Achieve Profit and Equity using Deep Learning

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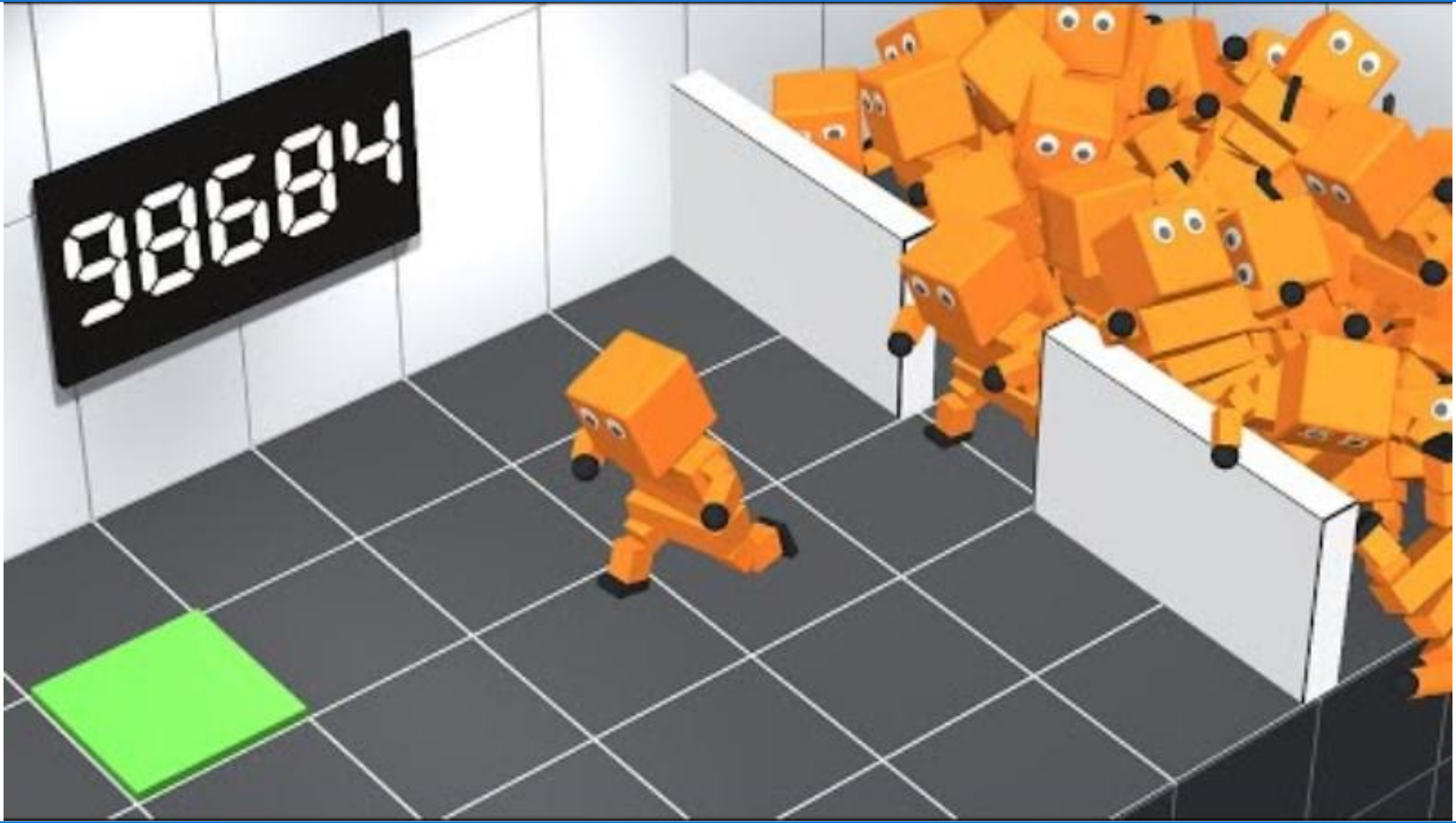
Purpose/Intro

Reinforcement Learning (RL) is a powerful technique for making decisions based on trial and error within an environment with rewards and penalties guiding the learning process. This presentation shows an example using RL in a toy environment with rewards based on increasing equity with a constraint of increasing pricing accuracy. Specifically, the agent decides proposed pricing factors based on the reward function.

Alterations to this setup are boundless and likely to improve performance based on the specific task at hand.

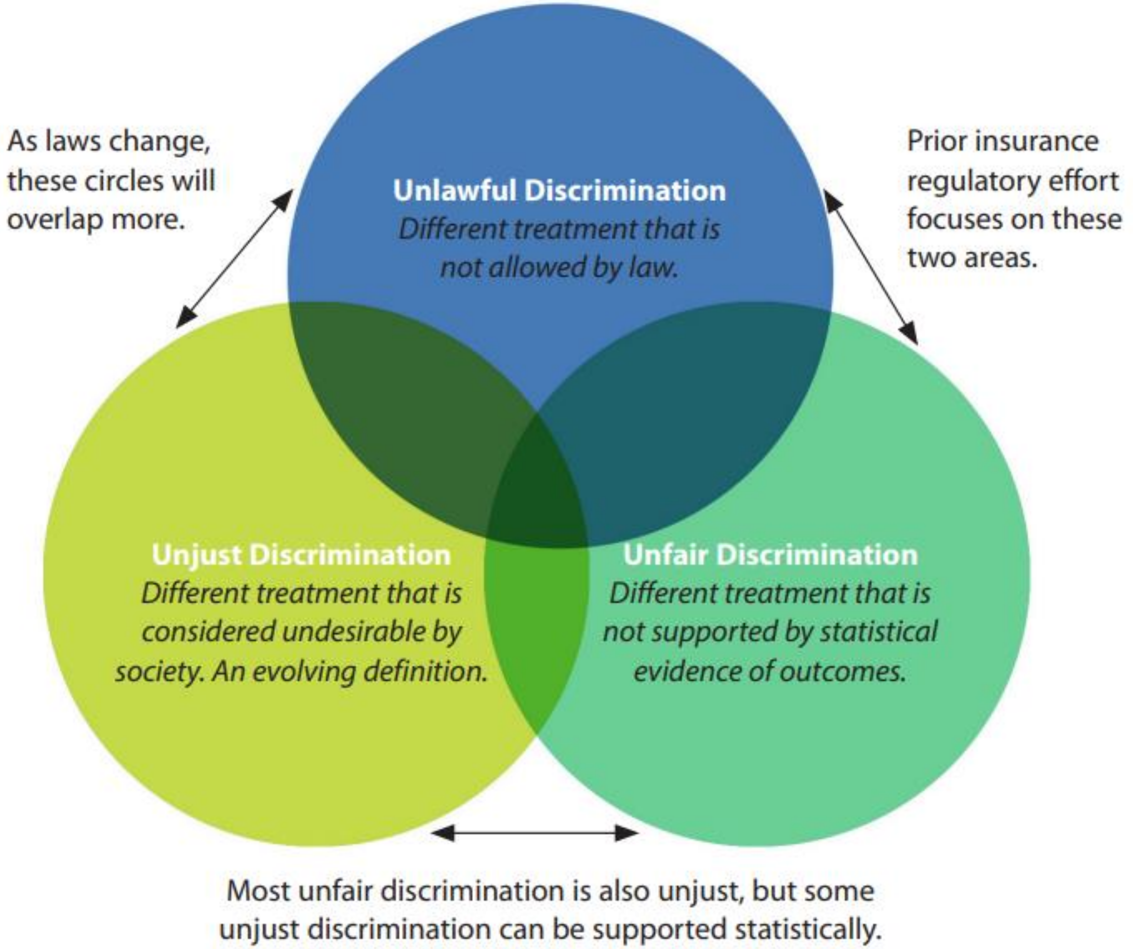
The philosophy of this presentation is to empower you to help drive more accurate decision making in your organization using this framework. We do not necessarily believe this exact algorithm and architecture will yield the best results for your specific use case. Consider this a broader research topic to inspire you to do more work on your own. RL is a broadly applicable method that may be preferable anytime a closed form solution is not easily achievable.

