Long-term dynamics of data-driven targeted support for job seekers

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1 Introduction

Research question: Assume we have a population of individuals, where the prospect on the labor market of each individual is controlled by the personal skill of that individual, described by a set of independent skill features. Additionally, each individual belongs to one of two groups, described by a protected attribute (e.g. gender). The average skill between the two groups is not the same, but still there is significant overlap between the groups. If an observer has knowledge about all skill features of an individual, they can with 100% accuracy compute the total skill of that individual, and knowledge about the protected attribute (i.e. which group the individual belongs to) does not yield any additional information with regard to the individual skill. We assume that the labor market (e.g. recruiters) do have access to all skill features, and thus make their decisions solely on the real personal skill of the individuals, as for them there is no additional information in the protected attribute.

We further assume that there is a public authority that helps individuals in improving their skill on the labor market, which we will call the Public Employment Service (PES). The improvement of the skill of the individuals by the PES is done with individualized services, based on the current skill on the labor market of that individual. Critically, however, this public authority does not have access to all skill features, but only to a subset. In addition, it has knowledge about the protected attribute. Since the total skill is not evenly distributed across the two groups, the knowledge of which of the protected groups the individuals belongs combined with historical data gives probabilistic information on the real skill: if the individual belongs to the group that has on average higher skill, the likelihood that this individual has high skill is larger than if it would belong the the other group, even if everything else remains the same. This additional information however has two potential problems: 1) it is only probabilistic and the resulting predictions are only accurate *on average*, and 2) it is based on a protected attribute - therefore, legal and/or ethical reasons might prohibit utilizing that information, as it results in different treatments based solely on the protected attribute.

The goal of this study is to investigate the long-term effects on the population if a public authority provides targeted help, based partly on protected attributes.

Does such targeted help reduce or strengthen existing group-inequalities? What is the long-term effect on general employment? What is the long-term effect on employment in each group? How does this compare to a system that is *not* using the protected attribute? Are there trade-offs between the - ethically problematic - inclusion of protected attributes in the targeting versus the global goal of high employment?

To address these questions, we use a combination of dynamical numerical modeling and statistics/machine-learning. We use synthetic data and an individual skill model that is as simple as possible while being just sophisticated enough to reflect inequalities and the possibility of having either full of only part knowledge of the skill of an individual.

Additionally, we make - admittedly simplistic - assumptions on the labor market.

We develop and use two different overall models: the first model is a simple model that has a fixed population, whose increase of skill over time is influenced by the PES. The targeting of the PES is again influenced by the past mean skill of the two groups, and this past-skill is updated over time as the population changes. This model is generic and abstract, and could also be interpreted for example as a model for targeted education, and labor market dynamics are only included in a very abstract way. Still, this model is interesting, as it is easy to follow and allows to test our intuition, and already captures the basic dynamics over time.

The second model is more complex and considers a pool of job-seekers. This pool has an influx and an outflux, and considers not only the abstract skill of an individual, but additionally the time an individual needs to find a job. This is more related to actual job-markets.

A central aspect of this study is that we consider different scenarios of the PES and how it distributes its resources across individuals with different skills.

What this study is not: This study is not a real-world assessment of any real world public employment service or similar institutions.

- Things to add:
- efficiency argument, we assume there is only a certain amount of help or support available, and the PES wants to distribute in efficiently (whereas "efficient" needs to be defined), this is the goal of the EPS
- combination of statistics/ML and system dynamics
- implicit assumption: in our model there is in principle no shortage of jobs. If people have high enough skill, they will get a job. So one can say that there are enough jobs for the number of people, but not necessary for their skill-level

1.1 Literature overview

literature on AMS algorithm

literature on fairness in general
debiasing

[3] showed that simulation studies can be used to study fairness issues in changing systems, and that the results ("fair" or "not fair" with repsect to a certain definition of fairness) can differ from a static analysis. They analyzed simple settings of credit-scoring for loans, attention allocation for different sites, and college admissions.

We use the concept of "labor-market-models" in a way that is very targeted towards our research question, and it should not be confused with labor market models from economics, which usually are used to study supply and demand of labor ([4]).

References

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2 Methods

2.1 Personal skill model and data generation

The basis of this study is the following setting: we have a population of N individuals. Each individual has a personal skill s_{real} that is composed of two independent skill-features x_1 and x_2.

$$s_{real} = \frac{1}{2}\left(x_1 + x_2\right) \tag{1}$$

We call it "real" because we will differentiate it from observed and from predicted/assumed skill and from the skill that the labor market ("recruiters") assigns to the inviduals later on.

In addition, each individual has a binary protected attribute x_{pr} that can have values of 0 and 1. In reality this could for example be gender, but here it is used in an abstract way. Central here is that the definition if s_{real} does not contain x_{pr}.

We draw x_1 and x_2 from truncated normal distributions. Normal distributions because personal features such as "talent" are usually assumed to be normally distributed (e.g. [1]). A truncated normal distribution is used instead of an untrancated one to ensure that no one has x_1 and/or x_2 higher than the maximum reachable values in the intervention model (see section 2.2.3).

Further we assume that x_1 is completely independent of x_{pr}, but x_2 is correlated with x_{pr}.

$$x_{1=}\sigma_{trunc}\left(0, 1\right) \tag{2}$$

$$x_{pr} = [0, 1] \tag{3}$$

For generating our artificial population, we draw x_1 from a truncated normal distribution, and x_{pr} from the binary distribution $[0, 1]$ with uniform probability.

