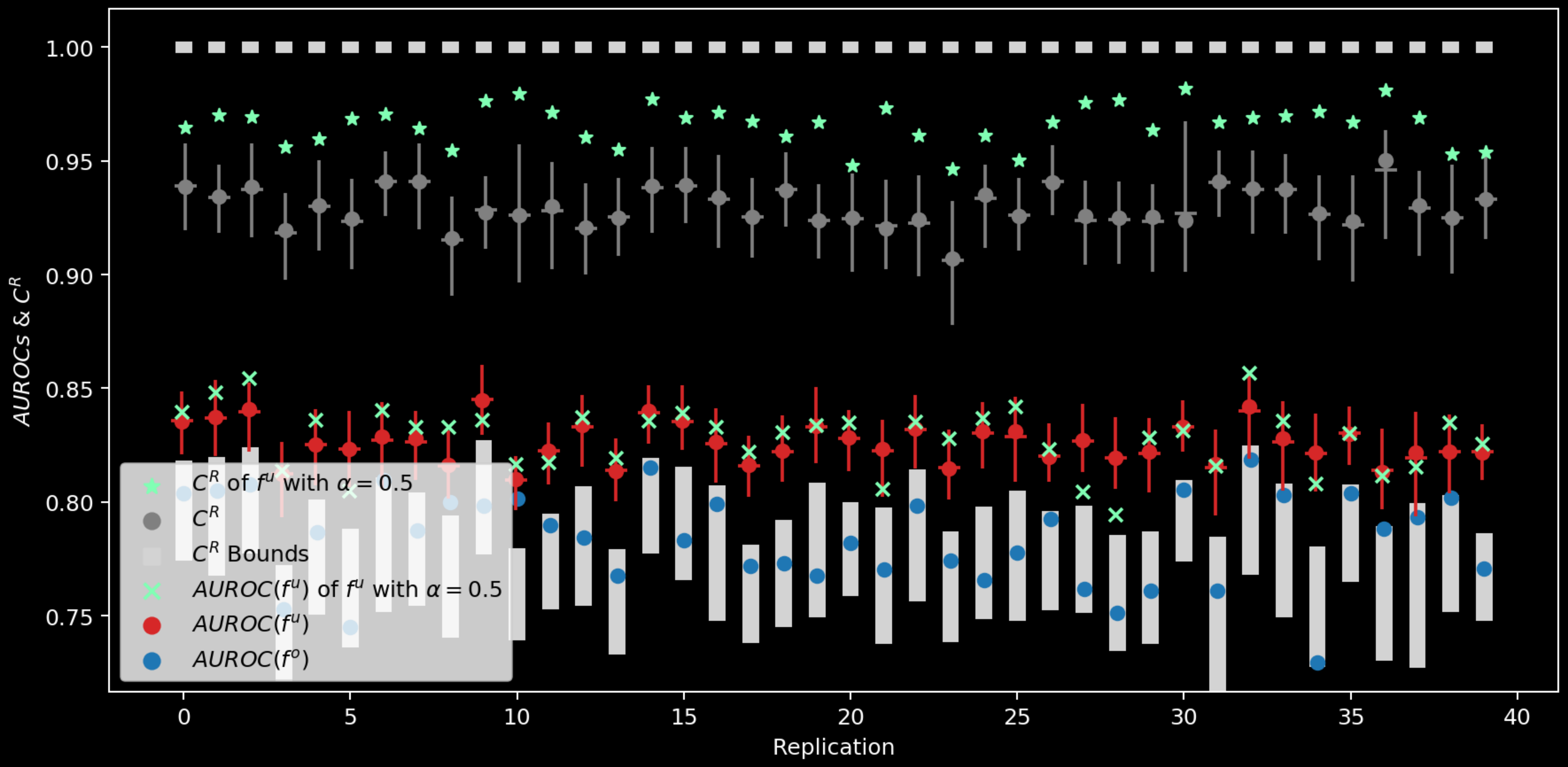


Q2: Performance results



Optimize for: C^R … $AUROC$ (left chart); C^R … $AUROC$ (right chart)

Q2: α=0.6 yields promising updated models



Summary of experiments

Do we get C^R for free when we make updated models targeting AUROC?

No.

Can we make updated models with higher levels of C^R?