Example of RL



Defining Bias/Fairness

- Proxy discrimination (NCOIL)
  - intentional substitution of a neutral factor for a factor based on a protected class
- Disproportionate impact
  - higher or lower rates for a protected class, controlling for other distributional differences
- Disparate impact
  - three-part legal definition



Source: American Academy of Actuaries, February 2024 Issue Brief

Sources of bias

Data

Sampling - data is not representative of the population for which the model will be used

Correlation – data reflects correlations with protected classes, for example different distributions of

- Driving record
- Homeownership
- Age
- Address

Modeling

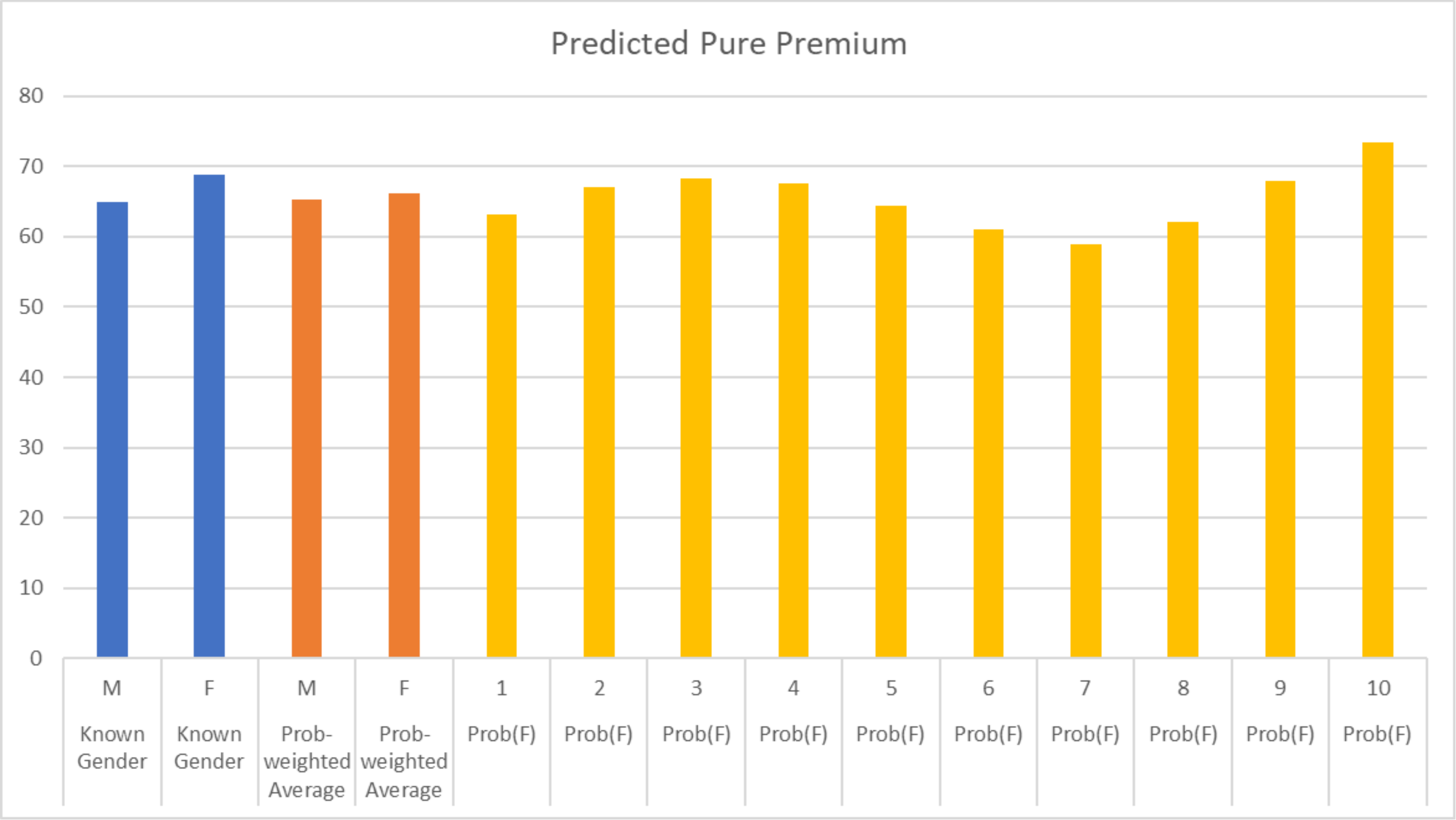
Confirmation bias – choosing data/model that is consistent with prior expectations

Availability bias – placing more reliance on data that is more readily or recently available

Source: American Academy of Actuaries, July 2023 Issue Brief, “An Actuarial View of Data Bias: Definitions, Impacts, and Considerations”