Thus, the probability of an individual belonging to a particular group (with respect to the protected attribute) is 50% for both groups, and both groups are therefore of equal or near equal size.

The second skill feature, x_2, is generated with the following formula

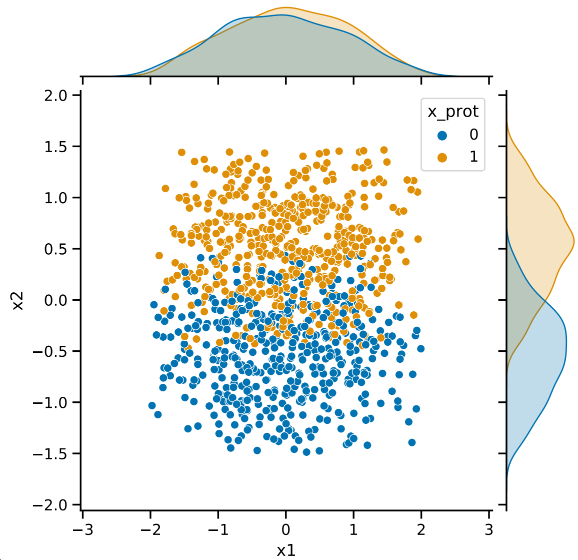
$$x_2 = \frac{1}{2}\left(\alpha_{pr} \cdot \left(x_{pr} - \frac{1}{2}\right) + \sigma_{trunc}\left(0, 1\right)\right) \tag{4}$$

the factor $\frac{1}{2}$is subtracted from x_{pr} to ensure that x_2 has a mean of zero. When x_2 is generated this way, then individuals in group 0 have *on average* lower x_2, and therefore on average lower s_{real}. To reflect this, we will from now on call the group with individuals with $x_{pr} = 0$ the *underprivileged group,* and individuals with $x_{pr} = 1$ the *privileged group.* Importantly, however, not all individuals in the underprivileged group have low x_2 and low s_{real}. There are individuals in the privileged group that have lower skill than some individuals in the underprivileged group, and there are individuals in the underprivileged group that have a skill that is above the population mean. The joint distribution of x_1 and x_2 and the distribution of s_{real} of the initial population is shown in fig. 1.

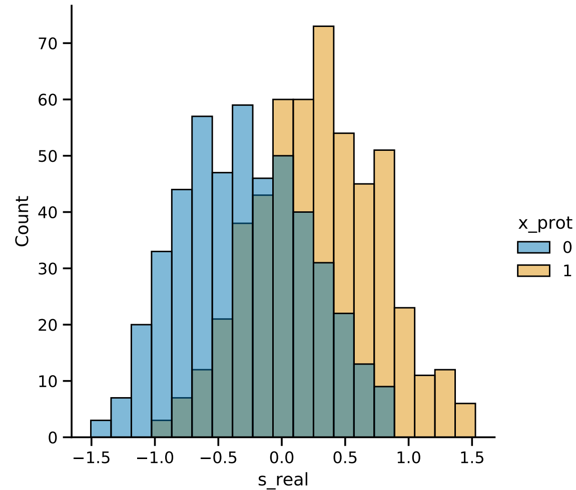
From the way x_1 x_2 are generated and the fact that, s_{real} per definition (e.q. (1)) can be completely inferred from x_1 and x_2 follow two central facts: given x_1 and x_2, there is no additional information contained in x_{pr} when one wants to infer s_{real}. If, however, one has 1) only access to x_1 and at the same time 2) information on the distribution of s_{real} over the two groups (e.g. the mean of s_{real} seperately for each group), and one wants to infer s_{real}, then including x_{pr} in addition to x_1 in a statistical prediction system yields additional information, even though s_{real} is completely defined by x_1 and x_2. This will form the backbone of our study.

2.2 Simple dynamical model

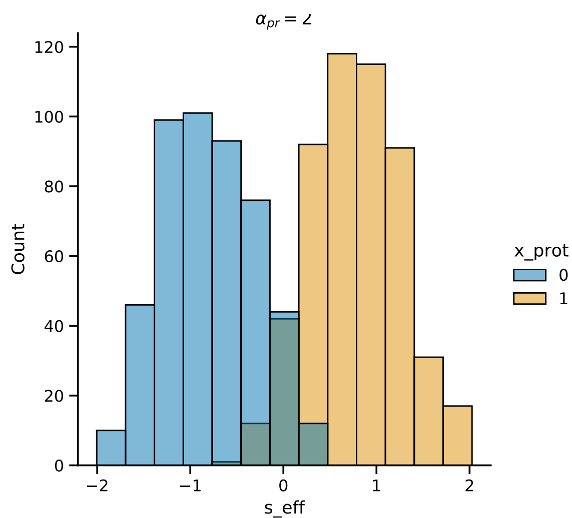
The simple model assumes that the population is made up of a fixed pool of individuals, without any in- or outflux. The job-market and individual employment is modeled in very abstract and indirect way. The simple model is depicted in fig. 2.



a)



b)



b)

Fig. 1: Initial population. a) distribution of the two skill features, b) distribution of real, c) distribution of effective skill (section 2.2.1) for the biased ($\alpha_{lb} = 0$) labor market, all split up according to the binary protected attribute

