Ethics in NLP

CSE 538

Ethics in NLP

Bias

Privacy

Ethical Research and Development

Ethics in NLP - Bias

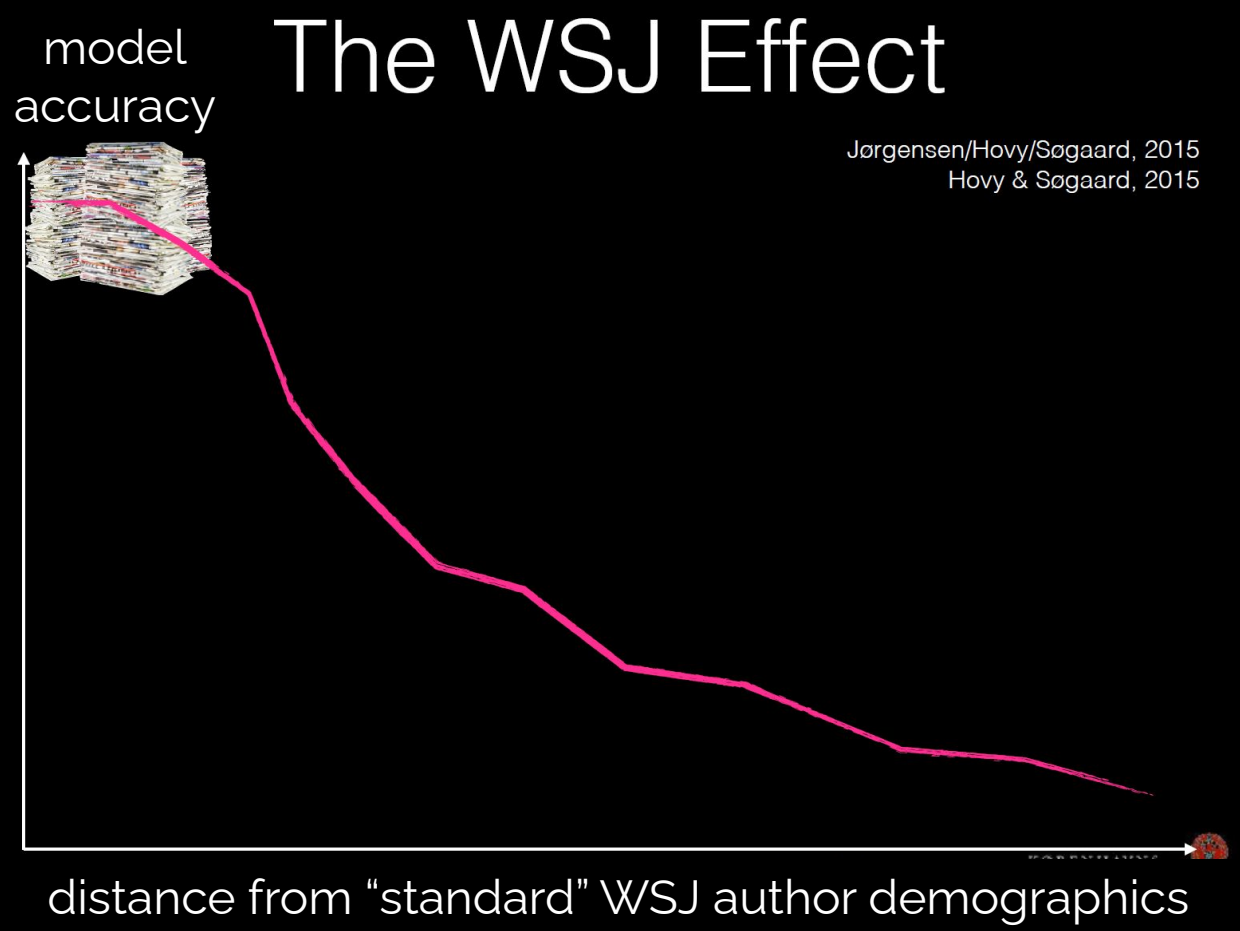
Consequences of Sociodemographic Bias in NLP Models:

- Outcome Disparity: Predicted distribution given A,
  are dissimilar from ideal distribution given A

- Error Disparity: Predicts less accurate for authors of given demographics.

Shah, D., Schwartz, H. A., Hovy, D. (2020). Predictive Biases in Natural Language Processing Models: A Conceptual Framework and Overview. *In ACL-2020: Proceedings of the Association for Computational Linguistics.*

Two Examples



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“Outcome Disparity”

Person-level

- attribute = 1
- attribute = 2

“Error Disparity”

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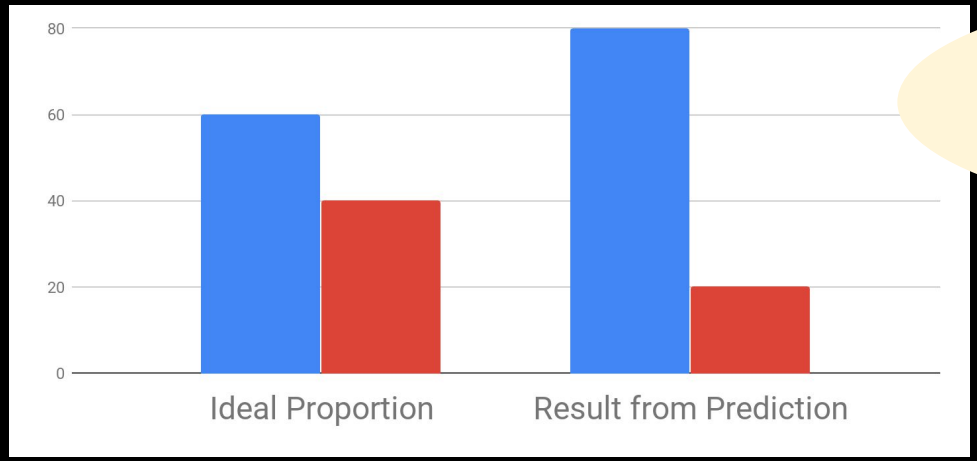

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“Error Disparity”

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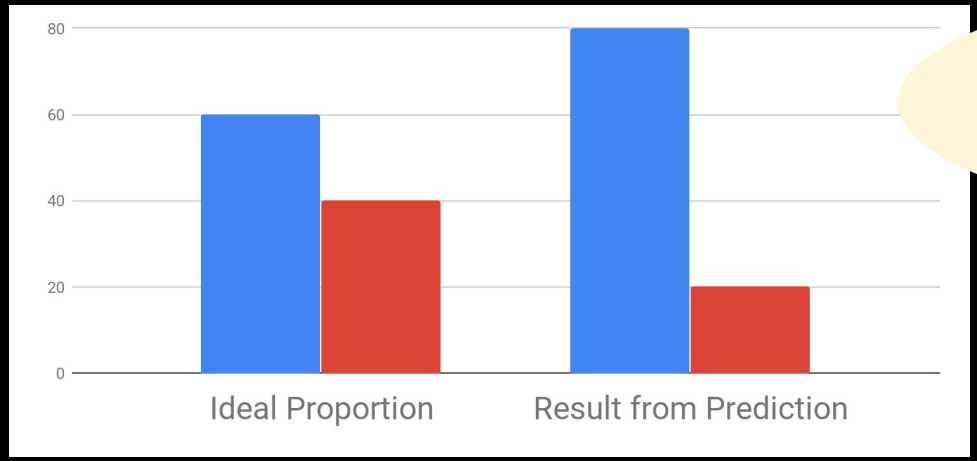