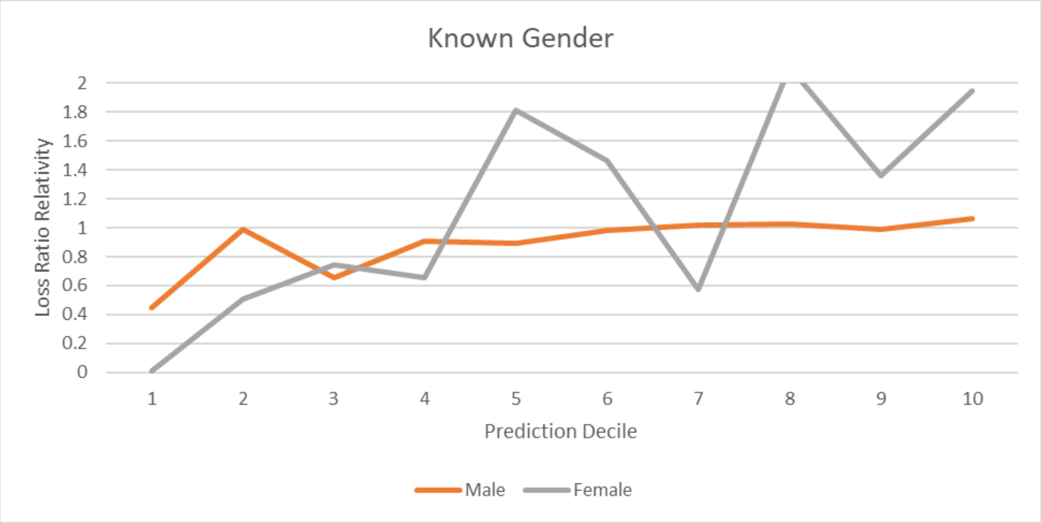
Bias metrics – demographic parity

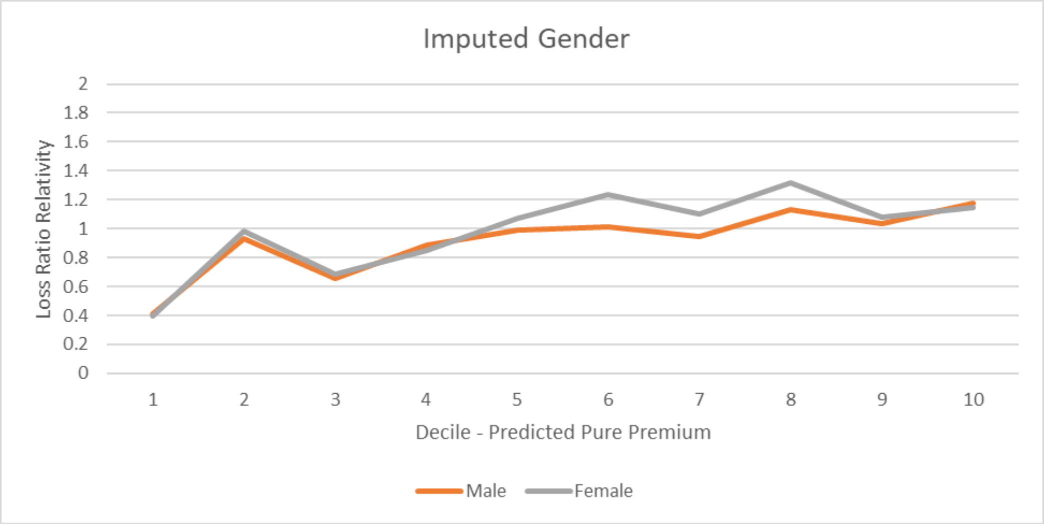
- Equal average premium by class
  - Also known as statistical parity or independence
- Conditional demographic parity
  - Average premium is the same after controlling on “legitimate” or “traditional” factors (see draft CO reg 3 CCR 702-10)

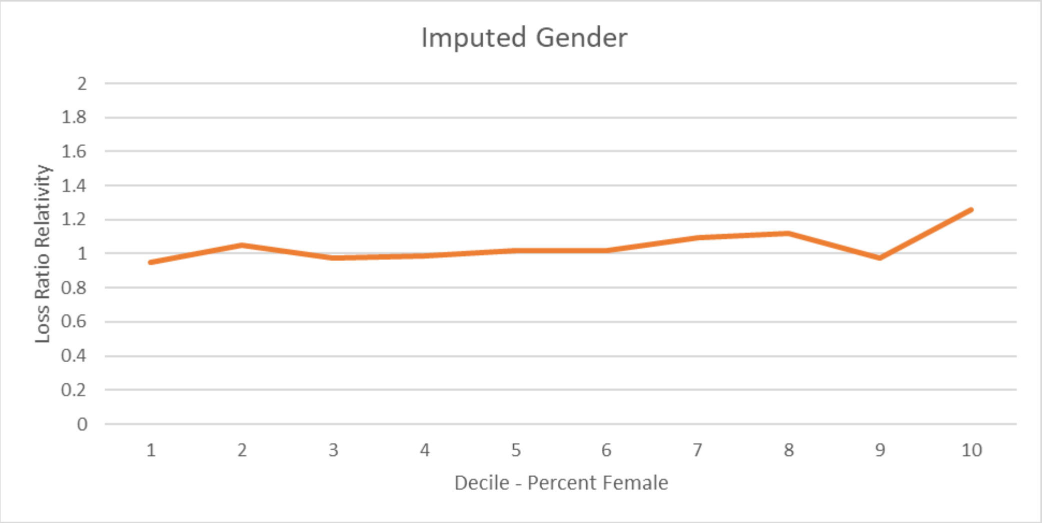


Bias metrics – predictive parity

- Equal loss ratios by class
  - Also known as sufficiency, loss ratio tests, or calibration tests







Bias metrics – proxy tests

		Driver Gender		
		excluded	known	imputed
Parameter	**Level**	**Estimate**	**Estimate**	**Estimate**
Intercept		7.9128	7.8830	7.8087
year	2010	-0.1922	-0.1963	-0.1877
year	2011	-0.4588	-0.4580	-0.4629
year	2012	-0.0356	-0.0474	-0.0351
year	2013	0.0000	0.0000	0.0000
vehicle_value		-0.0626	-0.0626	-0.0586
veh_val_q15		0.0688	0.0687	0.0650
veh_val_q35		-0.0259	-0.0250	-0.0252
driver_age		-0.0061	-0.0061	-0.0065
driver_gender	Female		0.2302	0.5019

