Together & Fair: On Meritocracy in Optimal Set Selection

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Together & Fair: The Roadmap

- 1. Algorithmic Decision Making
 - 1.1 Selecting Individuals
 - **1.2** Selecting Set of Individuals
- 2. Optimal Set Selection: A Decision Theoretic Formulation
- 3. Facets of Meritocracy in Set Selection
 - 3.1 A Quantifier of Merit: Expected Marginal Contribution (EMC)
 - 3.2 Two Stability Criteria for Meritocracy: Swap and Local
 - 3.3 A Connection between Policy Gradients and EMC: Separable Policies
- 4. A Case Study: Norwegian College Admissions Data

Algorithmic Decision Making Selecting Individuals





Figure: Job Recruitment











Assumption: The success of each candidate is independent from one another. → Individual's contribution to DM's utility is the estimated probability of success.

Algorithmic Decision Making

Selecting Set of Individuals



Figure: Student Groups for Projects



The EPL is one week away and our FPL Algorithm is ready to play

Our Moneyball approach to the Fantasy EPL (team_id: 386960)



Figure: Fantasy Premier League

Algorithmic Decision Making Selecting Set of Individuals



Figure: Participatory Budget

Figure: Committee Selection

A Meritocratic Decision Maker Selecting Sets: Team Building



Goal: The DM wants to build a team of two that can do football analytics.

Selecting Sets: Team Building



Observation: Individuals can have complementary skills or features, and a team is more than an individual.

Selecting Sets: Team Building



Selecting Sets: Team Building



Observation: Complementary features lead to higher probability of success for the team.
 ⇒ Individual's contribution to DM's utility is dependent on the possible teams.

Selecting Sets: Team Building



Result: Average of marginal contributions of Alice, Bob, Carla and David to all possible teams are: (1/12, 0, 0, -1/12).

Selecting Sets: Team Building





How to quantify 'merit' of an individual during a set selection?

What are the factors that influence merit?

How to maximise 'merit' of a set during selection?

Our Answers [BSBD21]

How to quantify 'merit' of an individual during a set selection?

Quantification of 'merit' depends on the expected contribution of the individual given the composition of the teams and their estimated utilities.

What are the factors that influence merit?

The utility function of the DM, the utility evaluator for the teams, and the probability of selecting a team.

How to maximise 'merit' of a set during selection?

Computing a policy, i.e. a vector dictating probabilities of selection, which maximises the total expected utility of the selected team.

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Optimal Set Selection A Decision Theoretic Formulation

Ingredients:

Population: $\mathcal{N} \triangleq \{1, ..., N\}$ denotes the set *n* individuals

Population's data: $\mathbf{x} \triangleq \{x_1, \dots, x_N\}$ denotes the set of features of *n* individuals

Outcomes: $y \in \mathscr{Y}$ denotes outcomes due to the selected set's performance

Utility: $u(\mathbf{a}, \mathbf{y})$ denotes the utility of the selection $\mathbf{a} \subseteq \mathcal{N}$ w.r.t. the outcomes \mathbf{y}

Policy: $\pi(\mathbf{a} \mid \mathbf{x})$, denotes the probability of selecting a subset $\mathbf{a} \subseteq \mathcal{N}$ given the data

Optimal Set Selection

A Decision Theoretic Formulation

Goodness of a Selection Policy: Expected Utility

$$U(\pi, \mathbf{x}) \triangleq \mathbb{E}_{\pi}[u \mid \mathbf{x}] = \mathbb{E}_{\pi}[\mathbb{E}[u \mid \mathbf{a}, \mathbf{x}]]$$
$$= \sum_{\mathbf{a} \subseteq \mathcal{N}} \underbrace{\pi(\mathbf{a} \mid \mathbf{x})}_{Policy} \sum_{\mathbf{y} \in \mathscr{Y}} \mathbb{P}(\mathbf{y} \mid \mathbf{a}, \mathbf{x}) \underbrace{u(\mathbf{a}, \mathbf{y})}_{Utility}.$$

 $\mathbb{P}(y \mid a, x)$ is a predictive model used by the DM for estimating outcome probabilities.