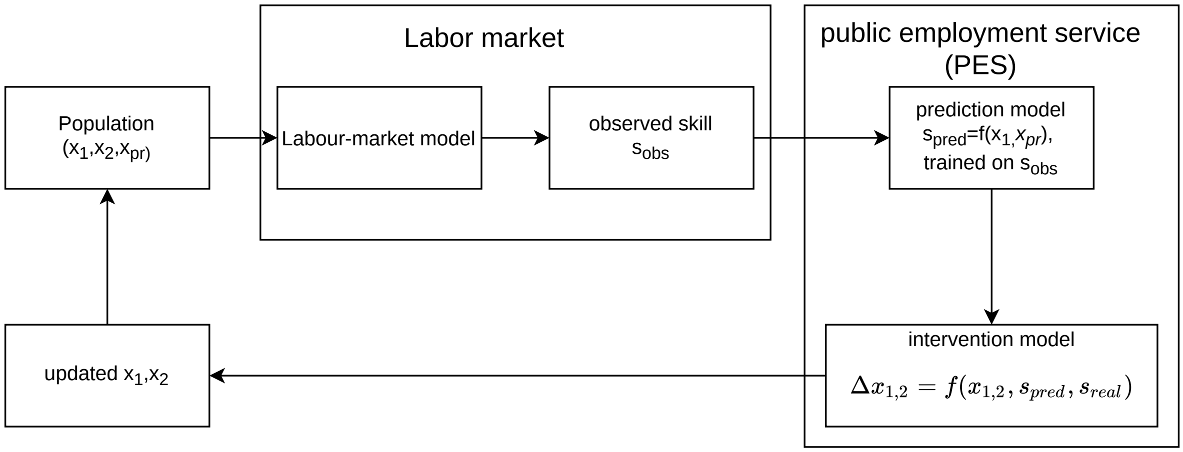


Fig. 2: Sketch of the simple dynamical model

2.2.1 labor market model

We use two different definitions of the labor market: a biased, and and biased one. Each ones assigns an effective skill . In the unbiased model labor-market prospect is simply the skill s_{real}:

$$x_{eff} = x_{real} \tag{5}$$

, thus the labor market has oracle-access to the real skill and does not alter it in any way. Note that this makes the - quite unrealistic - assumption that the labor-market 1) has perfect information on the skill of individuals and 2) is discrimination free in terms of individual fairness (individuals are not treated differently based on their protected attribute). It is important to point out that this labor market is *not* discrimination free under definitions of fairness based on group-fairness: as the labor-market does not even have access to the protected attribute, it can by definition not ensure group-fairness constraints, such as requiring that from each group the same fraction of people is hired, which in this abstract model would mean that the computation of s_{real} would need to be modified to ensure that each group has the same mean skill.

For the biased labor market model, the effective skill is partly dependent on x_{pr}:

$$x_{eff} = \begin{cases} x_{real} + \alpha_{lb} & x_{pr} = 1 \\ x_{real} - \alpha_{lb} & x_{pr} = 0 \end{cases} \tag{6}$$

For the unprivileged group the skill is made smaller due to the bias, and for the privileged group larger, by the same bias-parameter α_{lb}.

2.2.2 Prediction model

The prediction model is the statistical model used by the hypothetical PES. It is used to predict the labor-market prospects of an individual. In this abstract setting the labor-market prospect is, as mentioned above, s_{real}. The prediction model classifies individuals on having below or above average s_{real}. In a real setting this would be estimated from historical data (potentially updated from time time, or at each timestep). Here it is estimated from the current distribution of s_{real} over the two population groups.

As mentioned before, the basis of this study is that the PES has access to an incomplete set of skill-features only, namely solely to x_1, and additionally access to x_{pr}. To estimate (predict) the prospect class (above or below average s_{real}) from this, logistic regression is used to create the main (full) prediction model:

$$P\left(s_{real} > \gamma | x_1\right) = \frac{1}{1 + e^{-\left(\alpha_1 x_1 + \alpha_2 x_{pr} + \beta\right)}} \tag{7}$$

whereas the parameters α_1, α_2 and β are estimated from the current population, and γ is the threshold set for dividing the low and the high prospect class.

Additionally, we use a second prediction model - which we will call the *base model* - that does not use x_{pr}

$$P\left(s_{real} > \gamma | x_1\right) = \frac{1}{1 + e^{-\left(\alpha_1 x_1 + \beta\right)}} \tag{8}$$

Per definition of the data generation process, this base model has lower accuracy than the full prediction model.

In the initial timestep, γ is set to the mean of s_{real}, which equals to zero by definition of how the data is generated. For the following timesteps, we use two different strategies in the experiments: 1) *constant* γ, thus the threshold between the low and the high prospect class does not change, and 2) *adaptive*, where γ is set to the population-mean of s_{real} at each timestep.

