Zürcher Hochschule
für Angewandte Wissenschaften

zh aw School of Engineering

Mitigating Discriminatory Biases in Success Prediction Models for Venture Capitals

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Where would you invest?

Outline

1. Success prediction for venture capital
2. Fair success prediction for venture capital
3. Evaluating fair success prediction
4. Putting fair success prediction into practice

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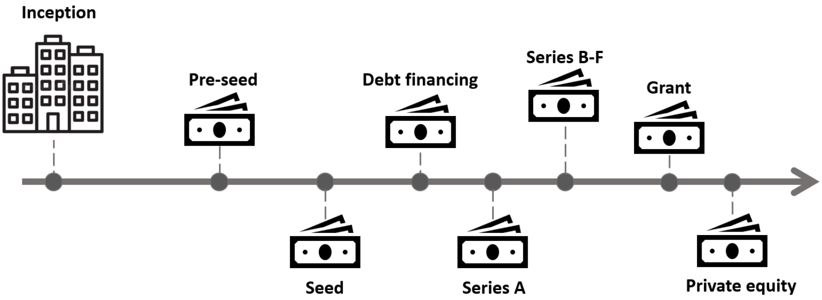
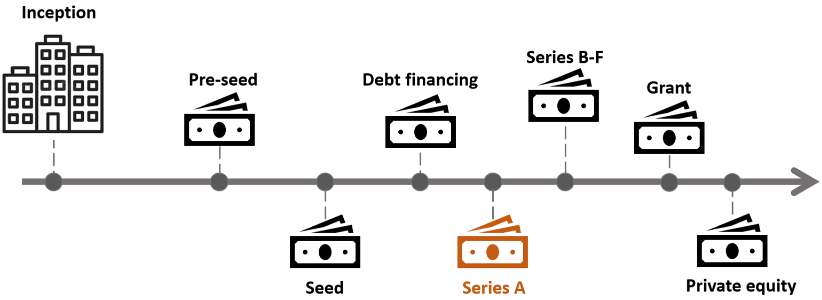
How is a successful startup defined?



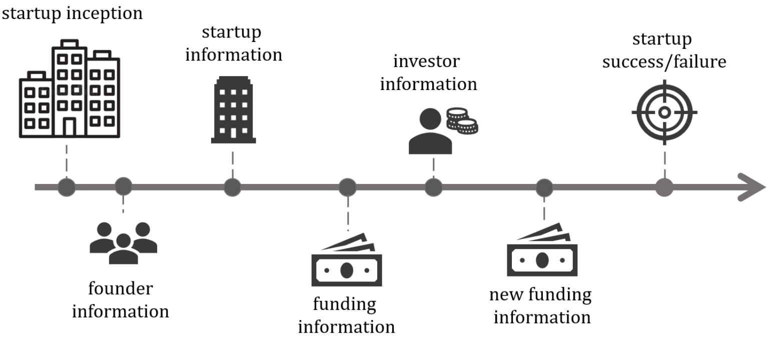
[1] Making it into a successful Series A Funding, accepted

Successful startups receive Series A funding



[1] Making it into a successful Series A Funding, accepted

Information available to predict startup success



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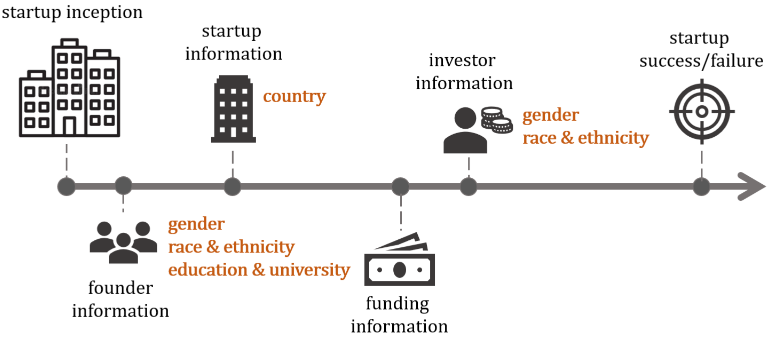
Outline

Fair success prediction for venture capital



How to measure fairness?