Optimal Set Selection

A Decision Theoretic Formulation

Goodness of a Selection Policy: Expected Utility

 $U(\pi, \mathbf{x}) \triangleq \mathbb{E}_{\pi}[u \mid \mathbf{x}] = \mathbb{E}_{\pi}[\mathbb{E}[u \mid \mathbf{a}, \mathbf{x}]]$ $= \sum_{\mathbf{a} \subseteq \mathcal{N}} \underbrace{\pi(\mathbf{a} \mid \mathbf{x})}_{\text{Policy}} \sum_{\mathbf{y} \in \mathscr{Y}} \underbrace{\mathbb{P}(\mathbf{y} \mid \mathbf{a}, \mathbf{x})}_{\text{Predictive model}} \underbrace{u(\mathbf{a}, \mathbf{y})}_{\text{Utility}}.$

Optimal Set Selection as Policy Optimisation

Given a family of parameterised policies $\Pi \triangleq \{\pi_{\theta} \mid \theta \in O\}$, compute the policy maximising the expected utility

 $\theta^*(\mathbf{x}) = \underset{\theta \in \mathcal{O}}{\operatorname{argmax}} U(\pi_{\theta}, \mathbf{x}).$

Optimal Set Selection

A Policy Gradient Algorithm

Algorithm A Policy gradient algorithm

- 1: Input: a model $\mathbb{P}(\mathbf{y}|\mathbf{a}, \mathbf{x})$, a population \mathcal{N} with features \mathbf{x} and a utility function u.
- 2: Initialise: θ^0 , $\delta > 0$, learning rate $\eta > 0$
- 3: while $\| \theta^{i+1} \theta^i \| > \delta$ do
- 4: Evaluate $\nabla_{\theta} U(\pi_{\theta}, \mathbf{x})$ from u, \mathbf{x} and \mathbb{P} .
- 5: $\overline{\theta^{i+1} \leftarrow \theta^i + \eta [\nabla_{\theta} U(\pi_{\theta}, \mathbf{x})]_{\theta = \theta^i}}$
- 6: *i* + +
- 7: end while
- 8: return $\pi_{\theta^{i+1}}$

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Expected Marginal Contribution

A Communitarian Quantifier of Merit

Expected Marginal Contribution (EMC)

Expected Marginal Contribution (EMC) quantifies the gain (or loss) in expected utility when a policy is constrained to always pick an individual *i*.

$$\mathsf{EMC}_i(U, \pi) \triangleq \sum_{\mathbf{a} \in \mathscr{A}} \pi(\mathbf{a}) [U(\mathbf{a} + i) - U(\mathbf{a})].$$

We quantify the 'merit' of an individual *i* using **EMC** for a given policy π , utility *U*, data **x**.





DM's Policy: $\pi = \pi_{egal}$ EMC(*U*, π_{egal}) = (1/6, 0, 0, -1/6)



DM's Policy: $\pi = \pi_{egal}$ EMC(*U*, π_{egal}) = (1/6, 0, 0, -1/6)

DM's Policy: π = never select A and D together, select other sets with equal probability

 $\mathsf{EMC}(U,\pi) = (\frac{3}{24}, \frac{1}{24}, -\frac{1}{24}, -\frac{2}{24})$

Properties of EMC

Generalising Shapley Value

Lemma (Axioms of Fair Coalition/Division)

1) Symmetry: If $U(\mathbf{a} + i) = U(\mathbf{a} + j)$ for all $\mathbf{a} \subseteq \mathcal{N}$,

 $\mathsf{EMC}_i(U, \pi) = \mathsf{EMC}_j(U, \pi) \qquad \forall \pi \in \Pi.$

2) Linearity: For all $\alpha, \beta \in \mathbb{R}$,

 $\mathsf{EMC}(\alpha U_1 + \beta U_2, \pi) = \alpha \, \mathsf{EMC}(U_1, \pi) + \beta \, \mathsf{EMC}(U_2, \pi) \quad \forall \pi \in \Pi.$

3) Null Players: If $i \in \mathcal{N}$ has zero contribution to every set,

 $\mathsf{EMC}_i(U,\pi)=0\qquad \forall \pi\in\Pi.$

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For the egalitarian selection policy $\pi_{\text{egal}}(\mathbf{a}) = \frac{1}{N\binom{N-1}{\|\mathbf{a}\|_1}}$, EMC(U, π_{egal}) = Shapley(U) [Sha51].

Meritocracy and Stability of Selected Set Swap Stability

Definition (Swap Stability)

If for any two individuals $i, j \in \mathcal{N}$ with $\pi(\mathbf{a}_i = 1) > \pi(\mathbf{a}_j = 1)$, a swap stable policy π satisfies $U(\pi + i - j) \ge U(\pi - i + j)^1$

A policy π is swap stable if an individual *i* is more likely to be selected than *j*, the expected utility of selecting *i* but not *j* is higher than the expected utility of selecting *j* but not *i*.