- Principal component analysis to show which variables are similarly impacting results
- Include protected class in model and check for coefficient changes
- Nonparametric matching

Bias mitigation methods - examples

Pre-model

- Drop/prohibit certain rating variables
- Re-weight or re-sample data
- Transform predictors (e.g. orthogonalization, optimal transport)

In-model

- Add constraints to optimization objective
- Adversarial debiasing

Post-model

- Limit factor spread
- Use Pope-Sydnor predictor

Selecting a bias metric/mitigation approach

In their paper "Algorithmic Fairness: Contemporary Ideas in the Insurance Context," Dolman and Semenovich state it would be prudent to act in four related ways:

Create Internal Clarity

be clear on why we consider our actions to be fair and reasonable

Acknowledge Imperfections

acknowledge the inherent tradeoffs required

Be Adaptable

adapt any answer over time, particularly as the research environment matures

Act With Humility

commit to openly discuss views which may contradict our own, to rectify any issues as they are identified, and to adapt according to society's evolving norms

Technical Stuff

Technical work done for this presentation used the following:

- Python language in Jupyter Notebook
- Python package stable_baselines3
- Proximal Policy Optimization (PPO) algorithm
- CPU on a laptop; there is opportunity to use GPU and increase performance

RL terminology you need (imagine Albert in the video):

- Environment: the rooms he was placed into and the obstacles presented
- Action Space: the available choices to make (movement of his limbs and torso)
- Reward: when he hit the green squares, he was given a positive reward
- Penalty: adjustments to the reward to disincentivize undesired actions
- Agent: Albert is the agent
- Timestep: each action occurs sequentially, once per timestep

Process Overview

For our process, we have the following components:

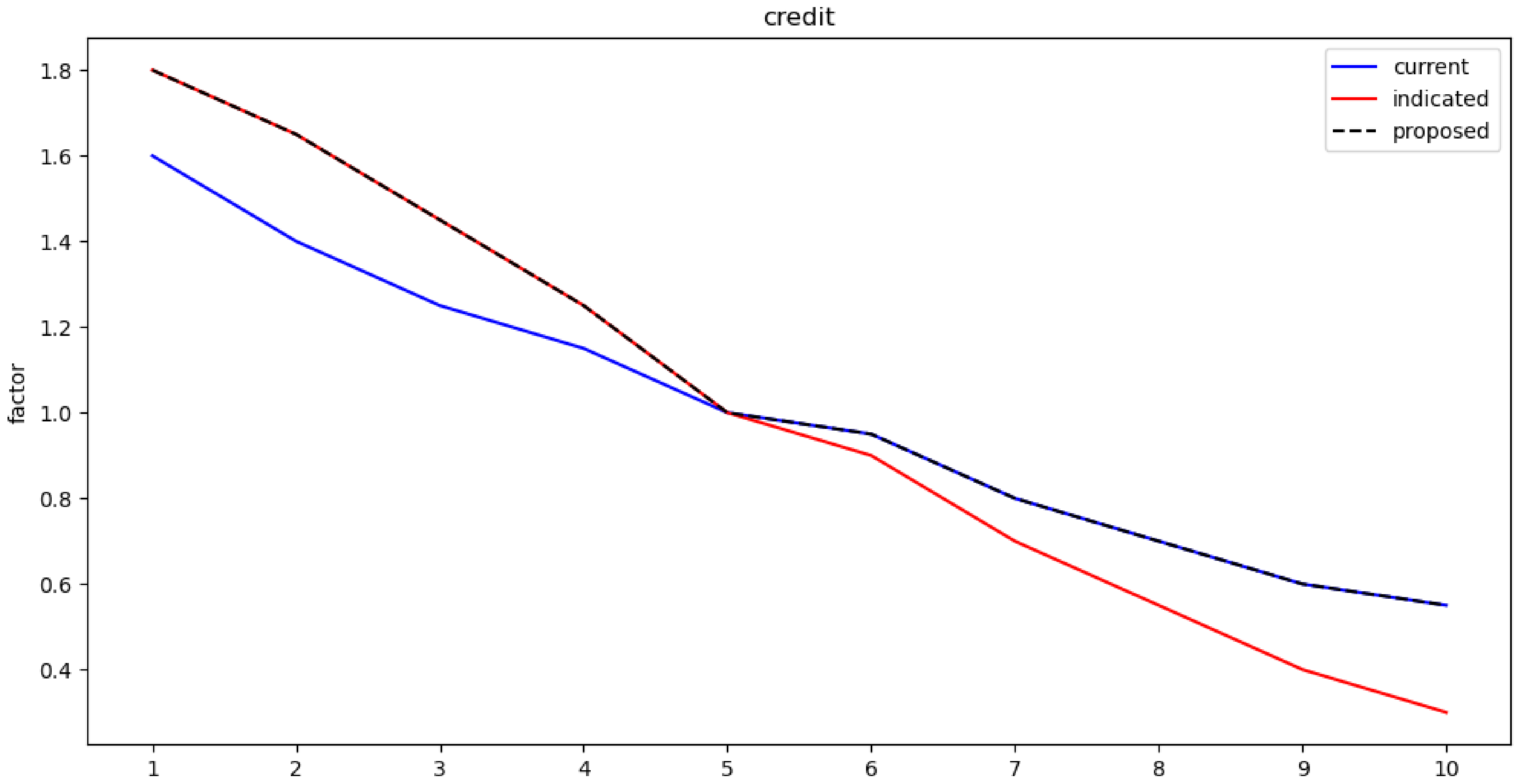
- Environment
  - In-Force book of policy characteristics & premium
  - Current and indicated pricing factors from pricing work (Credit, Age)
  - Inequity metric based on avg premium by % Black (derived from zip code data)
- Action Space
  - Selected pricing factors must be between current and indicated
- Reward Function
  - Reward function for each step is the incremental improvement in equity metric
- Penalty
  - If the pricing factor selected results in a worsening of the pricing accuracy, the reward is set to a large negative value.

For simplicity, our process assumes a single point in time. Accounting for future policy period expectations is trivial to add.

Unlike Albert, our agent doesn't need to generalize to other environments. We only need it to optimize the current environment. This makes our job much easier!