- **Equal opportunity:**

$$P(\hat{y} = 1 | z = z_1, y = 1) = P(\hat{y} = 1 | z = z_2, y = 1)$$

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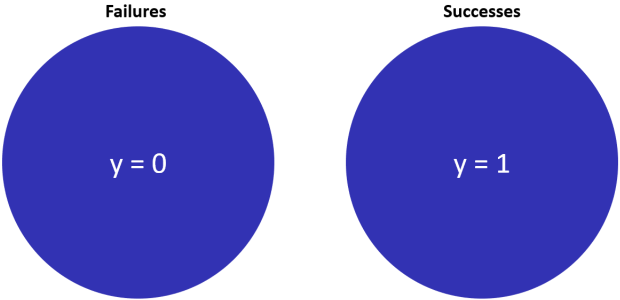

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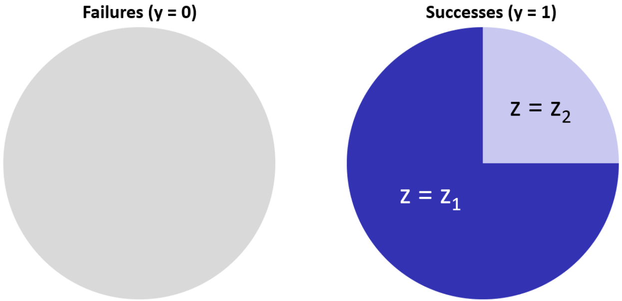

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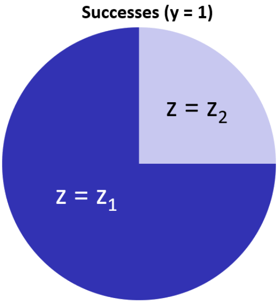


How to measure fairness?

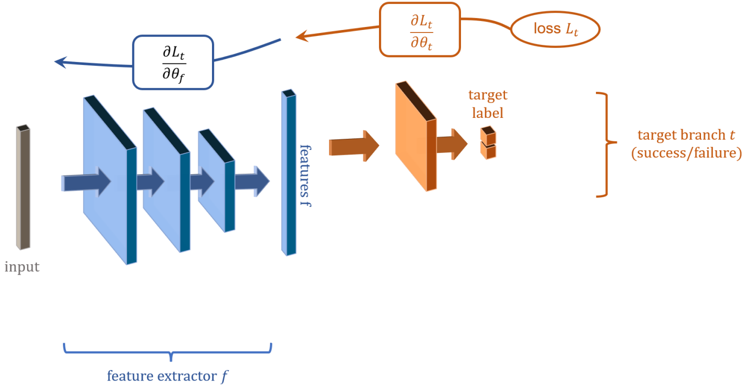
- **Equal opportunity:**

$$P(\hat{y} = 1 | z = z_1, y = 1) = P(\hat{y} = 1 | z = z_2, y = 1)$$

- **Equal opportunity gap:**

$$|P(\hat{y} = 1 | z = z_1, y = 1) - P(\hat{y} = 1 | z = z_2, y = 1)|$$

How can fairness be achieved?



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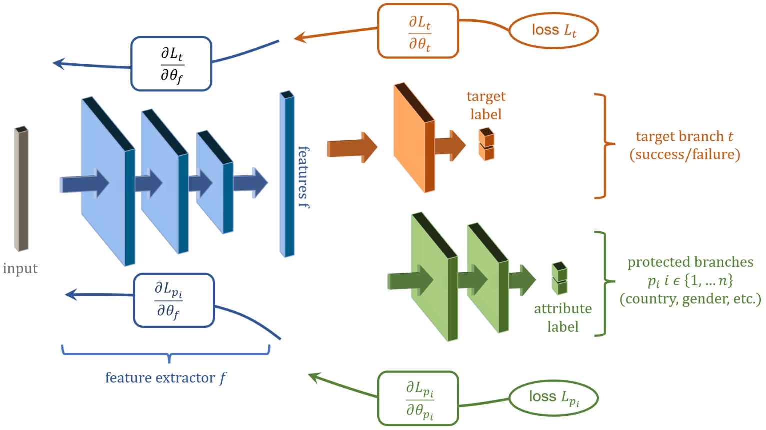