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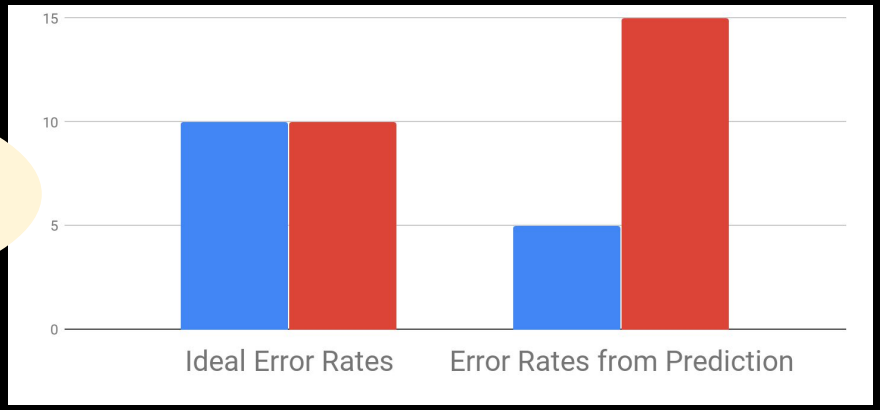
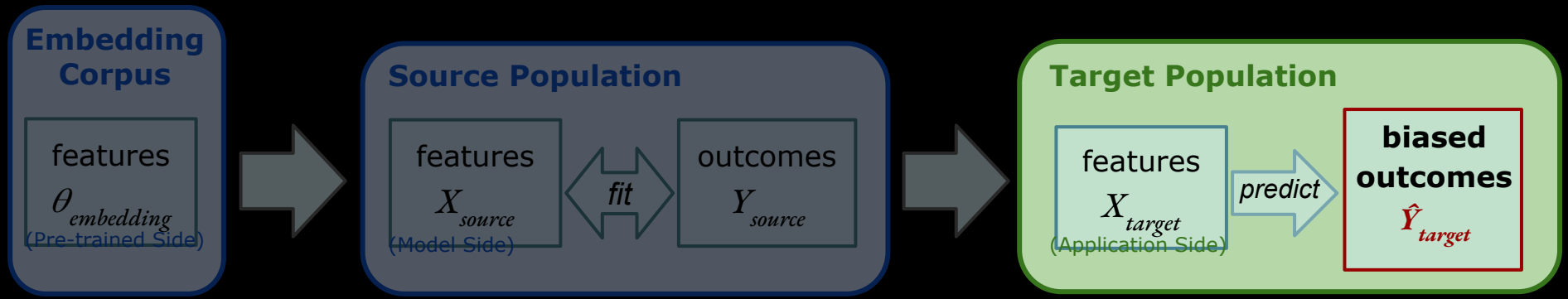
"Error Disparity"



Conceptual Framework:



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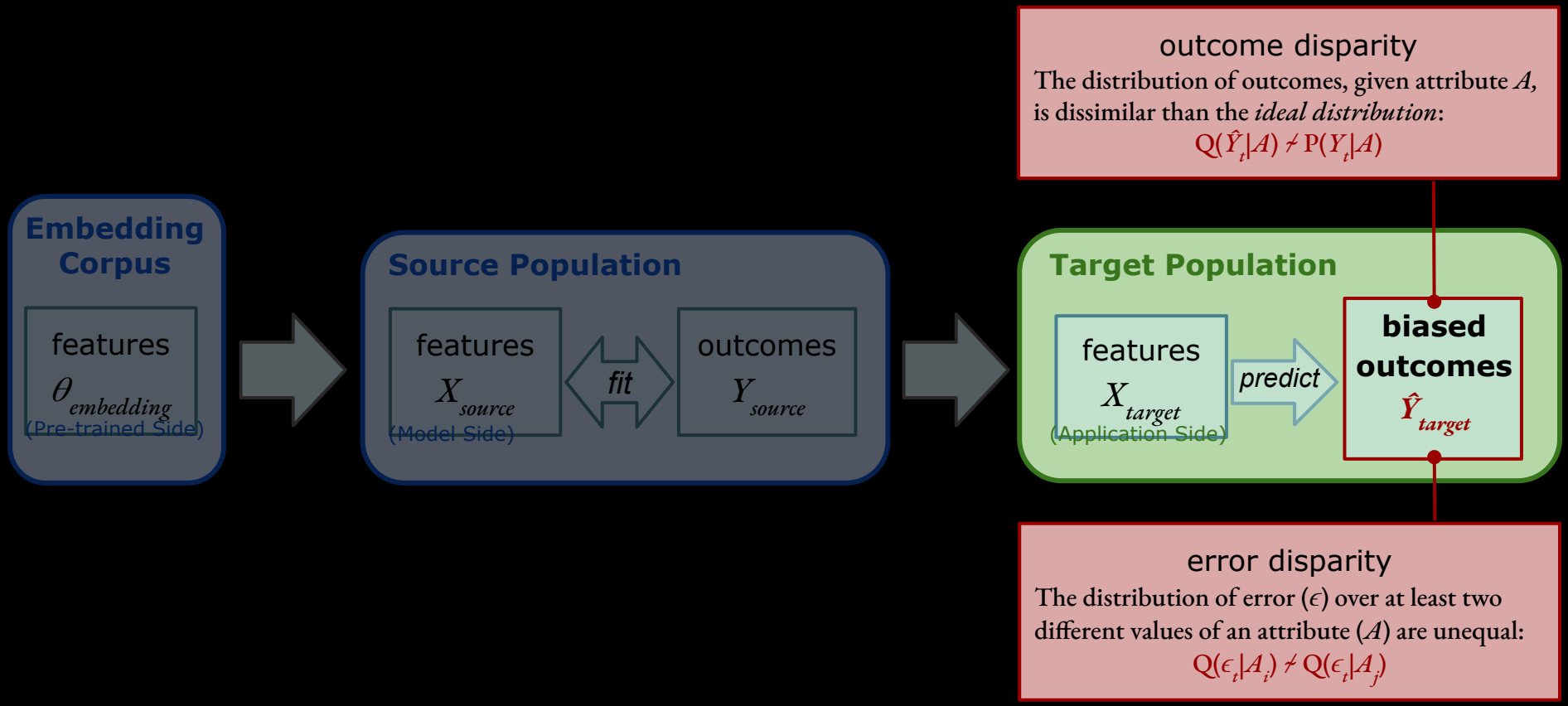
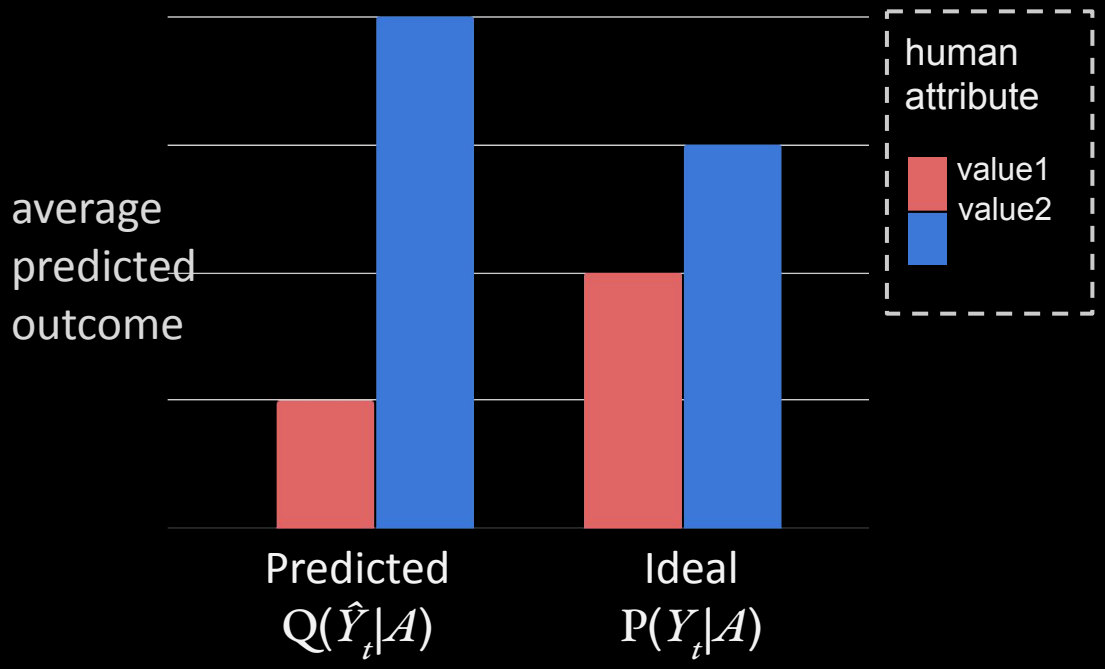