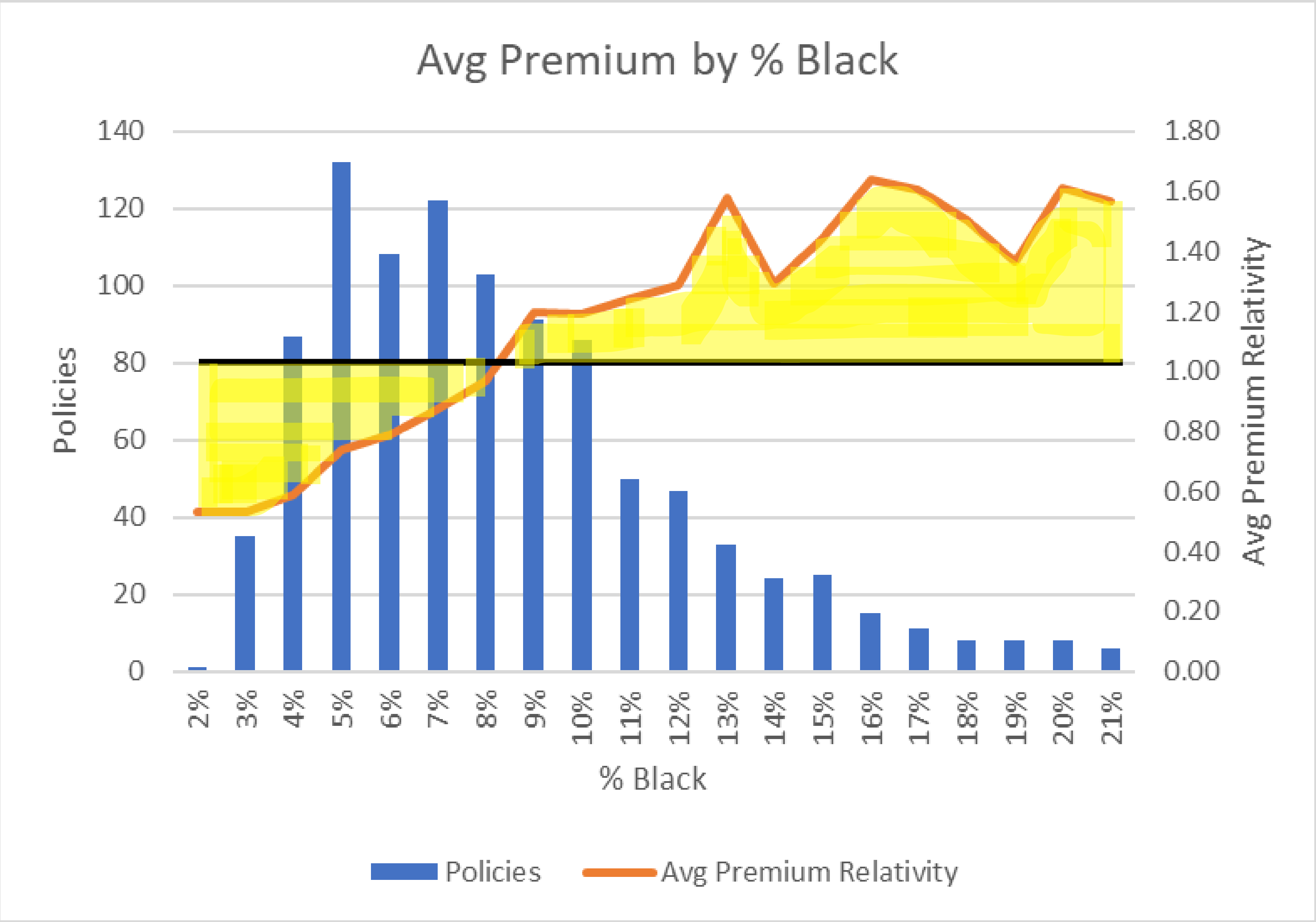
Baby Steps – Target UW Profit (different use case)

- Using target of UW profit for a single pricing factor, the agent does what UW and Sales think all actuaries do.
- We have probably all heard “A dollar of rate is better than a dollar of retention”.
- This naïve first step helps us to see that the agent learns in a very clear situation.



Inequity Metric

- We used % black which can be obtained from the U.S. Census Bureau by zip code
- Our inequity metric is the weighted average of the premium relativity difference from unity by % black, based on our own book.
- The absolute value of the highlighted yellow area represents the metric. We seek to minimize this.
- Our definition does not intend to imply what is "fair" or "equitable". It is one of many possible metrics to use. Determination of what is "fair" or "equitable" is beyond the scope of our work here.



Step 1 – Target Equity Setup & Expectation

- Instead using equity as our target, we expect a different result due to the distribution of our % Black by Credit.