2.2.3 Intervention Model

The intervention model describes the effect that the PES has on the individuals. For the simple model, we define the support that the PES provides in a single timestep as a change in the individual skill features x_1 and x_2 of an individual. We make the change dependent on the current value, with decreasing increments as the skill feature grows, approaching the limits set by the constants x_1^{max} and x_2^{max}:

$$x_1^{t+1} = max\left(x_1^t + k_1\left(x_1^{max} - x_1^t\right), x_1^t\right) \tag{9}$$

$$x_2^{t+1} = max\left(x_2^t + k_2\left(x_2^{max} - x_2^t\right), x_2^t\right) \tag{10}$$

The model parameters k_1 and k_2 define how fast x_1 and x_2 grow. For simplification, we set $k = k_1 = k_2$,and thus both skill features have the same growth rate. The value of k is central to our study, as it defines how heavily the intervention models affects different people. To this end, we make k dependent both on the real prospect class C_r, and the prospect class C_{pr} predicted by the prediction model. The fact that the growth rate is made depended on the predicted class reflects the idea of targeted help for different prospect classes, and that a prediction model is used for this. The real world idea is not only that different prospect classes receive a different *quantity* of help, but also a different *quality* that is better suited for that prospect group. Therefore, we also make k dependent on the real prospect group of each individual, as arguably if a certain type of help is better suited for the low than for the high prospect group, than this will have the adverse effect for an incorrectly classified person.

Since both C_r and C_{pr} are binary, this leads to a $2x2$ matrix k_{ij}:

	predicted low	predicted high
real low	k_{11}	k_{12}
real high	k_{21}	k_{22}

With different values for k_{ij} we can now define different scenarios. The difference between $k_{11}$and k_{22}defines how different the effect is of the intervention model is for the two different prospect classes, as intended by the PES. The difference between k_{11} and k_{21} and between k_{12} and k_{22} defines how individuals are adversely affected if they are incorrectly classified by the prediction algorithm, and receive the type of help that is in fact intended for the other group.

The values for the different entries of k_{ij} define how - in the abstract setting of our model - "attention" or "resources" are distributed across the different groups. In order to make the different scenarios better comparable, we constrain the absolute values in such a way that the geometric mean of all 4 entries must be the same in all scenarios. The geometric mean is the mean function usually used for variables related to growth-rates or similar. We set it to 1/50. This number was chosen more or less arbitrarily so that a typical simulation with constant decision function reaches its equilibrium on the order of 100 timesteps. Changing the scale would only change how much happens in a single timestep of the simulation, and not the overall behavior (with higher k, we will get the same result earlier, with smaller k, one needs to run the model for more timesteps). Since also the unit of a timestep is abstract and cannot be translated to a real world time, this does not change the results or their interpretation.

For better readability, the k-values presented in the text and the plots are all scaled with a factor of 50, so for the k-matrix for scenario 1 all entries will be displayed as 1. The choice of k-values will be called *scenarios*. Specifically, we will use the following scenarios (plus potential subscenarios):

1. "Agnostic": $k_{11} = k_{12} = k_{21} = k_{22}$. This is the base scenario, where all classes receive both the same quantity and quality of help, and this also has the same effect, independent of the actual labor-market prospects.
2. no targeting, but class-dependent effect: $k_{11} = k_{12}$, $k_{21} = k_{22}$, two sub-scenarios: a) $k_{11} > k_{22}$, b) $k_{11} < k_{22}$. In these scenarios, the PES provides the same help to everyone, but this helps works better (a) or worse (b) for individuals with real low prospects.
3. targeting, but no class-dependent effect. In this scenario k is only dependent on C_{pr}, not on C_r, $k_{11} = k_{21}$, $k_{12} = k_{22}$. In 3a more help is provided for the lowprospect group, in 3b more for the highprospect group.
4. targeting with class dependent effect. In 4a more help is provided for the lowprospect group, in 4b more for the highprospect group. In both 4a and 4b, falsely classified people get the least effective help.

Scenarios in detail The scenarios are summarized in table 1.

All parameters of the simple model are listed in table 2.

2.3 Complex Model

Our second model is more complex and slightly more realistic than the simple dynamical model. While it was designed with the dynamics of the real-world AMS-system in mind, it is still highly abstract and should not be confused with a complete model of labour market dynamics.

2.3.1 Population model

For the "natural" distribution of skill in the population we use the same model as for the simple model. The difference is that in the simple model, the population is fixed, with an initial distribution of skill. For the complex model, we assume that there is an (unlimited) *background-population* pool with the distribution of x_1, x_2, x_{pr} and s_{real} described by eqs (1-4). This background population and the distribution of the features of the individuals does not change throughout a model run, but acts as a pool for refilling the pool of job-seekers.

2.3.2 Labor market model

The labor market is modeled via a probabilistic function that for each individual defines the probability of finding a job at the current timestep, where this probability depends on s_{real} of that individual. We model the dependence on s_{real} as a logistic function:

$$P\left(job|s_{real}\right) = \frac{1}{1 + e^{-(\alpha_l s_{real} + \beta_l)}} \tag{11}$$

Tab. 1: overview of scenarios, defined by the k-matrix of the intervention model

1) no targeting, no class-dependent effect

	predicted high	predicted low
real high	1	1
real low	1	1

2a)no targeting, class-dependent effect (more on lowprospect group)

	predicted high	predicted low
real high	2	2
real low	1/2	1/2

2b)no targeting, class-dependent effect (more on highprospect group)

	predicted high	predicted low
real high	1/2	1/2
real low	2	2

3a) targeting (more on lowprospect group), no class-dependent effect

	predicted high	predicted low
real high	2	1/2
real low	2	1/2

3b) targeting (more on highprospect group), no class-dependent effect

	predicted high	predicted low
real high	1/2	2
real low	1/2	2

4a) targeting (more on lowprospect group), class-dependent effect (more for correctly classified)

	predicted high	predicted low
real high	$4 \cdot 8^{-\frac{1}{4}}$	$8^{-\frac{1}{4}}$
real low	$8^{-\frac{1}{4}}$	$2 \cdot 8^{-\frac{1}{4}}$