Outcome Disparity



outcome disparity

The distribution of outcomes, given attribute A, is dissimilar than the *ideal distribution*:

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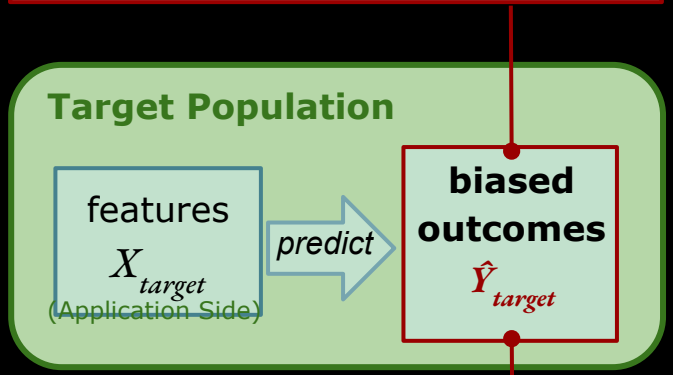

error disparity

The distribution of error (ϵ) over at least two different values of an attribute (A) are unequal:

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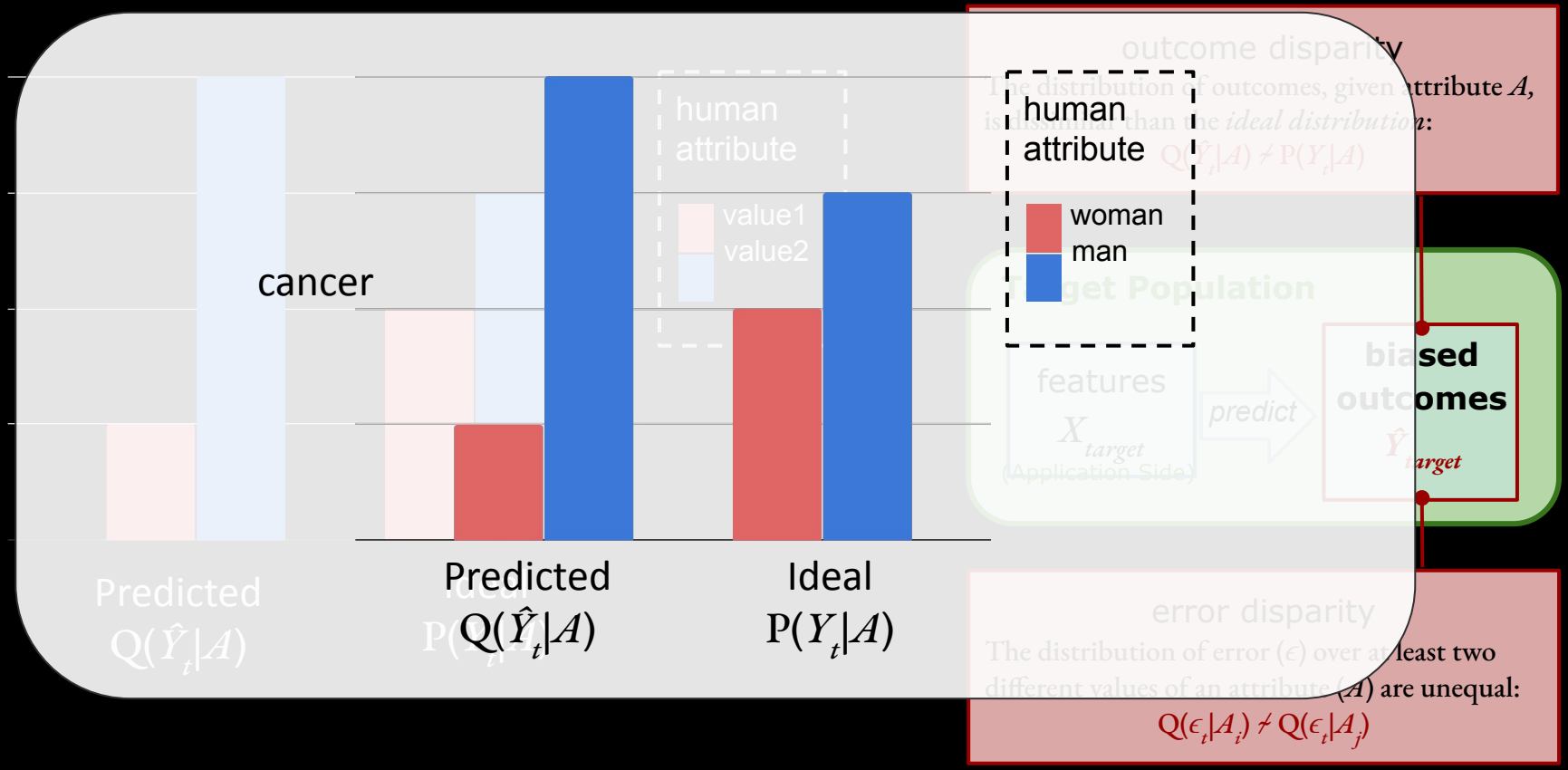
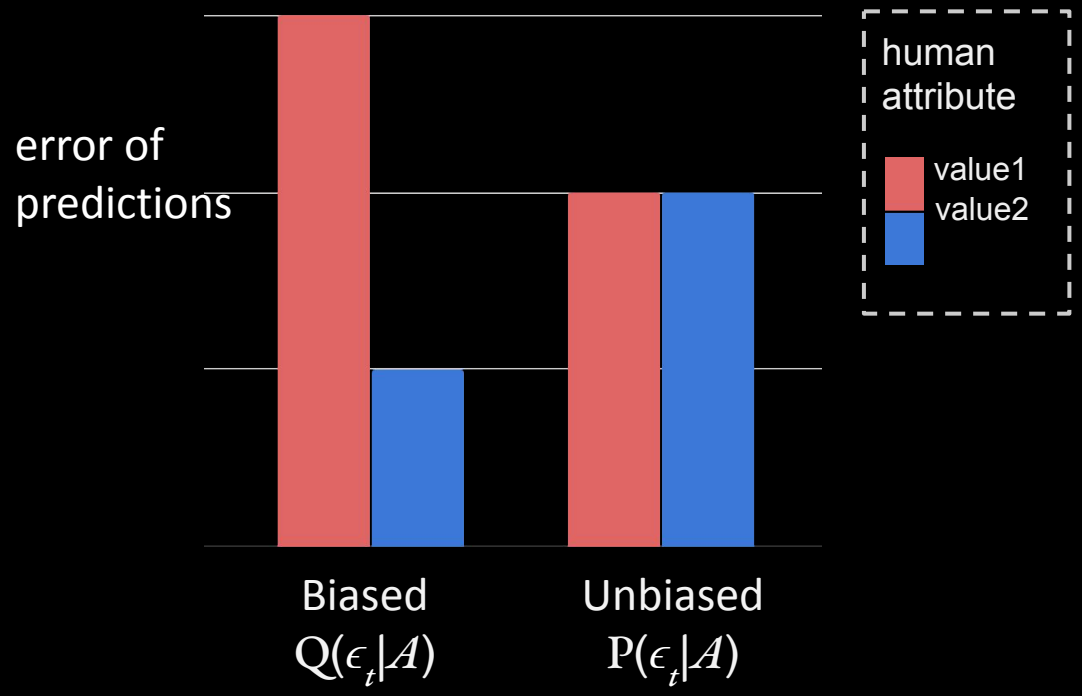
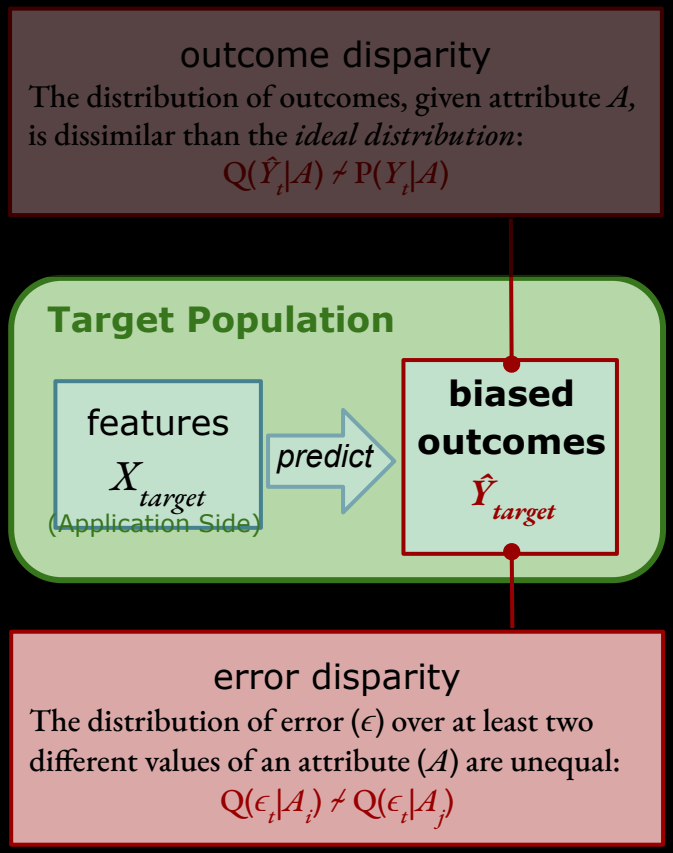
Outcome Disparity