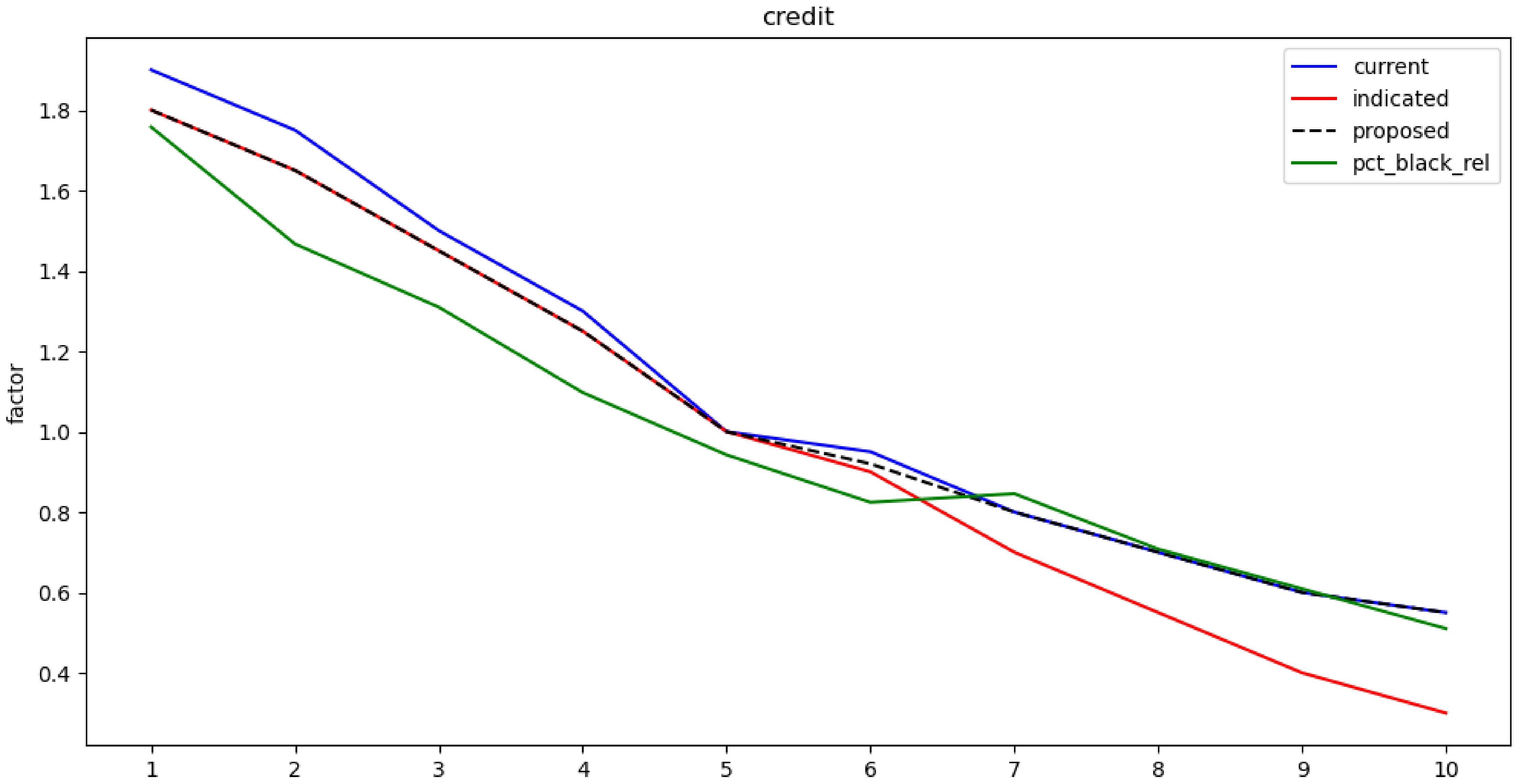
- We expect the agent to propose reductions to credit level 1-4 while leaving levels 6-10 unchanged.

credit	current	indicated
1	1.90	1.80
2	1.75	1.65
3	1.50	1.45
4	1.30	1.25
5	1.00	1.00
6	0.95	0.90
7	0.80	0.70
8	0.70	0.55
9	0.60	0.40
10	0.55	0.30

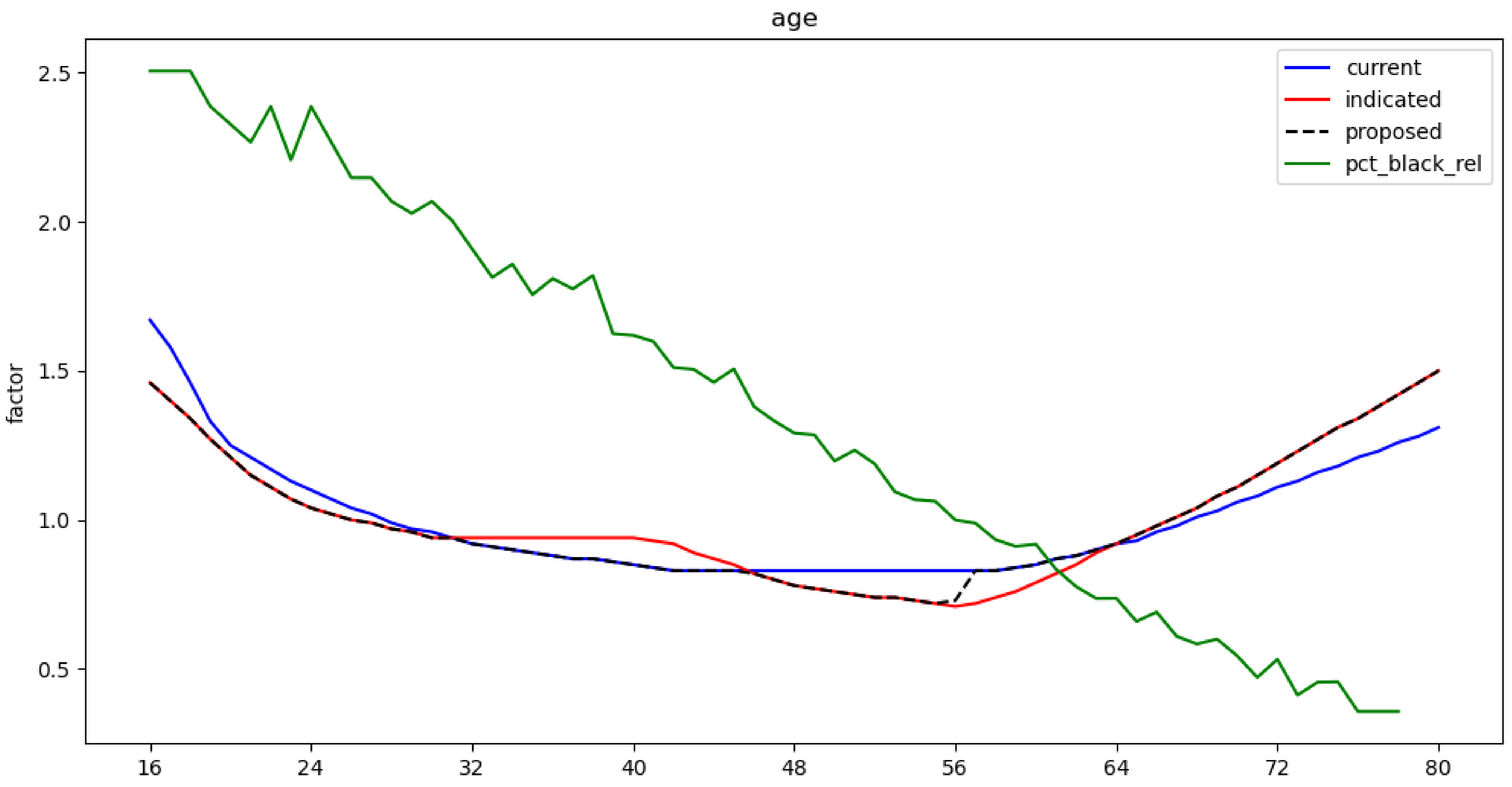
Credit	% Black
1	15.0%
2	12.8%
3	10.8%
4	8.9%
5	7.8%
6	6.7%
7	7.0%
8	6.1%
9	5.0%
10	4.1%
Grand Total	**8.4%**