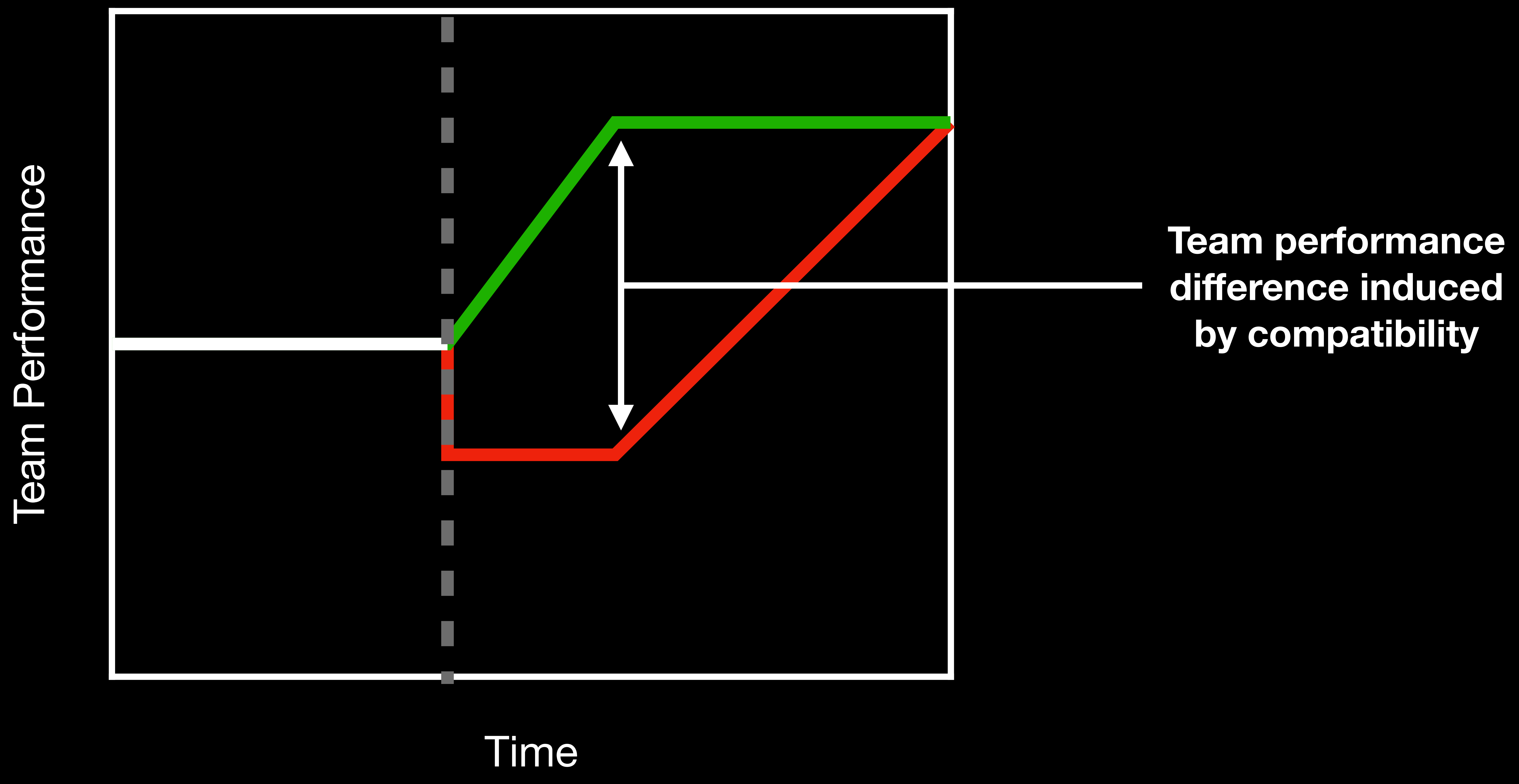
Yes, using our weighted loss function.

Does that come at a cost in terms of AUROC?

Sort of…

Why trade-off AUROC for C^R?

Why trade-off AUROC for C^R?