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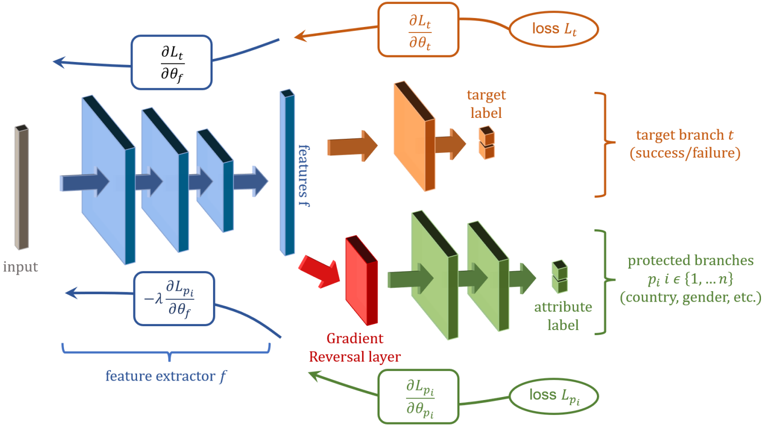

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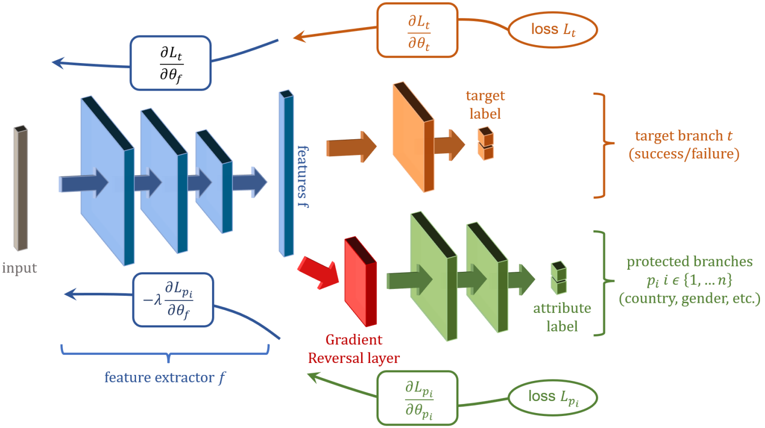

$$loss = loss_t + w_1 \cdot loss_{p_1} + \ldots + w_n \cdot loss_{p_n}$$

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Baseline model 1

Name*	Sector	Country	Currency	...
Hubrite	Hardware	USA	USD	...
RetailRiver	Retail	Italy	EUR	...
SolarZen	Energy	China	CNY	...
Finumo	FinTech	USA	USD	...

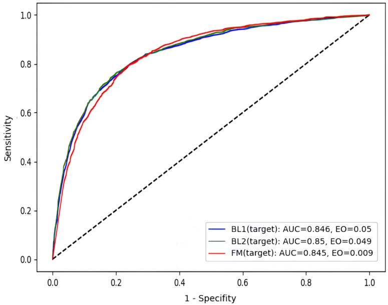
*company names are fictional

Baseline model 2

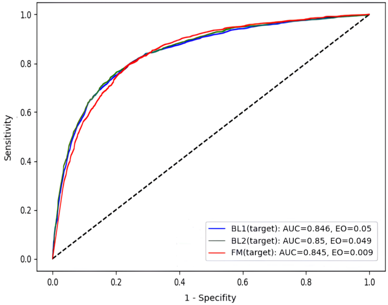
Name*	Sector	Country	Currency	...
Hubrite	Hardware		USD	...
RetailRiver	Retail		EUR	...
SolarZen	Energy		CNY	...
Finumo	FinTech		USD	...