Lemma (EMC Induces a Swap Stable Ordering)

 $\mathsf{EMC}_i(U, \pi - i - j) \ge \mathsf{EMC}_j(U, \pi - i - j) \iff U(\pi + i - j) \ge U(\pi - i + j).$

¹
$$U(\pi + i - j) \triangleq \sum_{\mathbf{a} \in \mathscr{A}} \pi(\mathbf{a}) U(\mathbf{a} + i - j).$$

Meritocracy and Stability of Selected Set Local Stability

Definition (Local Stability)

A policy π is locally stable if for any $i \in \mathcal{N}$, $U(\pi) \ge U(\pi + i)^2$.

Local stability guarantees that the expected utility of selecting *i* is lower than the expected utility of π .

Lemma (Local Stability is Equivalent to Negative EMC)

For $i \in \mathcal{N}$, $U(\pi) \ge U(\pi + i) \iff \mathsf{EMC}_i(U, \pi) \le 0$.

²
$$U(\pi + i) \triangleq \sum_{\mathbf{a} \in \mathscr{A}} \pi(\mathbf{a}) U(\mathbf{a} + i).$$

DM's Policy: $\pi = \pi_{egal}$



 $\pi_{
m egal}$ is swap stable but not local stable



DM's Policy: $\pi = \pi_{egal}$

 π_{egal} is swap stable but not local stable

DM's Policy: $\pi_{C,D}$ selects Carla and David

 $\pi_{{\rm C},{\rm D}}$ is locally stable and swap stable but not utility maximising



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DM's Policy: $\pi_{A,B}$ selects Alice and Bob

 $\pi_{C,D}$ is locally stable, swap stable and maximises utility



DM's Policy: $\pi = \pi_{egal}$

 π_{egal} is swap stable but not local stable

DM's Policy: $\pi_{C,D}$ selects Carla and David

 $\pi_{{\it C},{\it D}}$ is locally stable and swap stable but not utility maximising

DM's Policy: $\pi_{A,B}$ selects Alice and Bob

 $\pi_{{\it C},{\it D}}$ is locally stable, swap stable and maximises utility

A deterministic policy maximising utility is both swap- and local-stable, i.e. 'meritocratic'.

Separable Policies

A Study Relating Policy Gradient and EMC

A parameterised policy π_{θ} is separable over the population $\mathcal N$ if

$$\pi_{\theta}(\mathbf{a}) = \prod_{i=1}^{N} \underbrace{\pi_{\theta}(\mathbf{a}_i)}_{\text{Probability of selecting } i} \propto \prod_{i=1}^{N} g(\mathbf{a}_i, \theta_i)$$

for some function g and $\theta = (\theta_1, \ldots, \theta_N)$.

Separable Policies

Separable Softmax Policies

For separable softmax policies,

$$\pi_{\theta}(\mathbf{a}) = rac{e^{eta \theta^{\top} \mathbf{a}}}{\sum_{\mathbf{a}' \in \mathscr{A}} e^{eta \theta^{\top} \mathbf{a}'}}.$$

 $\beta \geq 0$ is the inverse temperature of the distribution.

Lemma

The gradient of the softmax policy π_{θ} is a linear transformation of the EMC. Specifically,

 $\nabla_{\theta_i} U(\pi_{\theta}) = \beta \pi_{\theta}(\mathbf{a}_i = 1) \operatorname{EMC}_i(U, \pi_{\theta}) \qquad \forall i \in \mathcal{N}.$

Separable Policies

Separable Linear Policies

Separable linear policies select individual *i* with probability θ_i , i.e.

$$\pi_{\theta_i}(\mathbf{a}_i) = \theta_i \mathbb{I} \{ \mathbf{a}_i = 1 \} + (1 - \theta_i) \mathbb{I} \{ \mathbf{a}_i = 0 \}.$$

Lemma

For separable linear policies, if $\pi_{\theta_i}(\mathbf{a}_i = \mathbf{0}) > \mathbf{0}$,

$$\nabla_{\theta_i} U(\pi_{\theta}) = \frac{\mathsf{EMC}_i(U, \pi_{\theta})}{\pi_{\theta_i}(\mathbf{a}_i = \mathbf{0})} \qquad \forall i \in \mathcal{N}.$$

EMC, Shapley Value, and Policy Gradient A Visual Comparison



Figure: EMC

Figure: Shapley value

Figure: Policy gradients (Linear)

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Experimental Analysis

Dataset

- Application data³: Applicants to all Norwegian university programs with features: birth date, semester of application, gender, citizenship, country of educational background, high school grades in form of GPA and summarised language/science points, other points, admission decision, each applicant's preference for a program.
- Exam data⁴: All students at Norwegian universities for all their taken exams including: courses, study program, and achieved grades.