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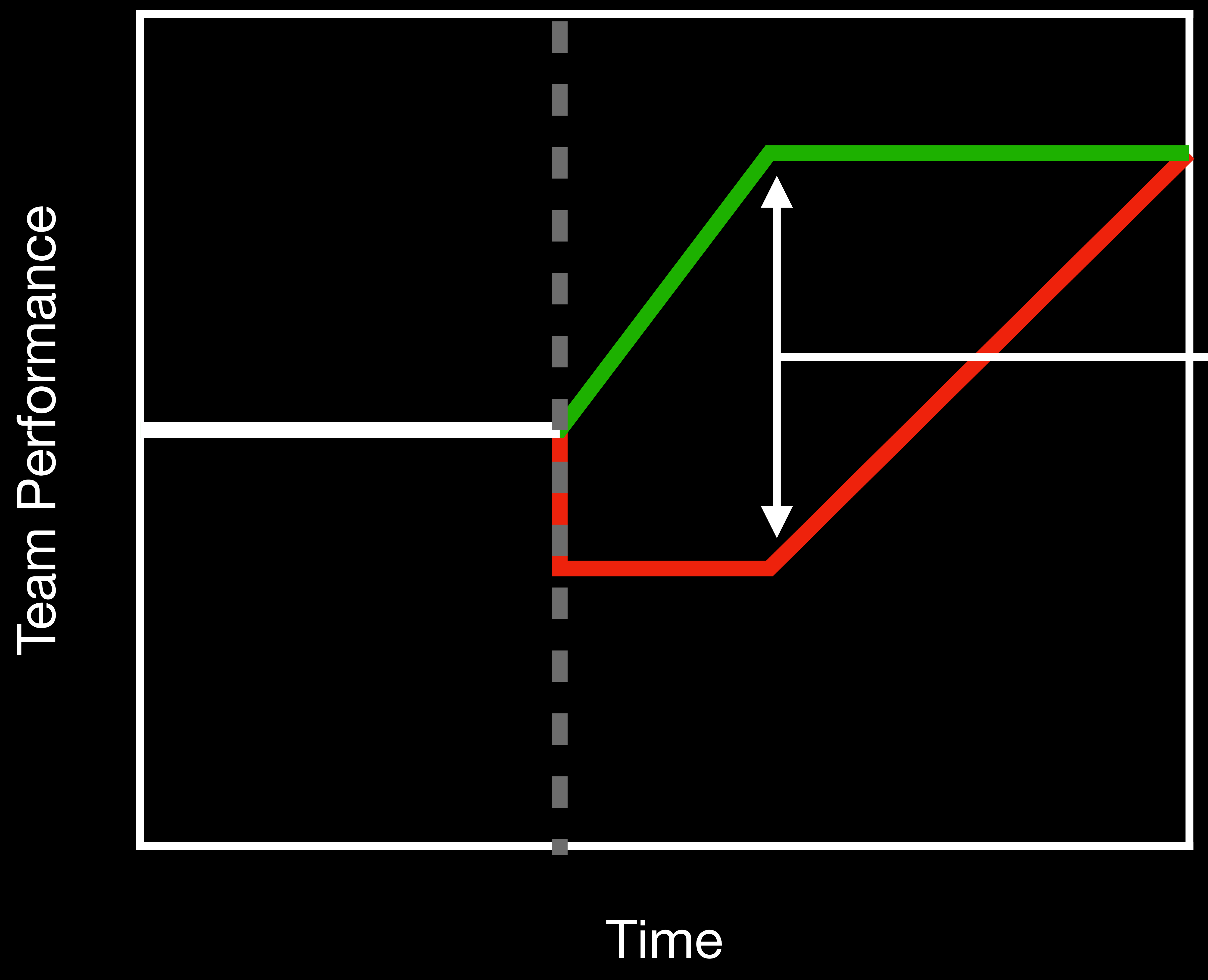
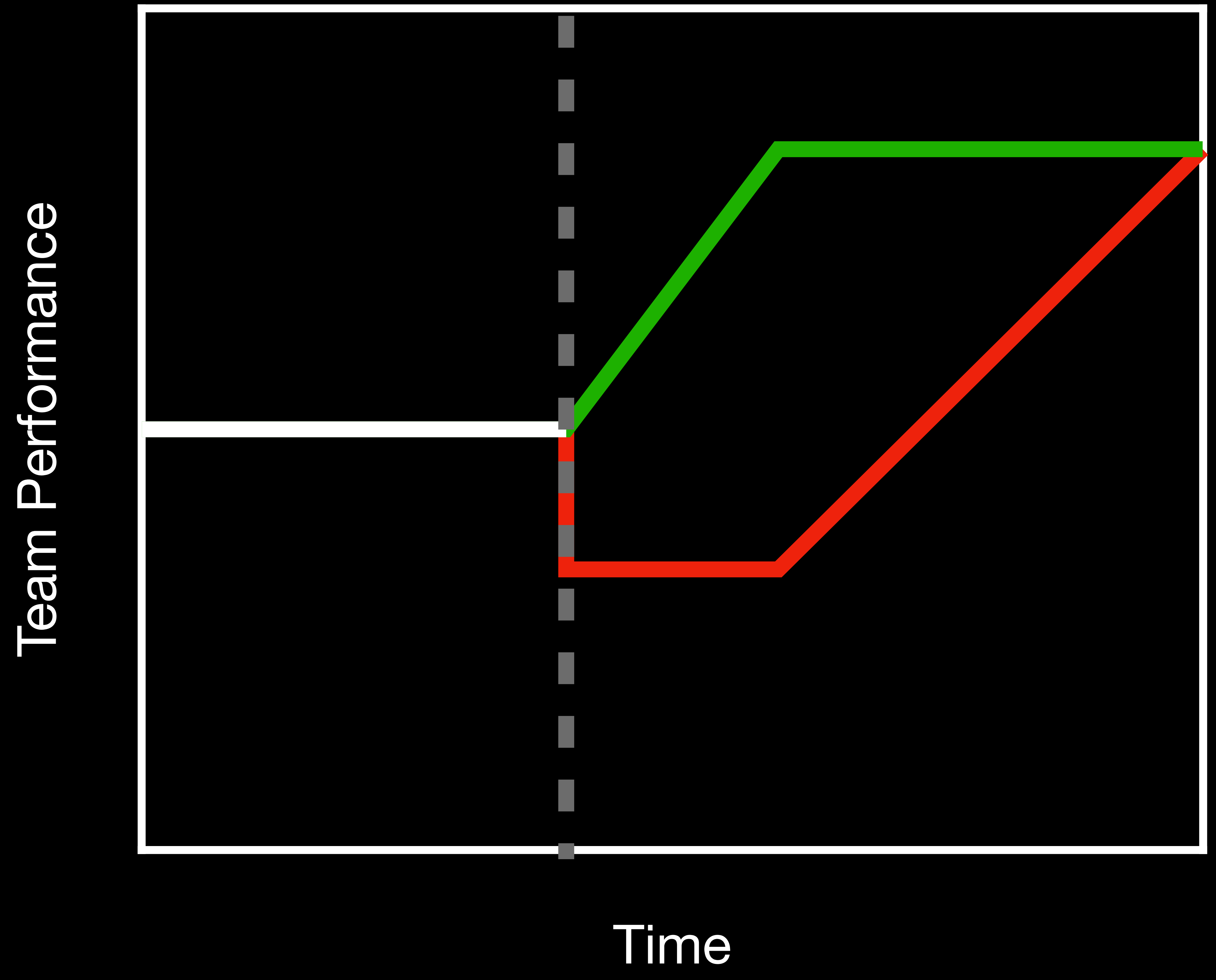