4b) targeting (more on highprospect group), class-dependent effect (more for correctly classified)

	predicted high	predicted low
real high	$2 \cdot 8^{-\frac{1}{4}}$	$8^{-\frac{1}{4}}$
real low	$8^{-\frac{1}{4}}$	$4 \cdot 8^{-\frac{1}{4}}$

Tab. 2: parameters of the simple model

parameter	default value	description
N	10000	size of active population
α_{pr}	2	dependence of x_2 on x_{pr}
x_{max}	2	truncation value for data generation
α_{lb}	-	bias in the labor market

Where α_l and β_l are parameters that need to be set a priori. At each timestep, $P\left(job|s_{real}\right)$ is computed for each individual on the pool of job-seekers. Each individual is removed from the pool of job seekers with probability P.

The choice for a logistic labor market function was made because it satisfies the following intuition about the labor-market: If an individual has very low skill, than the probability of finding a job is very low (close to zero), and if the skill slightly increases, then the chance is still very low. There is a soft threshold which one needs to reach in order to have a reasonable chance. Above this soft threshold, increases in s_{real} have a strong impact, and the higher skilled one is, the higher the chances of finding a job. Eventually, however, this reaches a plateau, as the probability of finding a job is already close to 1, and additional skill does basically not change anything anymore. The parameters α_l and β_l define this "middle" region in which changes of s_{real} have a strong impact on the probability. β_l defines the position of this middle region, and α_l how broad/steep it is.

Note that we made $P\left(job|s_{real}\right)$ independent of the time an individual is already unemployed. The intuition behind is that in our idealized setting, the skill of an individual is solely defined by s_{real}, which the labor market knows. Therefore, in this setting, the fact that someone has been unemployed for a long time does not yield additional information about their skill. In reality this is different, as long-term unemployment as additional information could be a reason for an employer to not hire someone.

2.3.3 Public Employment Service

Similar to the simple model, the PES in the complex model uses a logistic regression model that classifies individuals as either low or high prospect, with x_1 and optionally x_{pr} as predictors. The classes are, however, not defined by setting a threshold on s_{real}, but by setting a threshold on the time T_u that it took individuals in the historical record to find a job. This history is continuously build up throughout a modelrun with all individuals that found a job.

Intervention Model The treatment of individuals differs between the high and the low prospect group in two ways: in the amount of help (increase of x_1 and x_2) they receive, and how long this help takes. The highprospect group receives the help immediately, and is available on the labor-market in the next timestep. The low-prospect group, on the other hand, receives help that takes time and removes them from the labor-market for a period of time ΔT_u.

The change of x_1 and x_2 under different scenarios is modeled in the same way as for the simple model (see section 2.2.3).

An important difference, however, is that in the simple model, it is easy to know the true prospect of an individual (as it is solely defined by s_{real}). In the complex model, this is less straightforward. Here, the prospect is the *expected* time T_u that the individual will be unemployed. The real time that this individual will need cannot be known, as it 1) evolves from the model and 2) is linked to s_{real}, but only in a *probabilistic* way.

For the complex model, we therefore defined the "real prospect" of an individual as T_u estimated from the historical data, using s_{real} as predictor (in contrast to the predicted prospect, which uses x_1 and x_{prot} as predictor).

This real prospect (grouped into below or above the fixed threshold) is then used in the scenarios (only in those scenarios in which it makes a difference if an individual is classified incorrectly)

Each modelrun is started with a spinup phase. TODO: expand description of spinup phase

Individuals that have been unemployed for too long (set by T_u^{max}) leave the system automatically.

All parameters of the complex model are listed in table 3.