Error Disparity





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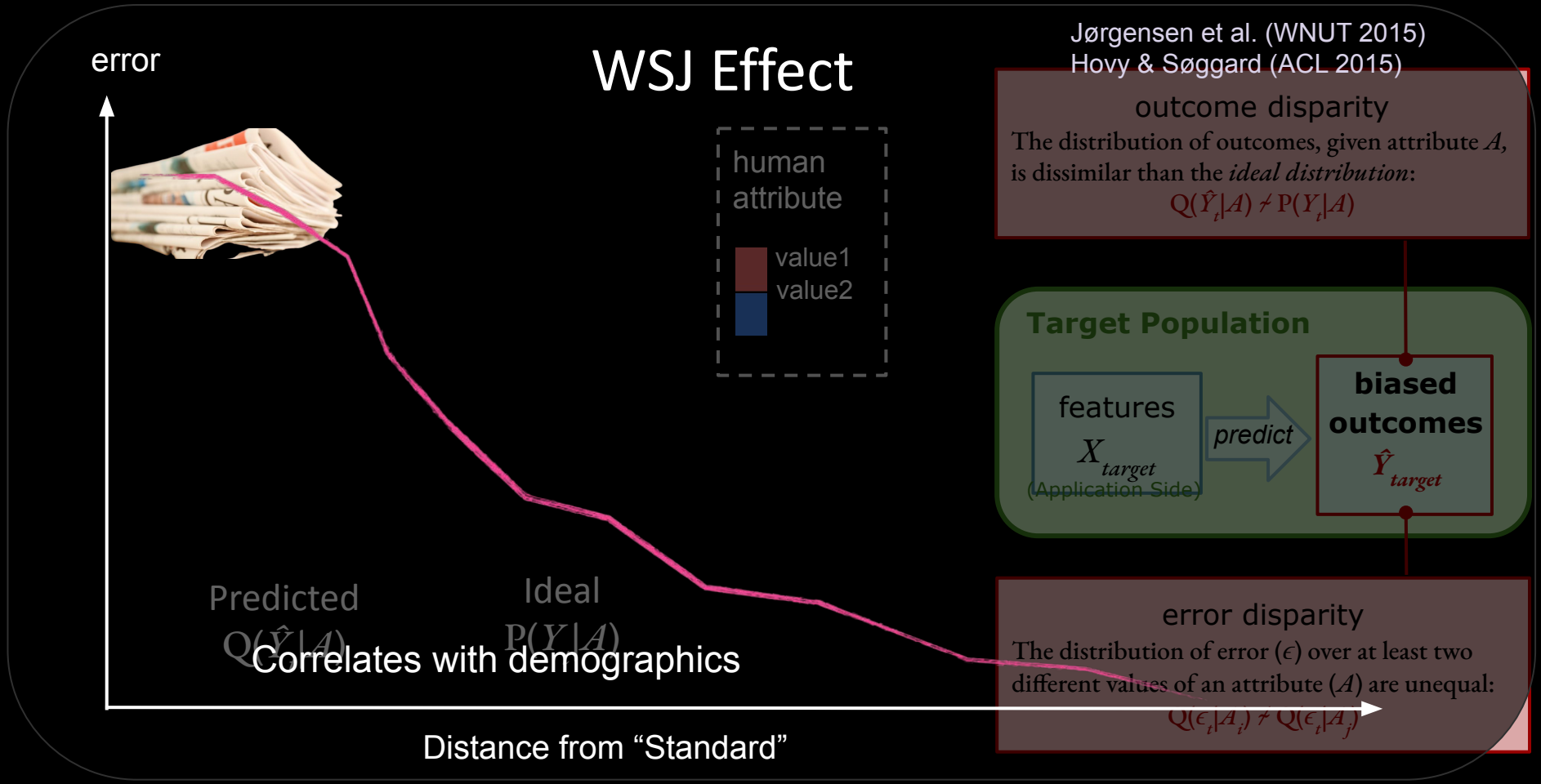
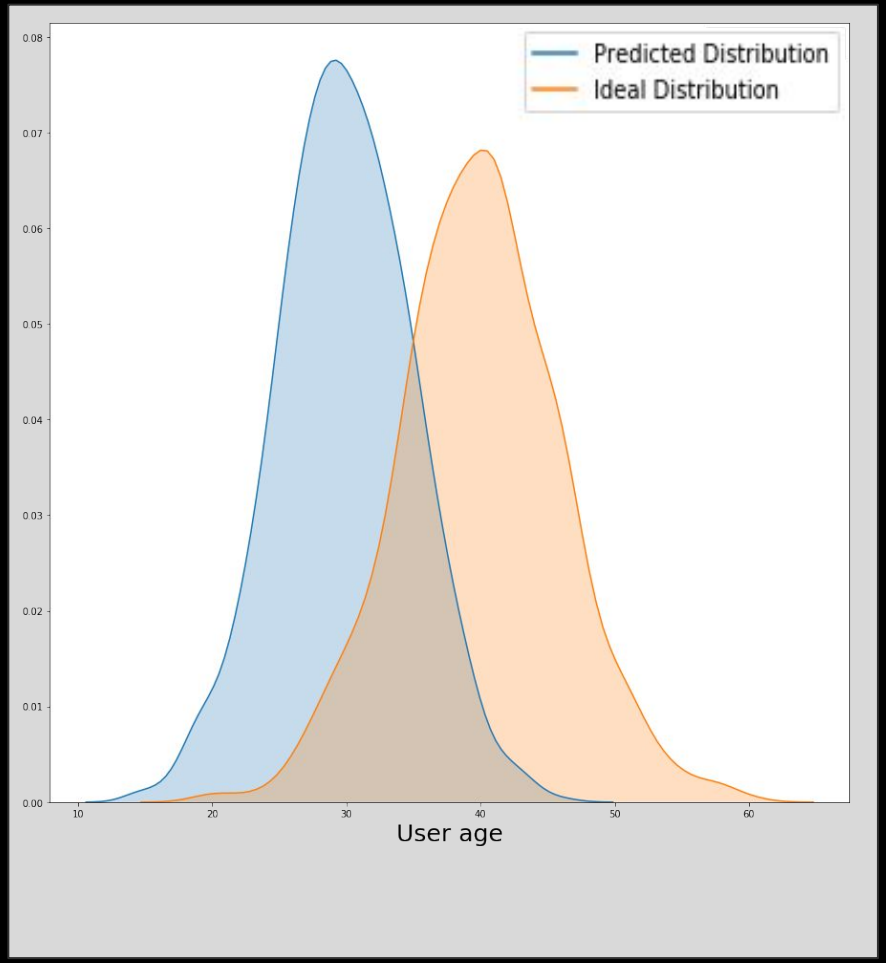