Team performance difference induced by compatibility

Affects physician users.
<u>Impacts patient lives.</u>

Why trade-off AUROC for C^R?



We should optimize for good team performance.

C^R is a new compatibility measure inspired by AUROC

Not threshold dependent: ↑ clinical utility

Has direct relationship with AUROC

Can balance AUROC and C^R

Using $\widetilde{\mathscr{L}^R}$ → ↑C^R & ↑AUROC

Real-world model updating case-study

eotles@umich.edu
@eotles

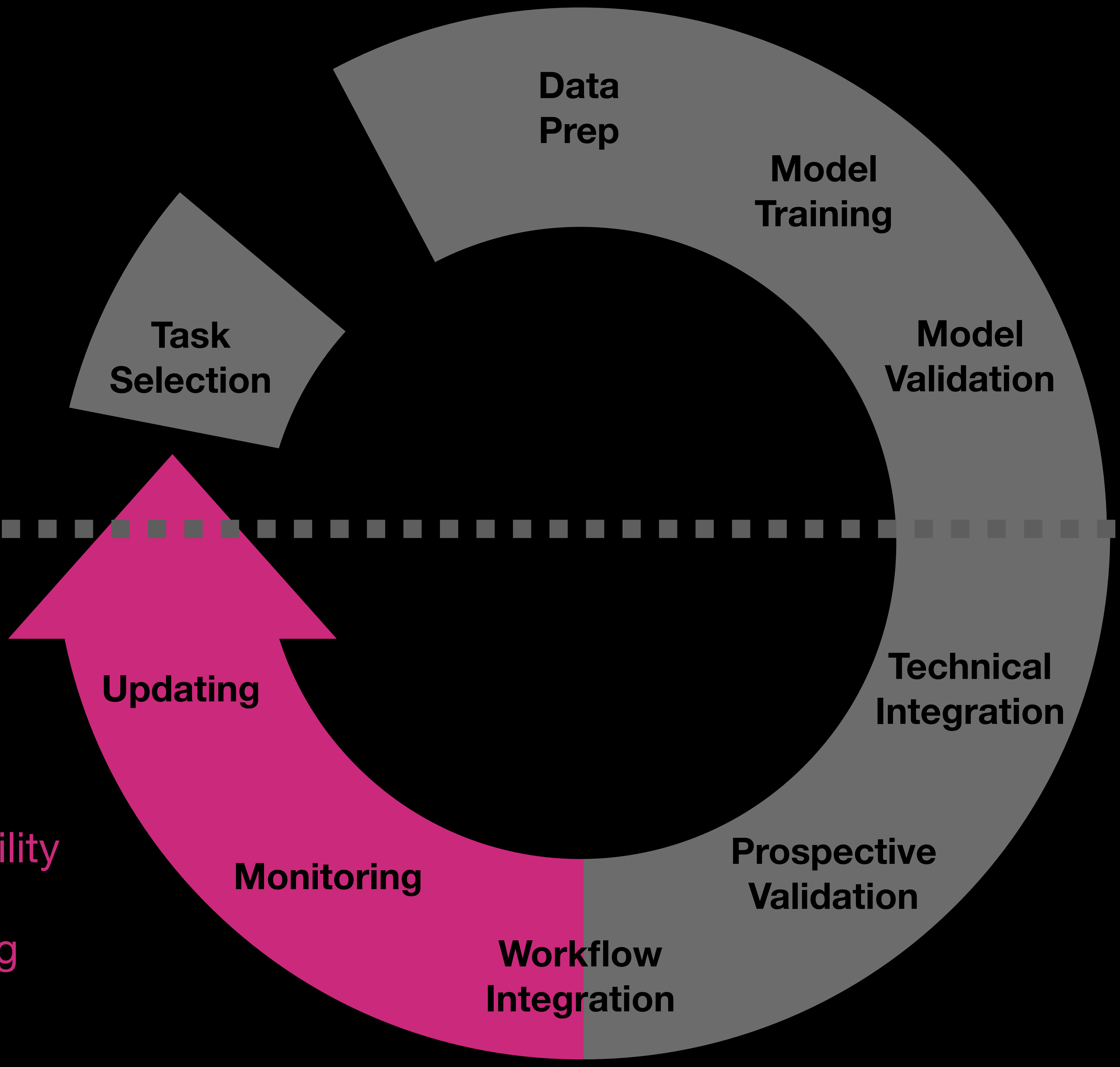
My work enables model developers to find these desirable updated risk stratification models.