% Black by credit guided by FTC study, cited on citations slide

Step 1 – Credit Factor; Success



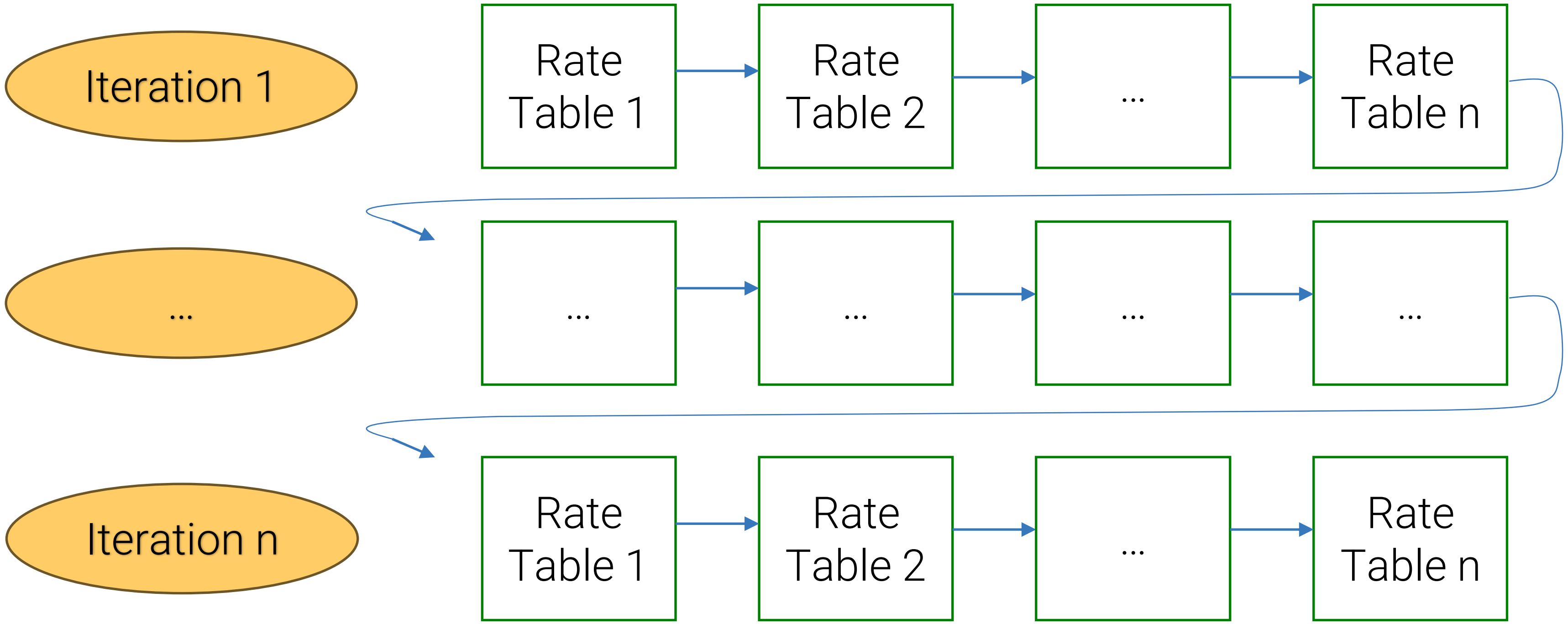
Step 2 – Age Factor



Process Flow

This toy example is pretty simple. There are pricing factors for credit based insurance score decile and policyholder age. The agent optimizes one pricing factor at a time. We can run multiple iterations so that interactions between the pricing factor curves can be worked out iteratively.

1 iteration was run here – the diagram serves as theory for more complicated use cases.