Disparities



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Target Population

features X_{target} (Application Side) → *predict* → **biased outcomes** $\hat{Y}_{target}$

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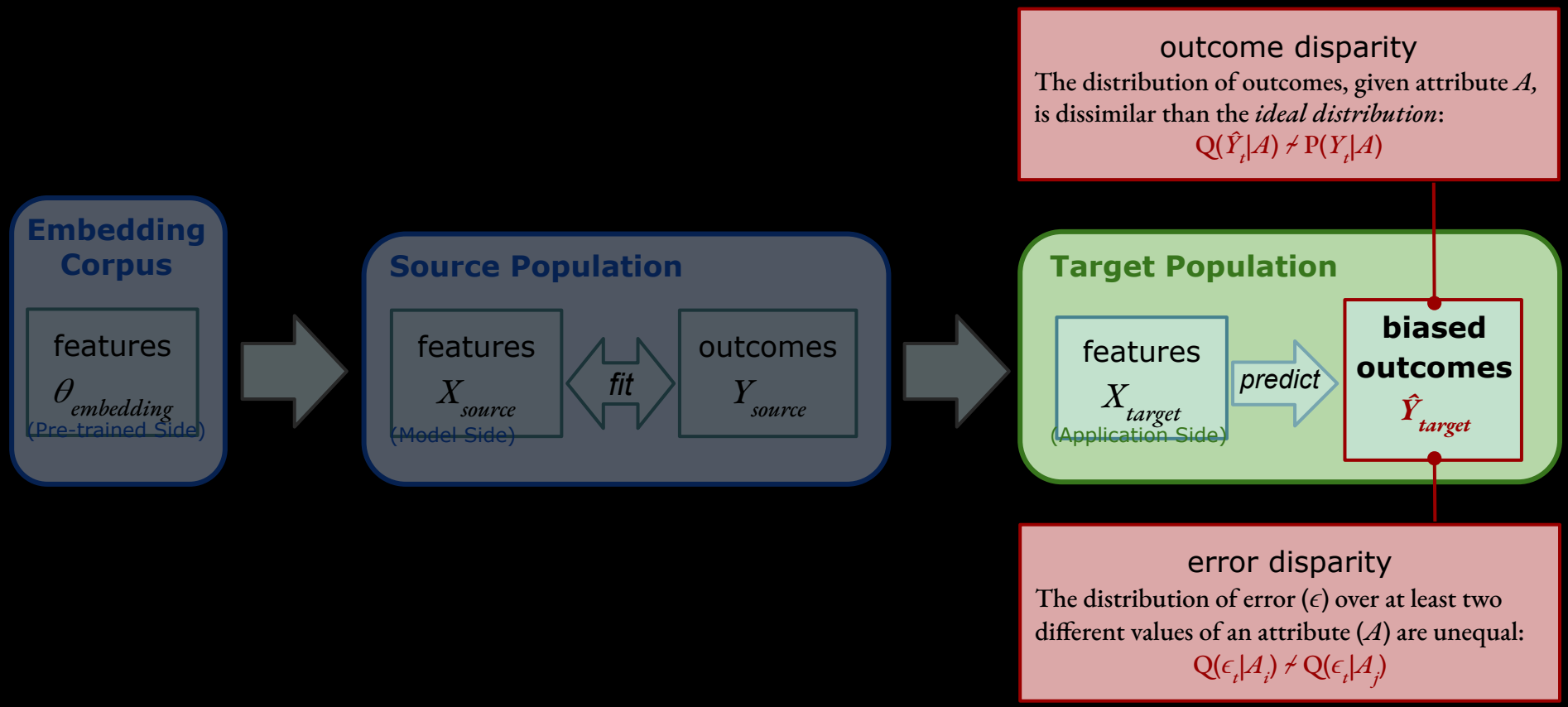
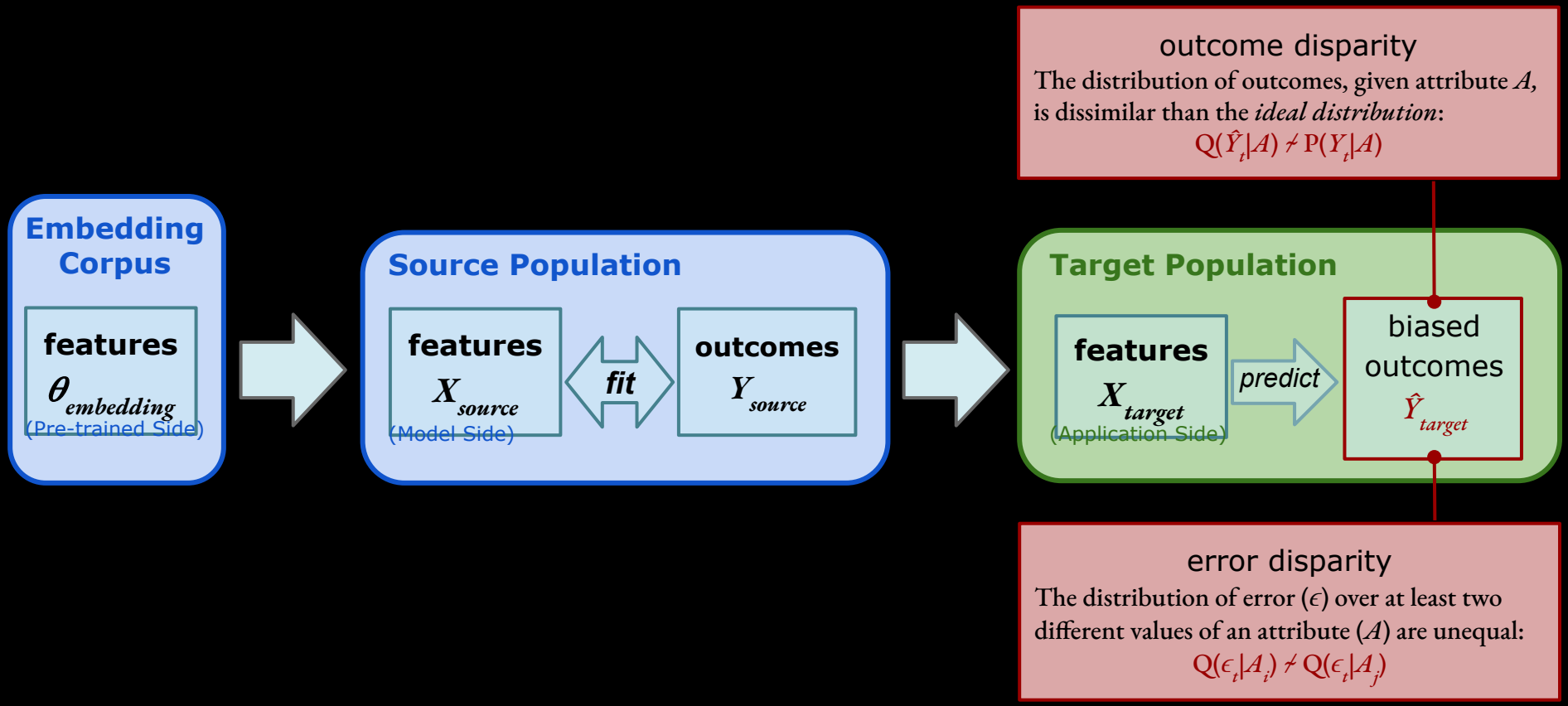
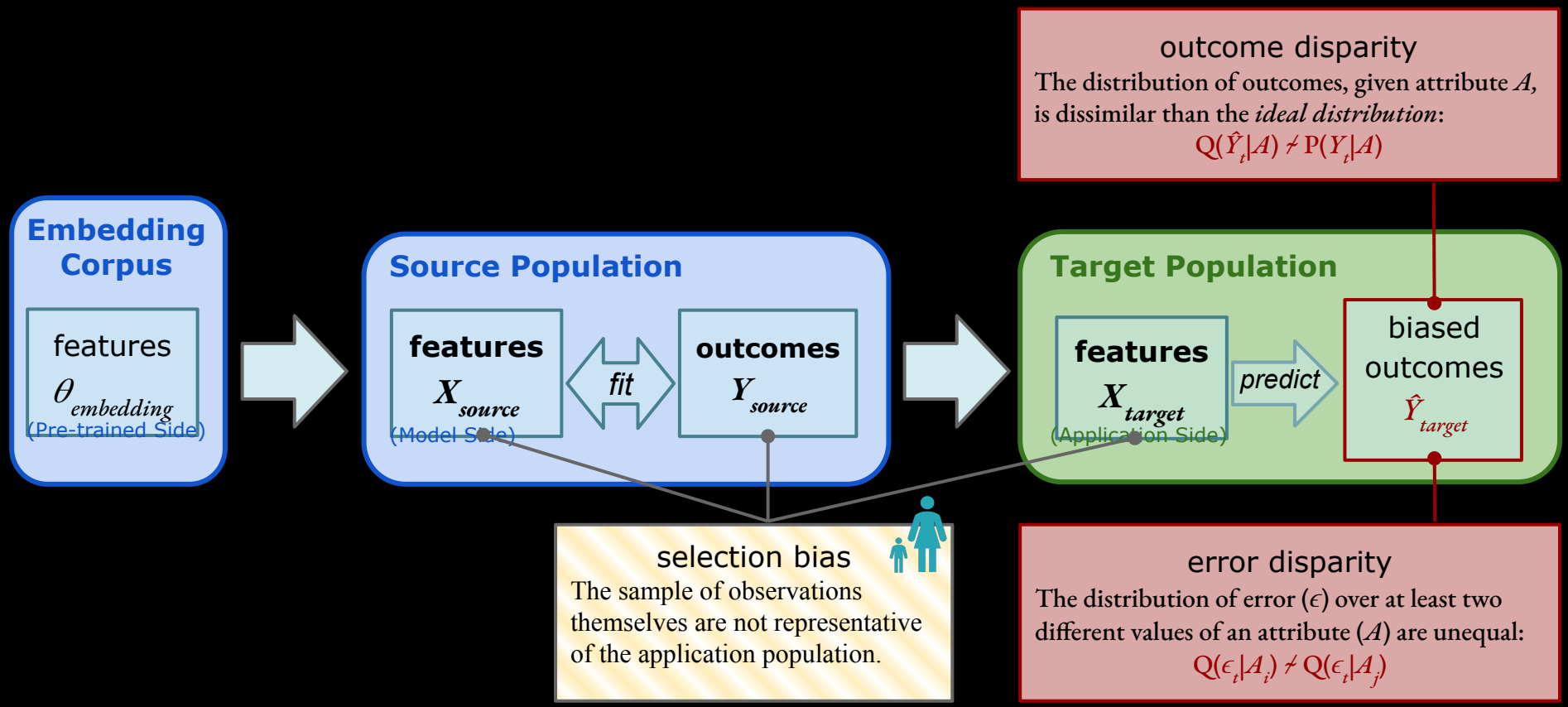
Disparities