Updated models may be assessed with our new rank-based compatibility measure.

Model developers may use our weighted loss function to create model updates with improved C^R.

Additionally, we present a real-world model updating case-study.

The ML Lifecycle



RTW Prediction

Assess value of longitudinal observations for return to work prediction

Ötleş *et al.*, JAMIA '22

Performance Gap

Characterize changes to prospective performance after model implementation

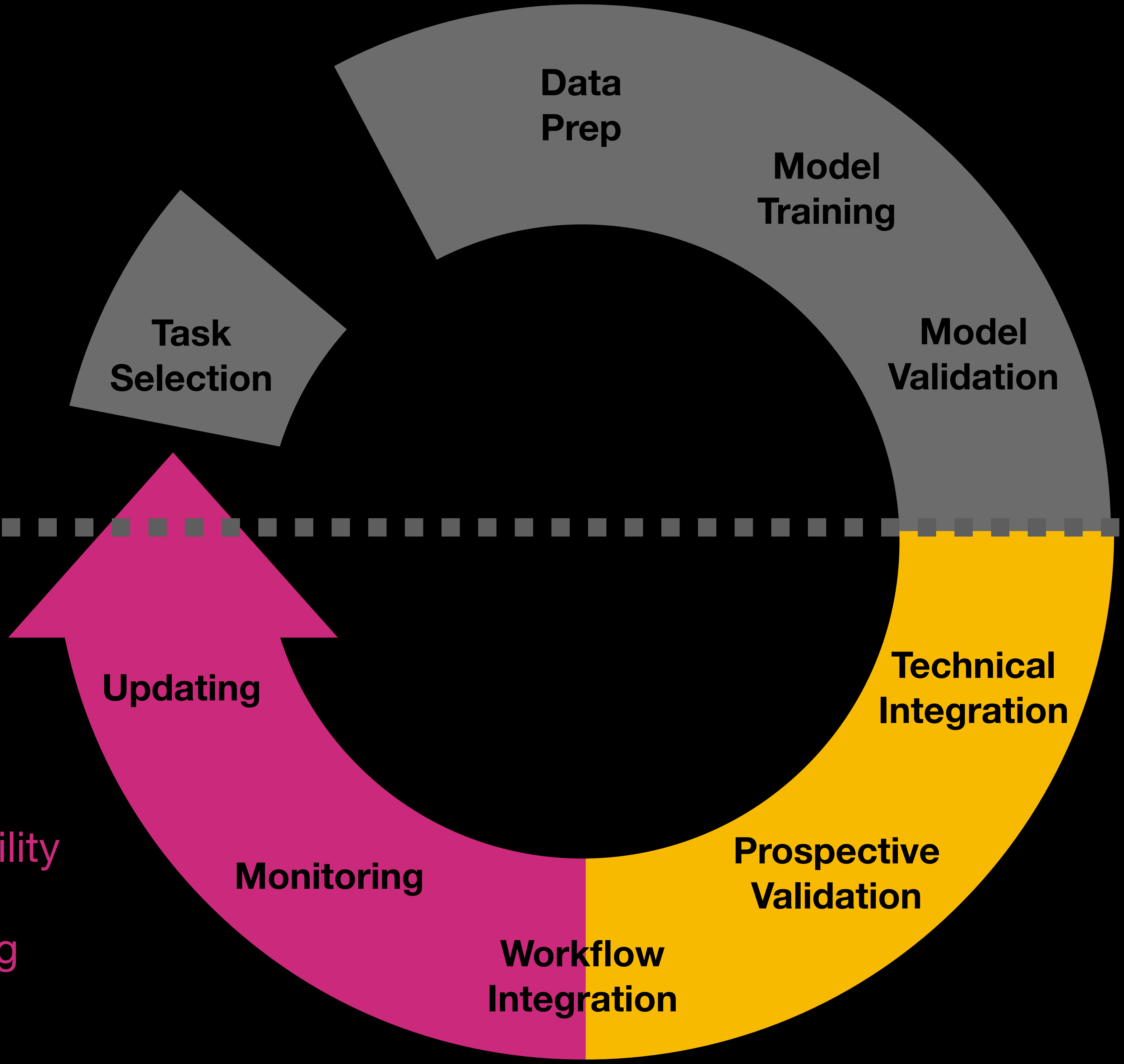
Ötleş *et al.*, MLHC '21

Updating Models

Develop rank-based compatibility measurement & optimization approaches for model updating

Ötleş *et al.*, MLHC '23

The ML Lifecycle



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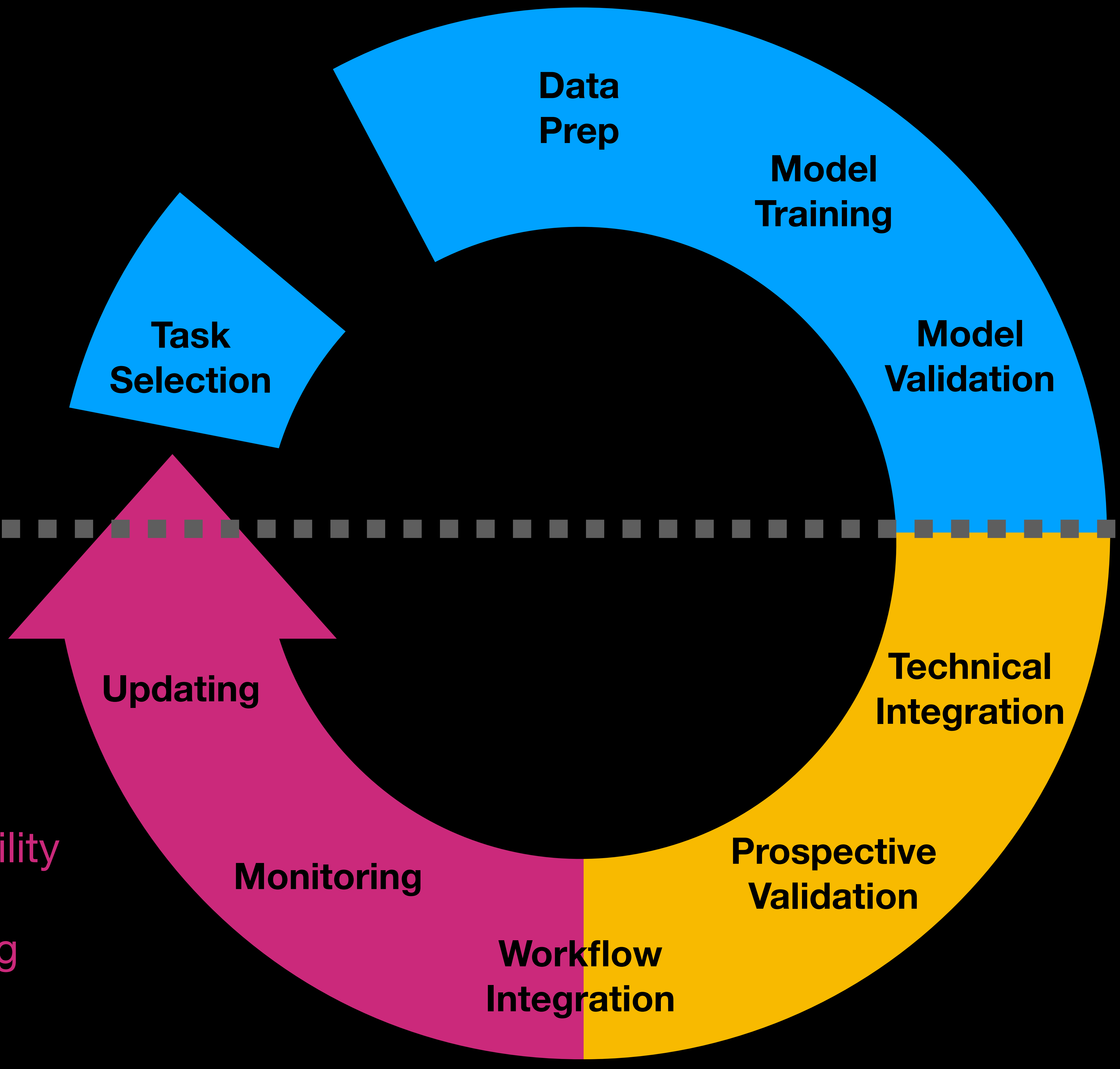
The ML Lifecycle