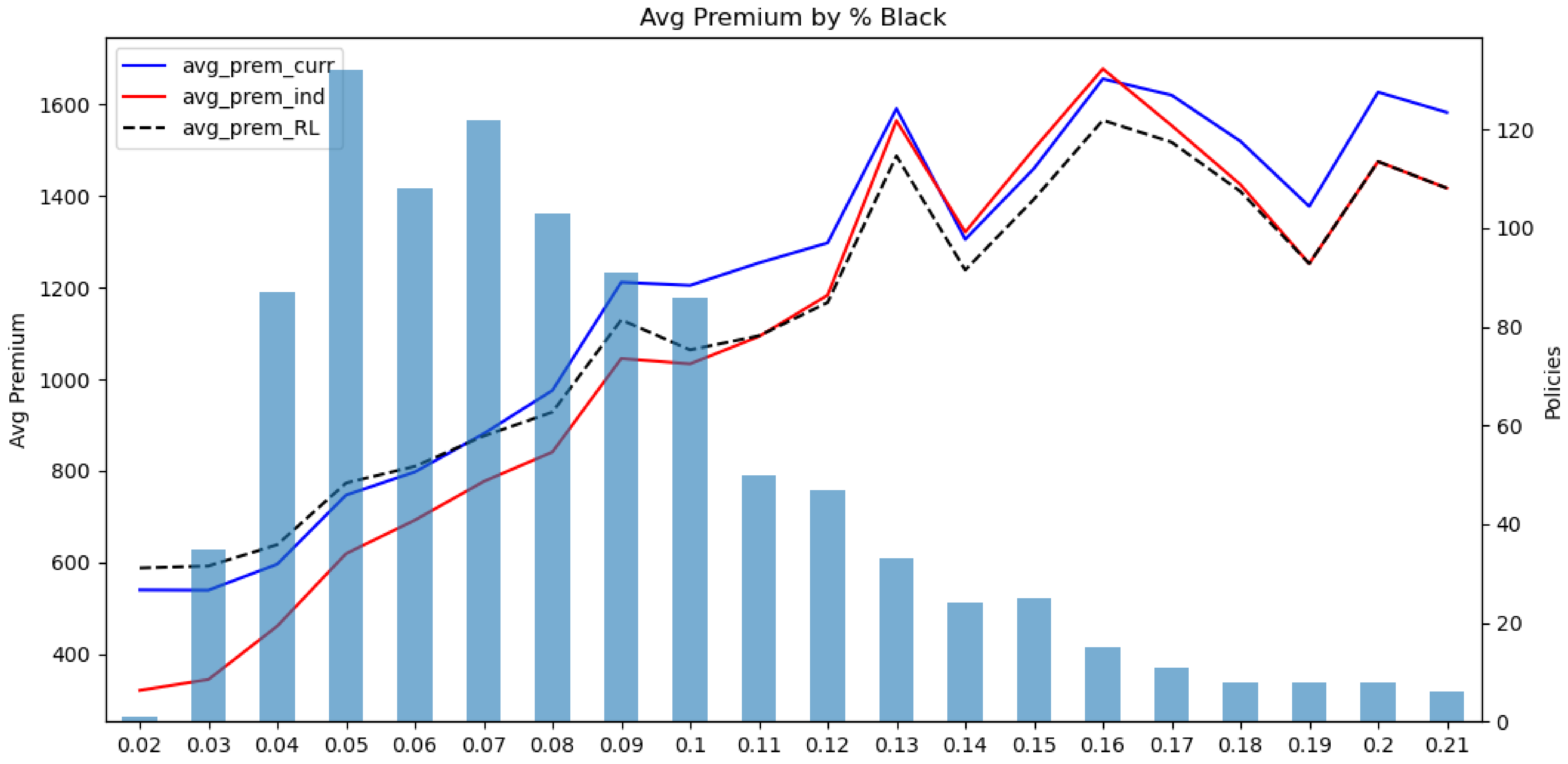
Process Notes & Results

- The reward function is an all-purpose metric which can account for “everything”. Whatever you want to include, it essentially comes down to the agent evaluating the results of a dislocation given the actions it chooses at each timestep.

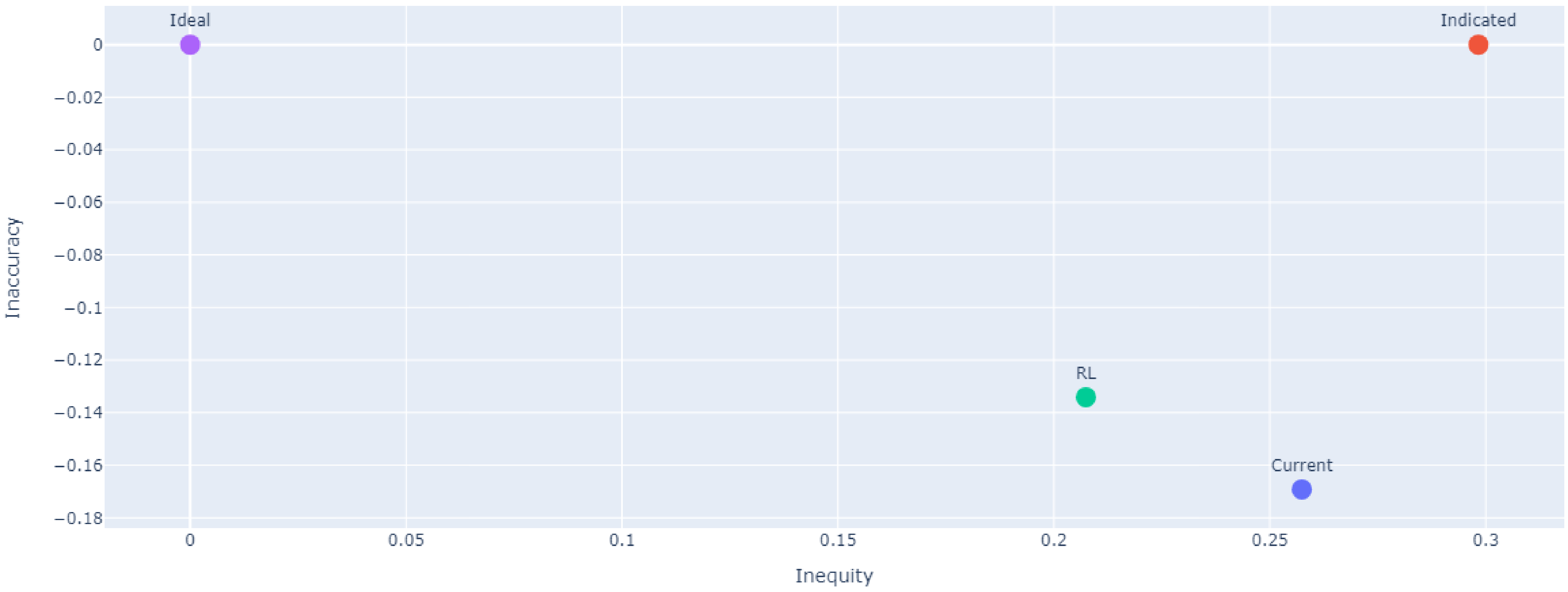
- Penalties are applied within the reward function based on whatever actions need to be avoided for the task at hand.

- The following slides show the results of the process.

Avg Premium by % Black



Inequity vs Inaccuracy



Conclusions

- The process shown here can be used to help guide business decisions around pricing factors to move toward equitable outcomes. Choice of equity/fairness metric(s) is open to expansion.

- There are many other frameworks for bias mitigation. This is another option for you to consider.

- This is a general framework that may be applied to other purposes as you see fit. RL is a powerful tool with many existing and future applications.

- Code and toy data is available here: https://github.com/RuthlessActuary2023

Questions?

Citations

- % Black by credit was guided by the following study:
https://www.ftc.gov/sites/default/files/documents/reports/credit-based-insurance-scores-impacts-consumers-automobile-insurance-report-congress-federal-trade/p044804facta_report_credit-based_insurance_scores.pdf?WT.qs_osrc=fxb-184546610

- American Academy of Actuaries, “Discrimination: Considerations for Machine Learning, AI Models, and Underlying Data”.
https://www.actuary.org/sites/default/files/2023-08/risk-brief-discrimination.pdf

- American Academy of Actuaries, “An Actuarial View of Data Bias: Definitions, Impacts, and Considerations”.
https://www.actuary.org/sites/default/files/2023-07/risk_brief_data_bias.pdf

- American Academy of Actuaries, “Approaches to Identify and/or Mitigation Bias in Property and Casualty Insurance”.
https://www.actuary.org/sites/default/files/2023-02/CPCdataBiasIB.2.23_0.pdf

- Dolman and Semenvich, “Algorithmic Fairness: Contemporary Ideas in the Insurance Context”.
https://www.actuaries.org.uk/system/files/field/document/B9_Chris%20Dolman.pdf