Goal: DM is interested in maximising good course results of admitted students across all three considered disciplines/courses and demographic parity among selected students.

³ https://dbh.nsd.uib.no/dokumentasjon/tabell.action?tabellId=379

⁴ https://dbh.nsd.uib.no/dokumentasjon/tabell.action?tabellId=472

Experimental Analysis

Utility Function of the DM

- Utility (Log-linear): $u(\mathbf{a}, \mathbf{y}) = \sum_{j=1}^{3} \log \left(\sum_{i \in \mathcal{N}} \mathbf{a}_{i} \cdot \mathbf{y}_{i,j} \right) c \cdot \|\mathbf{a}\|_{1}^{3}$ *c* is the cost associated with admitting a student.
- Demographic fairness (Statistical Parity):

 $|\pi(\mathbf{a}_i = 1 | i \text{ is male}) - \pi(\mathbf{a}_j = 1 | j \text{ is female})| \le \varepsilon.$

Predictive model: DM uses a regression model for estimating P(y | x, a), i.e. the course results y of this year's applicants x.

³ The potential outcomes of non-admitted applicants do not contribute to the utility

Expected Utility and Deviation from Meritocratic Stability Demographically Oblivious Policy



Figure: True Outcome

Figure: Predicted Outcomes

Expected Utility and Deviation from Meritocratic Stability Demographic Fairness Constrained Policy



Figure: True Outcome

Figure: Predicted Outcomes

Take-away: Summary of Contributions

- **Problem Formulation:** Optimal set selection can be reduced to a policy optimisation problem given the utility of DM and a predictive evaluation model.
- Meritocracy in Set Selection:
 - -> Expected marginal contribution (EMC) is the quantifier of an individual's 'merit' or contribution to DM's expected utility.
 - -> EMC generalises fairness axioms of team building obtained for Shapley values.
 - -> A meritocratic policy should satisfy swap and local stabilities.
- Policy Optimisation and EMC:
 - -> Policy gradient and EMC for separable policies are proportional.
 - -> A deterministic utility maximising policy satisfies meritocratic stabilities but a stochastic utility maximising policy might not.
- Case of College Admissions: Historical and egalitarian policies deviate quite a bit from meritocracy, while linear separable poicies reach closest to meritocracy.

Take-away: What's Next?

- Stochastic utility maximising policies might not satisfy swap stability.
 - -> The proof shows that we might require *individually smooth* policies in the sense that similar individuals (in terms of compatibility across optimal sets) are being selected similarly often. Studying the family of individually smooth policies!
- Meritocratic fairness conflicts with demographic fairness constraints [Bin20].
 - -> Our experiments show that constrained policy optimisation can solve this setting and EMC for constrained policies can quantify deviation from meritocracy.

Studying the EMC for constrained policies, and the corresponding trade-off between meritocracy and demographic fairness.

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How to define and ensure meritocracy in optimal set selection?

Use expected marginal contribution given DM's policy and utility function.

Our Paper: https://arxiv.org/pdf/2102.11932.pdf

Performance Metrics

To measure violations of swap stability, we suggest to use

$$\mathsf{Dev}_{\mathsf{swap}}(\pi, \mathbf{x}) = \sum_{i,j \in \mathcal{N}} \left(\pi(\mathbf{a}_i = 1 \mid \mathbf{x}) - \pi(\mathbf{a}_j = 1 \mid \mathbf{x}) \right)^+ \left(U(\pi - i + j, \mathbf{x}) - U(\pi + i - j, \mathbf{x}) \right)^+$$

where $(X)^+ \triangleq \max\{0, X\}$. Here, large values of $\text{Dev}_{\text{swap}}(\pi, \mathbf{x})$ indicate large deviations from swap stable decisions. Note that our choice of Dev_{swap} not only accounts for the number of infringements, but also the magnitude of the deviation from swap stability. For instance, if $U(\pi + i - j) \ll U(\pi - i + j)$ while $\pi(\mathbf{a}_i = 1) \gg \pi(\mathbf{a}_j = 1)$, the measured deviation from swap stability is accordingly large. In particular, if $\text{Dev}_{\text{swap}}(\pi, \mathbf{x}) = 0$, the policy π is swap stable. To measure the deviation from local stability, we use the cumulative positive EMCs under policy π :

$$\mathsf{Dev}_{\mathsf{local}}(\pi, \mathbf{x}) = \sum_{i \in \mathcal{N}} (\mathsf{EMC}_i(U, \pi, \mathbf{x}))^+.$$