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Performance Gap

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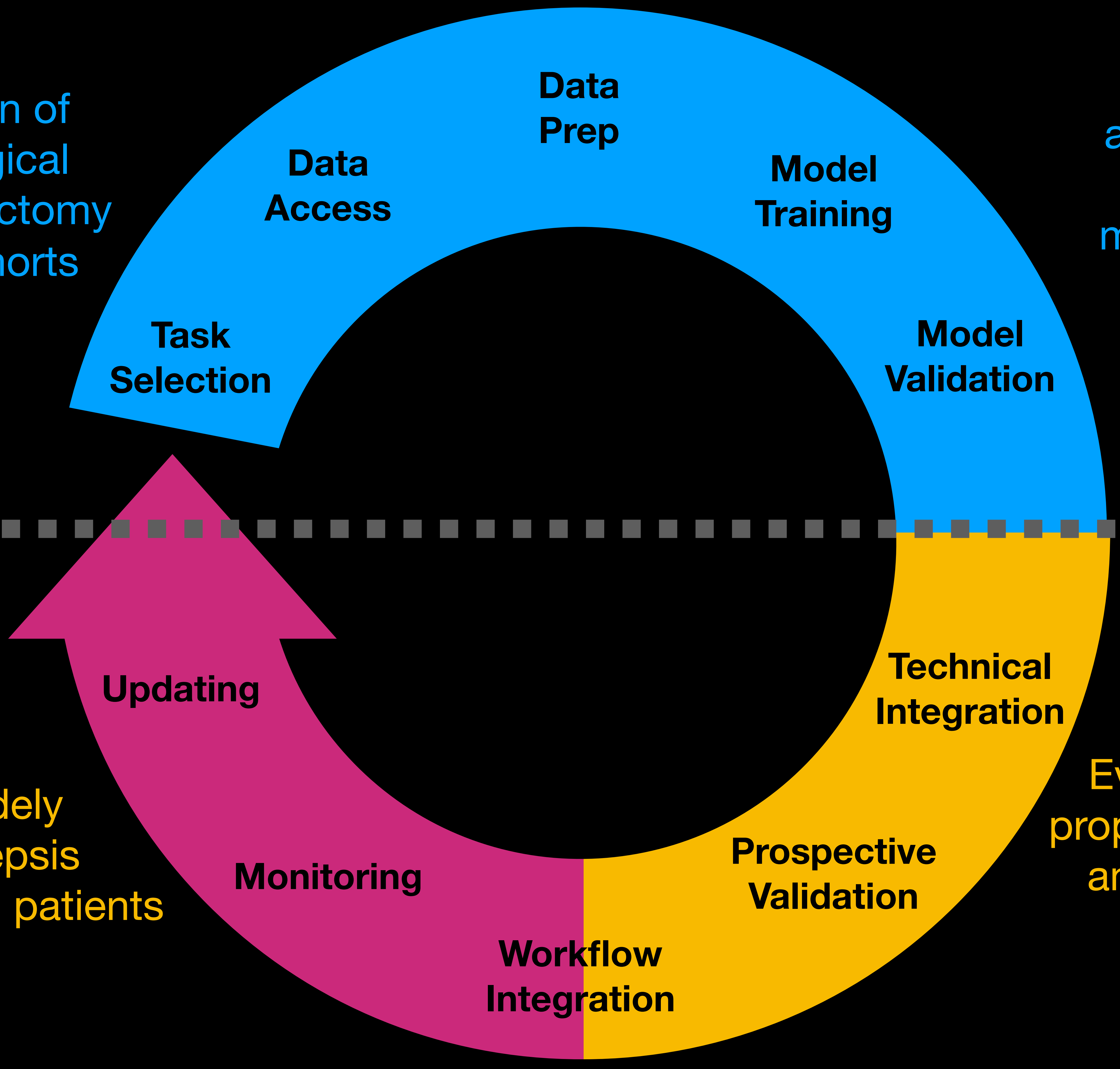
Ötleş *et al.*, MLHC '21

Other projects

Development and validation of models to predict pathological outcomes of radical prostatectomy in regional and national cohorts
Ötleş *et al.*, 2022