2.4 Metrics

We use the following metrics to analyze the results

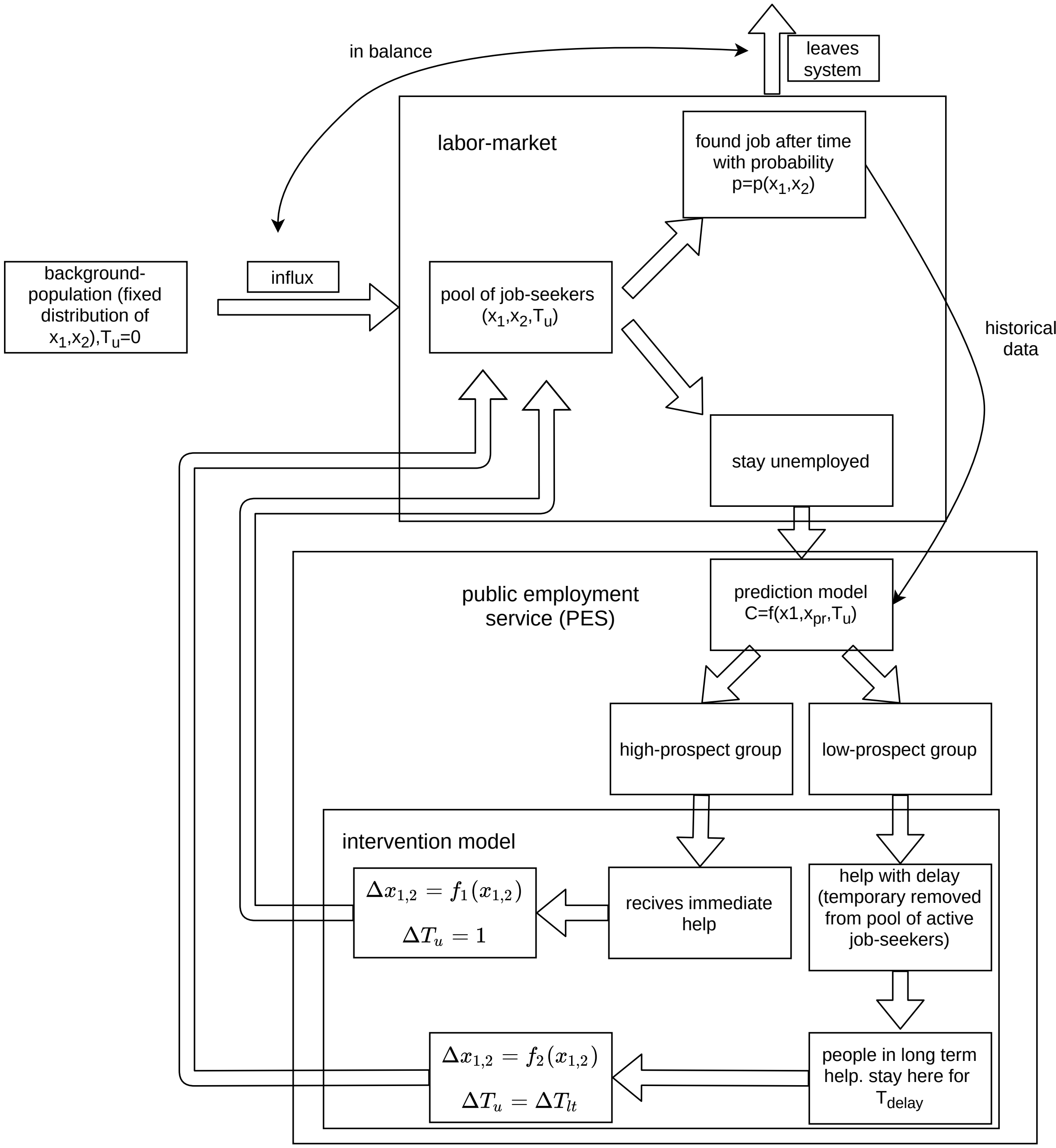


Fig. 3: Outline of the complex model. The labor market selects job-seekers from the pool of job seekers, with a probability dependent on the skill of the individual. Individual who find a job leave the system, individuals who have not found a job are transferred to the PES. The PES divides them into two groups, according to their predicted prospects on the labor market. The group with high prospects receives little help (increase in skill), but it receives this immediately and goes back to the pool of job seekers in the next timestep. The group with low prospects, on the other hand, receives more help, but in order to achieve this the individuals in the low prospect group are withheld from the labor market for T_{delay} timesteps.

Tab. 3: parameters of the complex model

parameter	default value	description
N	10000	size of active population
α_{pr}	2	dependence of x_2 on x_{pr}
x_{max}	2	truncation value for data generation
ΔT_u		time that the lowprospect group is withdrawn from the active poo
T_u^{max}		time after which job-seekers that did not find a job leave the syster
α_l	0	location of the logistic job-market function
β_l	10	steepness of the logistic job-market function
T_u^{γ}	10	threshold (in timeunites) that defines the border between highrospect and lowprospect grou

Between group skill difference computed for each timestep

$$BGSD_{real} = \overline{S}_{real,x_{pr}=0} - \overline{S}_{real,x_{pr}=1} \tag{12}$$

$$BGSD_{eff} = \overline{S}_{eff,x_{pr}=0} - \overline{S}_{eff,x_{pr}=1} \tag{13}$$

Fraction of the underprivileged group classified as high-prospect computed for each timestep

$$\frac{n\left(x_{pr}=0 \wedge C=1\right)}{n\left(x_{pr}=0\right)} \tag{14}$$

Time after all underprivileged are classified as high-prospect This metric only makes sense for the model with a constant decision function.

3 Results

3.1 Simple model

The simple model was run with the two different decision rules : constant decision rule, meaning that the threshold of predicted skill for grouping into low or high prospect group stays constant over the course of the simulation, or adaptive, meaning that it is updated at each timestep. For each decision rule, two different labor market configurations are used: an unbiased labor-market ($\alpha_{lb} = 0$), and a labor market biased against the underpriviliged group ($\alpha_{lb} = 0.5$). For each model configuration, all 7 scenarios (including sub-scenarios) are computed ,where for each scenario both the base model - in which the PES does not use x_{pr} for estimating the skill - and the full model - in which the he PES *does* not use x_{pr}.

, the results for adaptive decision rule in fig. 5.

We start by discussing the results with constant decision rule. They are shown in fig. 4. Panels a) and b) show the evolution of BGSD and the fraction of the underprivileged group as high prospect over the course of the simulation. Each color represents a scenario, whereas the solid lines are for the full model (where the PES uses both x_1 and x_{pr} for predicting s_{real}), and the dashed lines are for the base model (where the PES uses solely x_1).