Origins of Bias



Selection Bias




Selection Bias
proportion of sample
human attribute
value1
value2
Embedding Corpus
features
$\theta_{embedding}$
(Pre-trained Side)
Source Population
Source
$Q(A_S)$
features
X_{source}
(Model Side)
Target
$P(A_T)$
fit
outcomes
Y_{source}
Target Population
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The sample of observations themselves are not representative of the application population.
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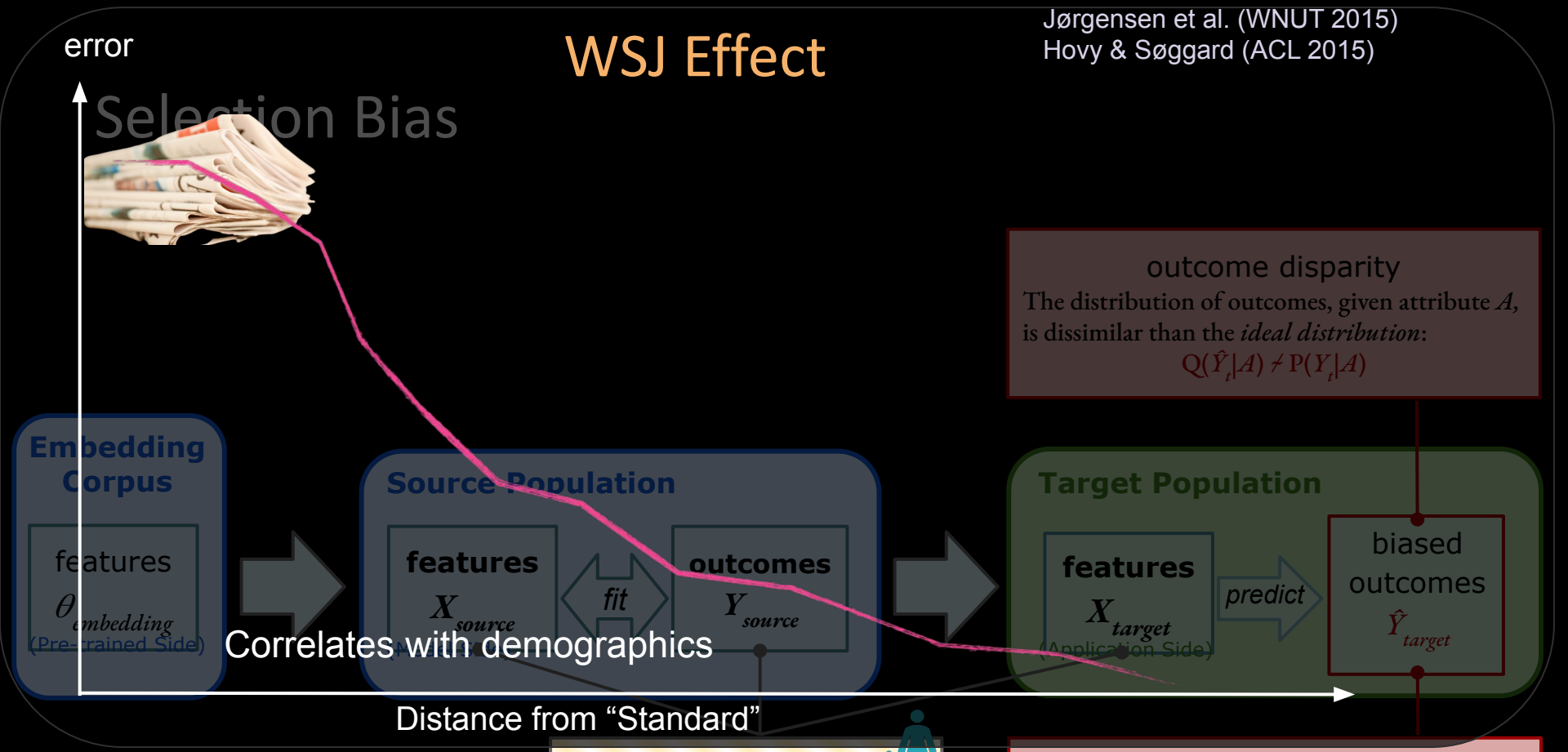
WSJ Effect

Jørgensen et al. (WNUT 2015)
Hovy & Søggard (ACL 2015)



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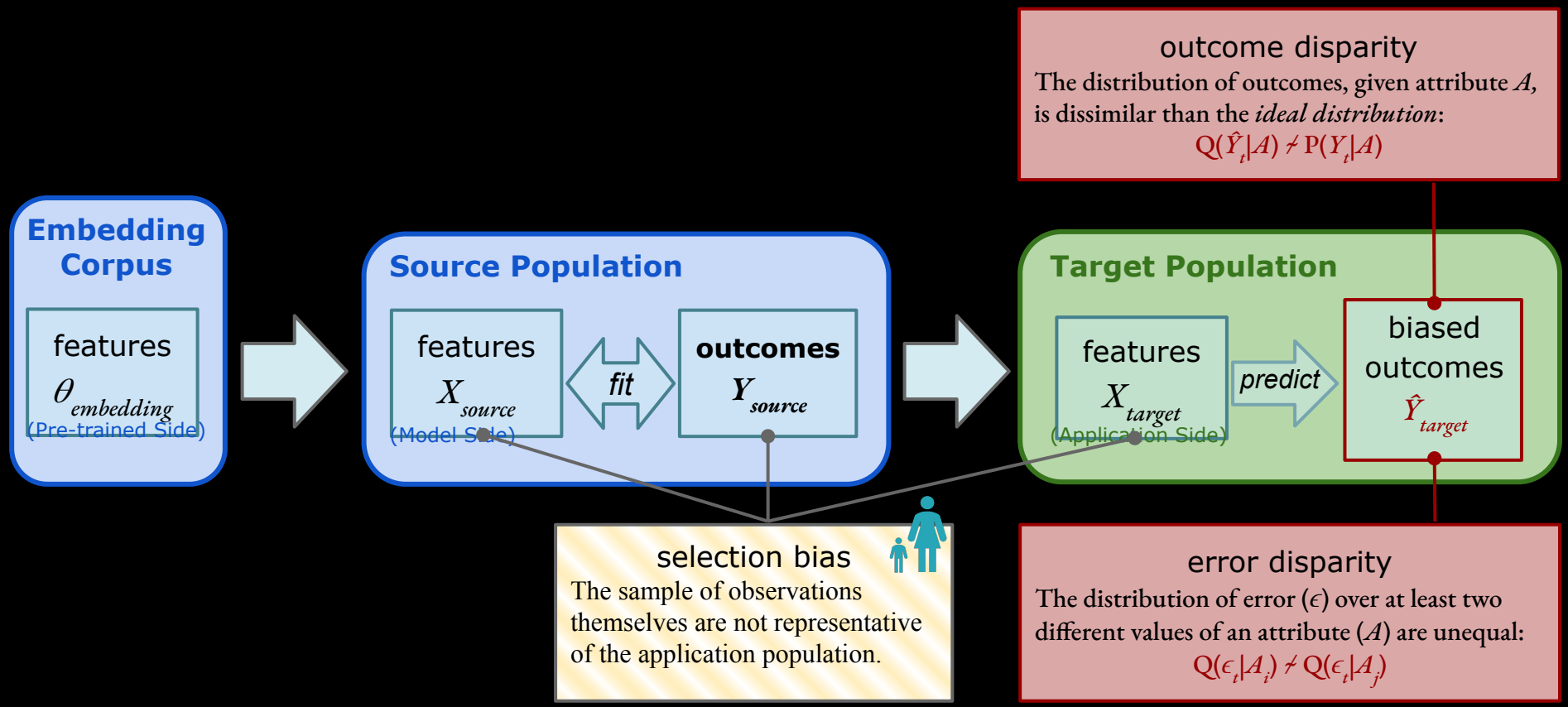
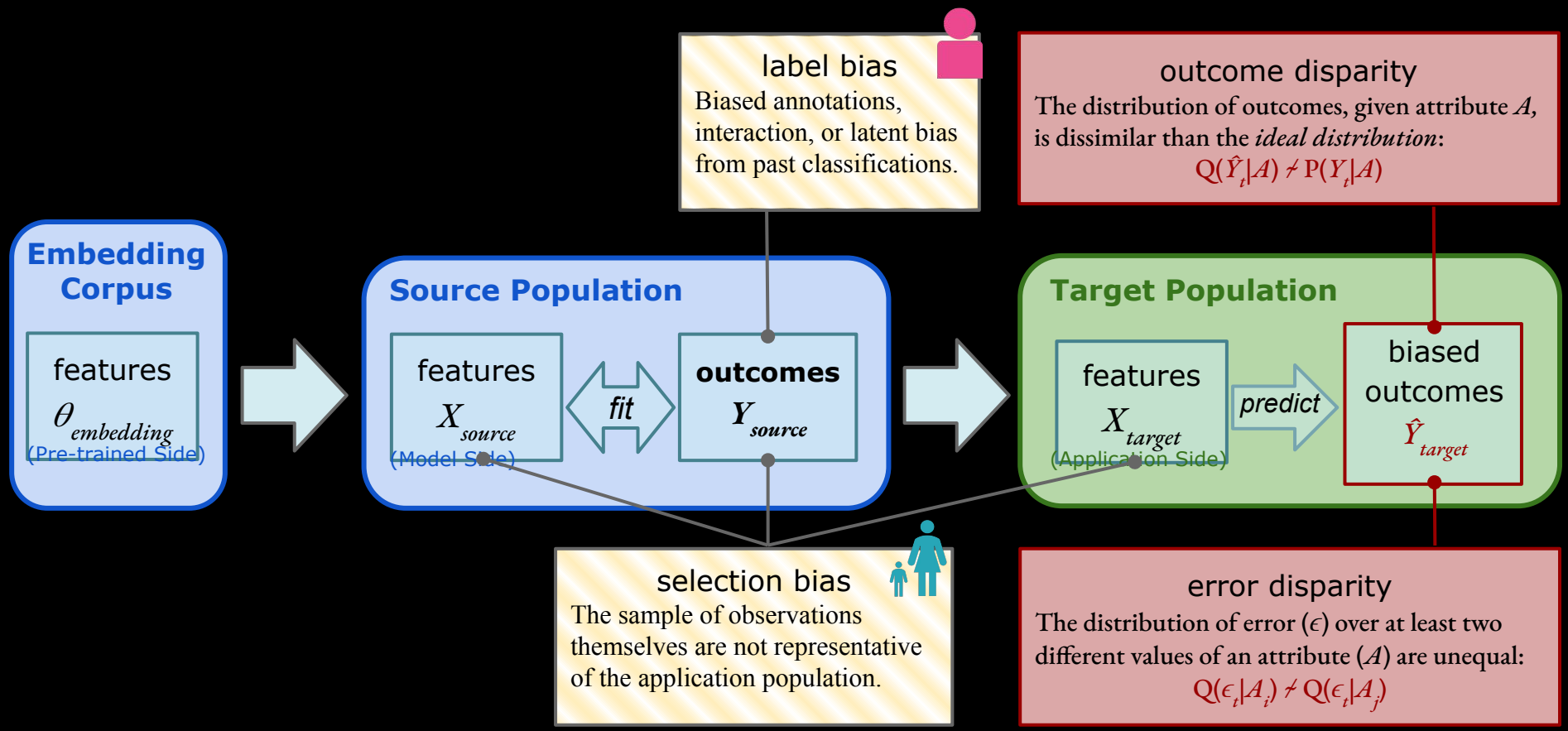