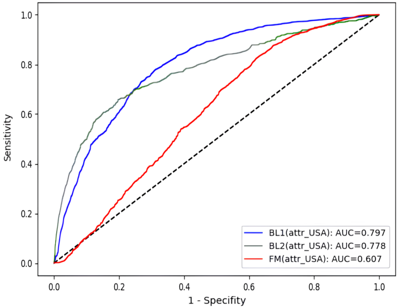
*company names are fictional

Protecting binary attribute USA: predict target

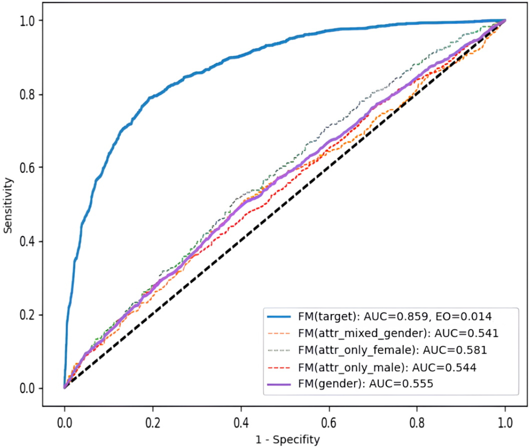


Protecting binary attribute USA: predict target and protected





Protect categorical attribute gender



Protect multiple categorical attributes

- Protecting a single sensitive attribute can increase equal opportunity gap
- Performance metrics remain at a satisfying level in our case

Model	AUC	EO
BL1	0.849	0.061
BL2	0.839	0.041
FM_country	0.847	0.070
FM_gender	0.859	0.065
FM_education	0.861	0.052
FM_university	0.853	0.054
FM_race	0.871	0.071
FM_ethnicity	0.843	0.071
FM	0.827	**0.033**

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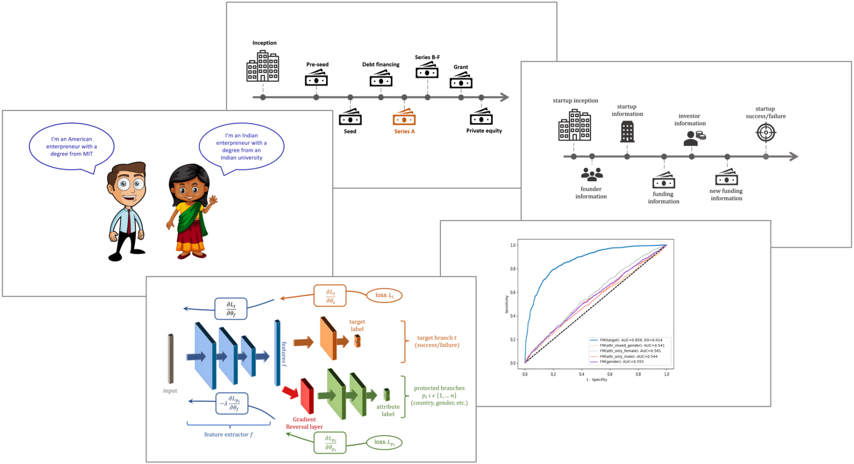
Putting fair success prediction into practice

- Not sufficient to simply remove sensitive attributes
- Experts need to determine which attributes to protect in the specific situation
- Gradient reversal can be employed to improve group fairness
- Trade-off between performance and fairness can occur

Q&A



Inception
Pre-seed
Debt financing
Series B-F
Grant
Seed
Series A
Private equity
startup inception
startup information
investor information
startup success/failure
founder information
funding information
new funding information
I'm an American entrepreneur with a degree from MIT
I'm an Indian entrepreneur with a degree from an Indian university
FM(target): AUC=0.859, EO=0.014
FM(attr_mixed_gender): AUC=0.541
FM(attr_only_female): AUC=0.581
FM(attr_only_male): AUC=0.544
FM(gender): AUC=0.555
Sensitivity
1 - Specifity
loss L_t
$\frac{\partial L_t}{\partial \theta_t}$
$\frac{\partial L_t}{\partial \theta_f}$
input
features f
target label
target branch t (success/failure)
Gradient Reversal layer
attribute label
protected branches p_i $i \in \{1, \dots n\}$ (country, gender, etc.)
$-\lambda \frac{\partial L_{p_i}}{\partial \theta_f}$
feature extractor f
$\frac{\partial L_{p_i}}{\partial \theta_{p_i}}$
loss L_{p_i}

Let's connect

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- LinkedIn:
  Michèle Wieland

References I

Yiea-Funk Te, Michèle Wieland, Martin Frey, Asya Pyatigorskaya, Penny Schiffer, Helmut Grabner. *Making it into a successful Series A Funding: An Analysis of Crunchbase and LinkedIn Data*. Available at SSRN 4217648.