A key feature of the model setting with constant decision function is that - after enough time - the BSGD decreases, independent of scenario. At the same time, the fraction of underpriviliged individuals classified as highprospect increases until it finally reaches 1. At this point, all individuals - both privileged and underprivileged have reached a skill that classifies them as high-prospect. This is because the skill-threshold does not change over time, and, independent of scenario and current skill, each individual individual gets at least a small improvement in skill at each timestep. Therefore, the end/equilibrium-state of the simulations is not of high interest in this setting. There are, however, some other interesting things to learn out of these simulations.

- only for some scenario is there a difference between base and full model (makes sense from definitions of scenarios....)
- scenarios that help the better group more increase inequality in the beginning, but then it falls (as it must because the end state is full equality per definition here)
- in scenarios the decrease inequality in the beginning, using the full model (with protected attribute) is better! (because the classification is better). discuss that this does NOT mean that it is better for each individual - there are still false classifications.

One interesting thing we can learn from these simple simulations is how the scenario influences the time it takes until everyone in the underprivileged group is classified as high-prospect. This can be deduced from the lower parts of panels a) and b) in fig 4 - it is the time when the lines reach a value of 1. For clarity, this is information is condensed in panels c) and d) of the same figure. Each bar shows exactly this time, split up by scenario (x-axis and color) and whether the base or the full prediction model is used (different hashing). In both the unbiased and the biased labor-market the ordering of the scenarios in the sense of how long it takes to reach equality is the same. Scenario 2a - no targeting, but more effect on the lowprospect group - reaches equality earliest, whereas scenario 2b - no targeting, but more effect on the highprospect group - takes longest to reach equality.

Clearly visible is also the impact of the PES using the full vs the base prediction model (cf left-hand with right-bars). For the two scenarios that target more towards the lowpropsect group (3a and 4a) using the full model reduces the time to reach equality. For the scenarios that target more towards the high-prospect group (3b and 4b), the picture is more nuanced. In scenario 3b - which targets more towards the highprospect group, but has no penalty for misclassification - using the full model increases the time for reaching equality. For 4b - which also targets more towards the highprospect group, but has a penalty for misclassification - it is reversed. (DOES THIS MAKE SENSE? fullmodel->less missclassifications-??)

- cf 1 and 3a: with 3a equality reached faster, but only with the full model. With the base model, it takes longer to reach equality! More or less same for 4a! –> including the problematic predictors does have an advantage for the underprivileged group (at least on average), both in the unbiased and the biased labor market.

We now turn to the modelruns that use an adaptive decision rule (at each timestep, the real high and lowprospect groups are defined by whether individuals have higher or lower skill than the average skill at this particular timestep). The results are shown shown in fig. 5. In contrast to the runs with constant decision rule, these runs do never reach equality in the sense that everyone is categorized as high-prospect, as the boundary between low and high-prospect is constantly adapted. The between-group skill difference in real skill reaches an equilibrium of zero, independent of scenario and whether there is a bias in the labor market or not. When we instead look at between-group skill difference of effective skill (the one seen by the labor-market), then the runs with an unbiased labor market show the same as for the real skill - as they must by definition - whereas for the biased labor-market the BGSD of effective skill does not equilibrate at zero, but at a positive value.

In terms of BGSD, the runs with adaptive decision function are qualitatively similar to the runs with constant decision function.

3.2 Complex model

4 Discussion and conclusion

What if only "decision support", and the decision by the model is only input to a human? It is known that humans tend to rely on such systems (https://journals.sagepub.com/doi/10.1518/001872097778543886).