Early identification of patients admitted to hospital for covid-19 at risk of clinical deterioration: model development and multisite external validation study
Kamran *et al.*, 2022

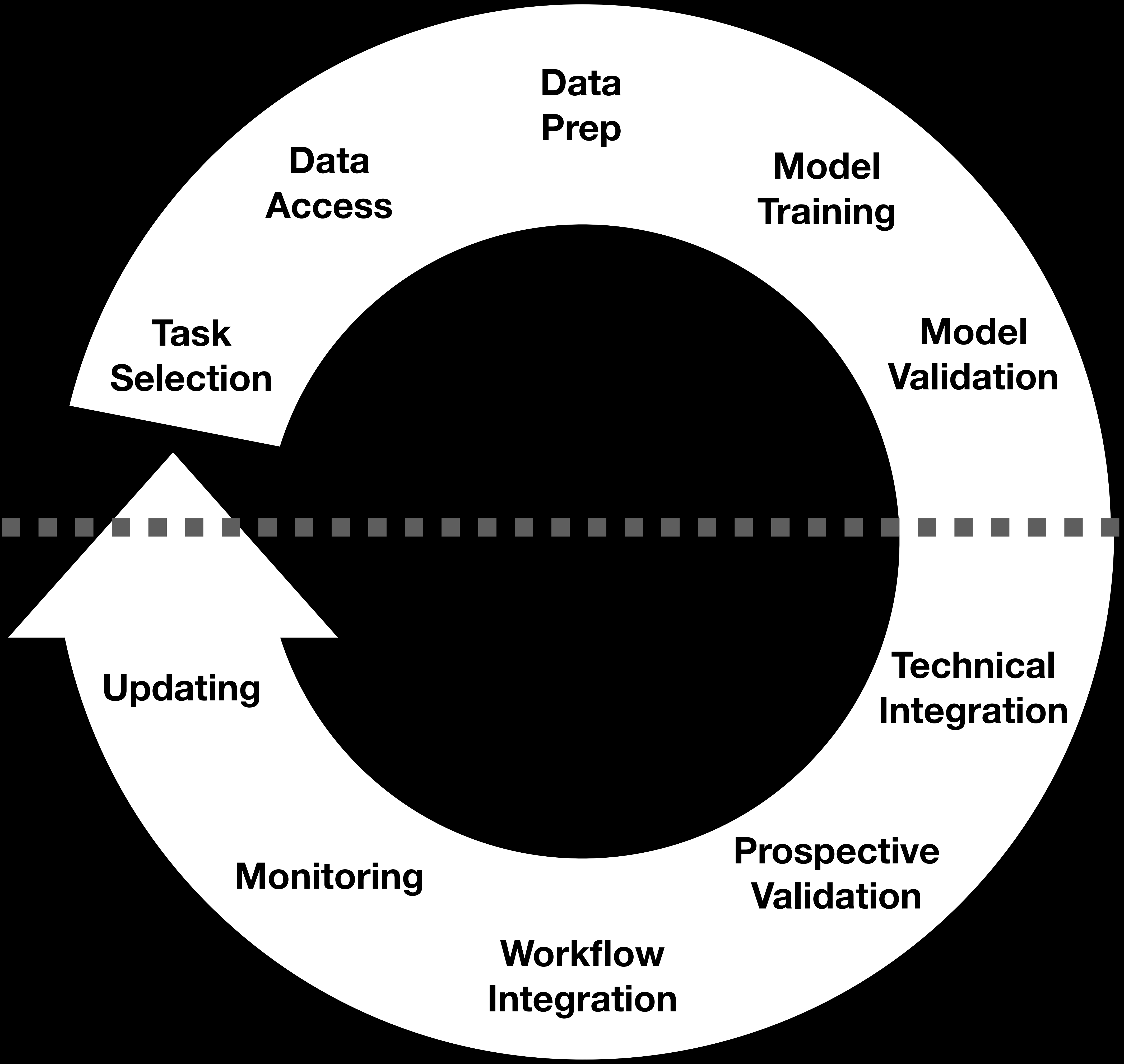


External validation of a widely implemented proprietary sepsis prediction model in hospitalized patients
Wong *et al.*, 2022

Evaluating a widely implemented proprietary deterioration index model among hospitalized patients with COVID-19
Singh *et al.*, 2021

Time plays a crucial role in the development and implementation of ML models used in healthcare.

Development



Implementation

Future directions

Developing models less sensitive to infrastructure shifts

Updating

- Personalized updating
- Understanding user preferences for model updating
- Updating models over time to ensure best team performance

Thesis: by focusing on the longitudinal nature of healthcare, we can improve the performance of predictive models during development & implementation.