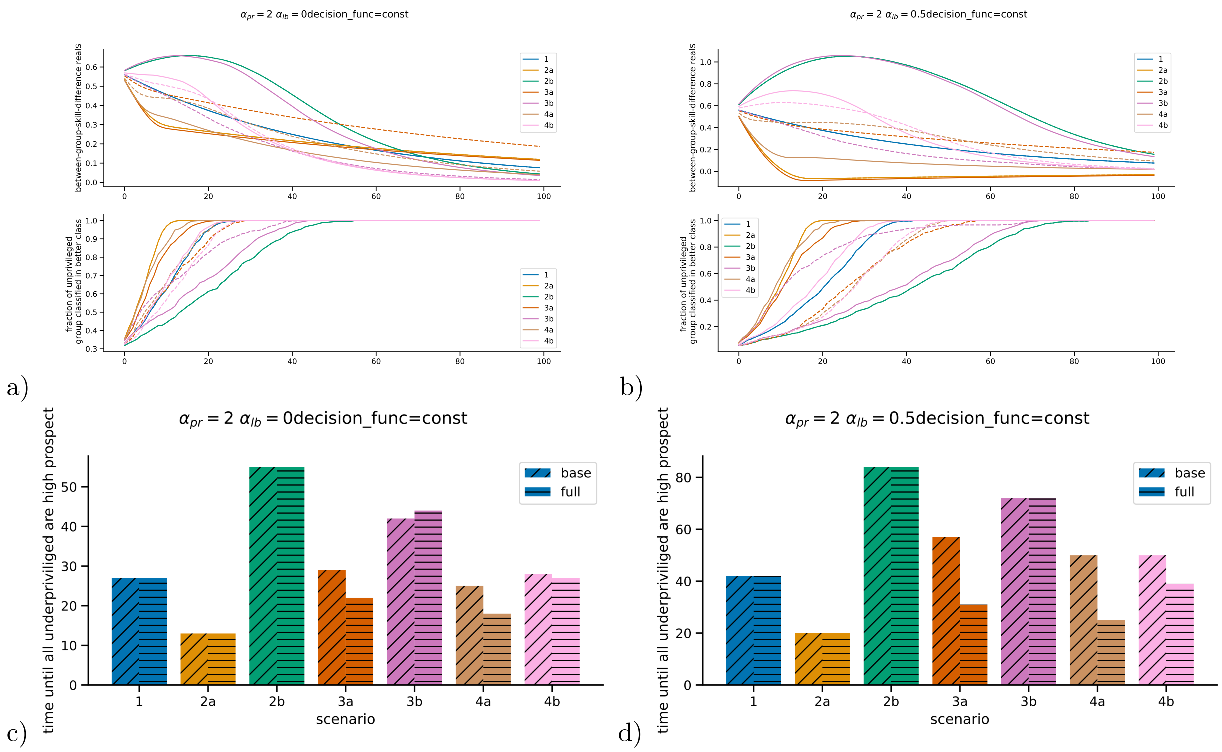


Fig. 4: Results for the model with constant decision function a,b: Upper panels: time evolution of the between-group skill difference (mean skill of privileged group - mean skill of underprivileged group)(($BGSD_{eff}$), lower panels: time evolution of fraction of individuals in from the underprivileged group that are classified as belonging to the high-prospect group. c,d: time at which 100% of the underprivileged group are classified as “high prospect”, split up by scenario (color) and modeltype (hatching). a,c: results for “fair” labor market ($\alpha_{lb} = 0$), b,d: results for labor market biased against underprivileged group ($\alpha_{lb} = 0.5$)

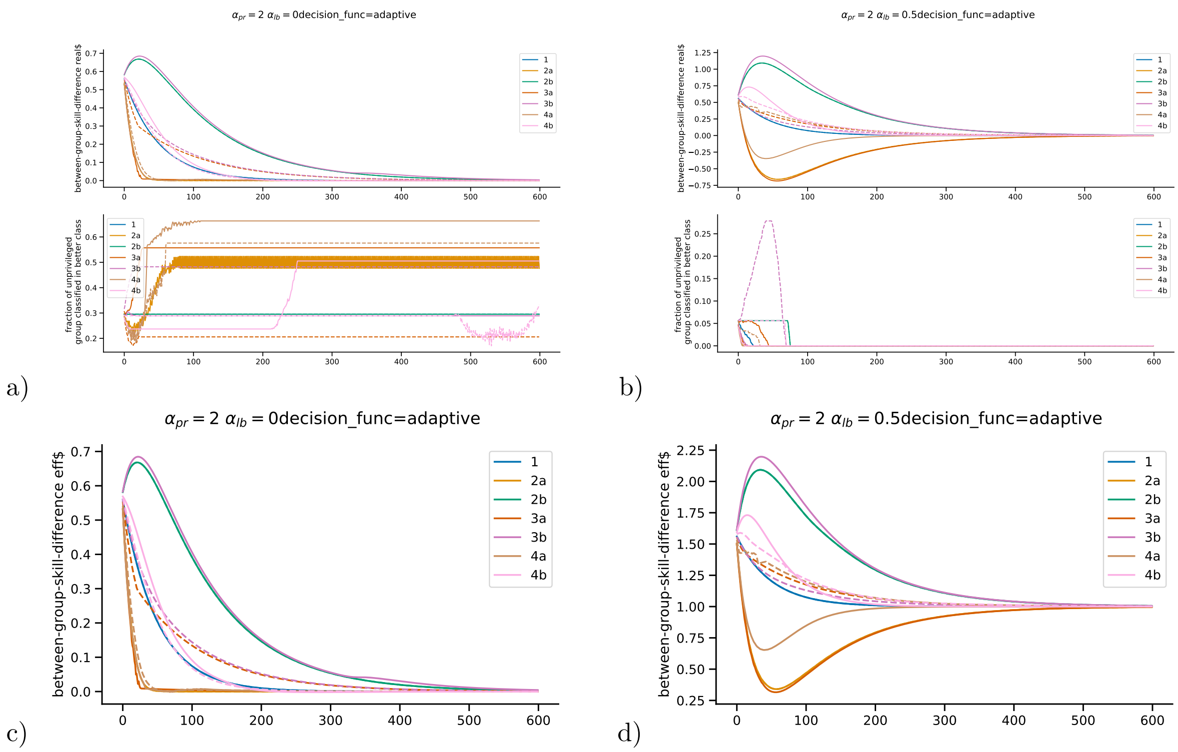


Fig. 5: Results for the model with adaptive decision function. a,c: results for “fair” labor market ($\alpha_{lb} = 0$), b,d: results for labor market biased against underpriviliged group ($\alpha_{lb} = 0.5$)c,d: between group skill difference of $s_{eff}(BGSD_{eff})$. TODO: remove lower parts of panels a) and b)

We assume that success on the labor market is based solely on the individual skill, and that observations of the labor market (e.g. who finds a job) are thus a measure of skill. In reality, this view has been challenged fundamentally, as luck is a much more important ingredient for success than individual talent (see [2] and references therein).

Coda and Data Availability

The software for this study was written in Python and is published with this paper. It allows full reproduction of the results of this study as well as further experimentation with the model parameters.