Label Bias


label bias
Biased annotations, interaction, or latent bias from past classifications.
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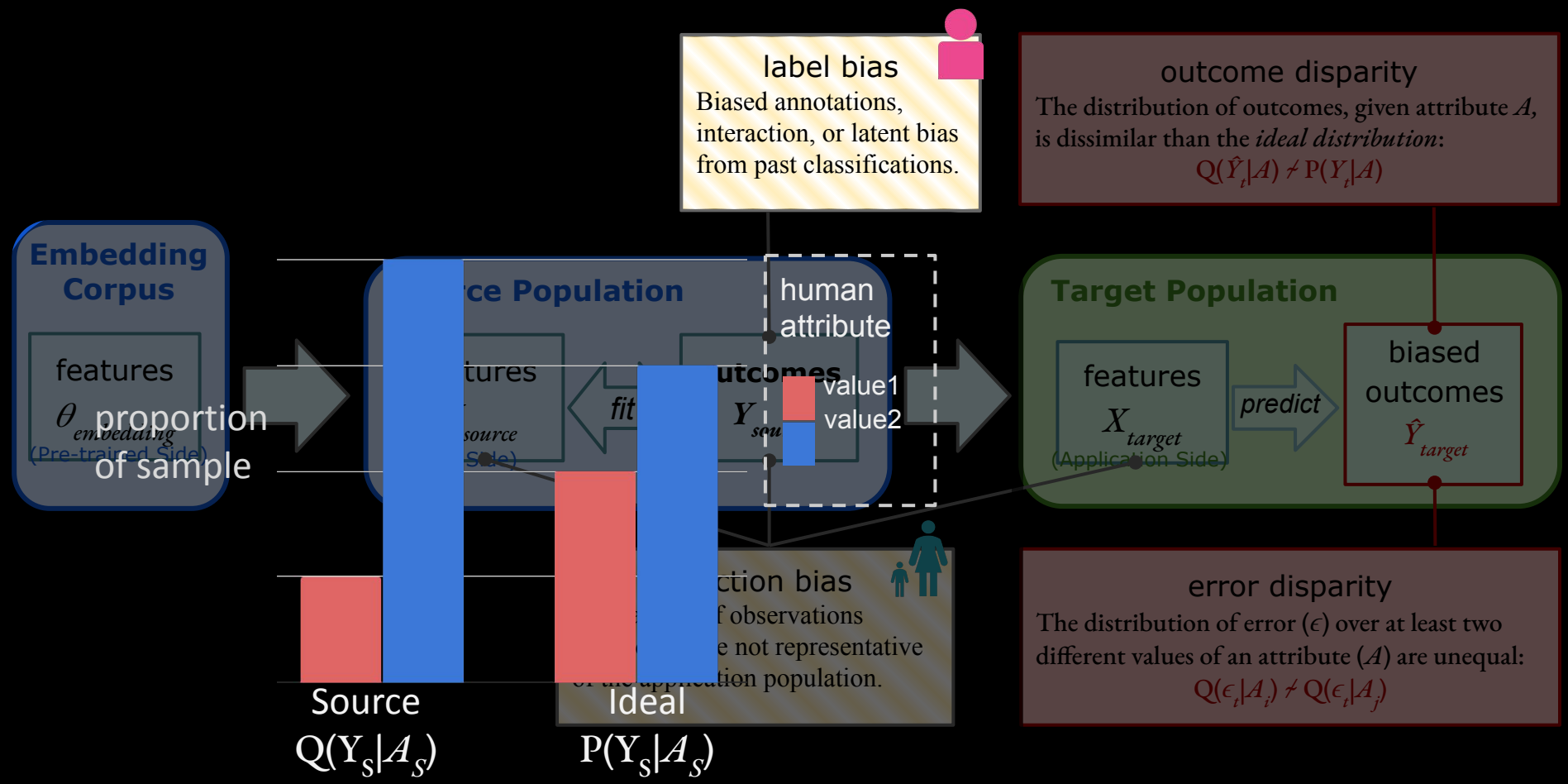
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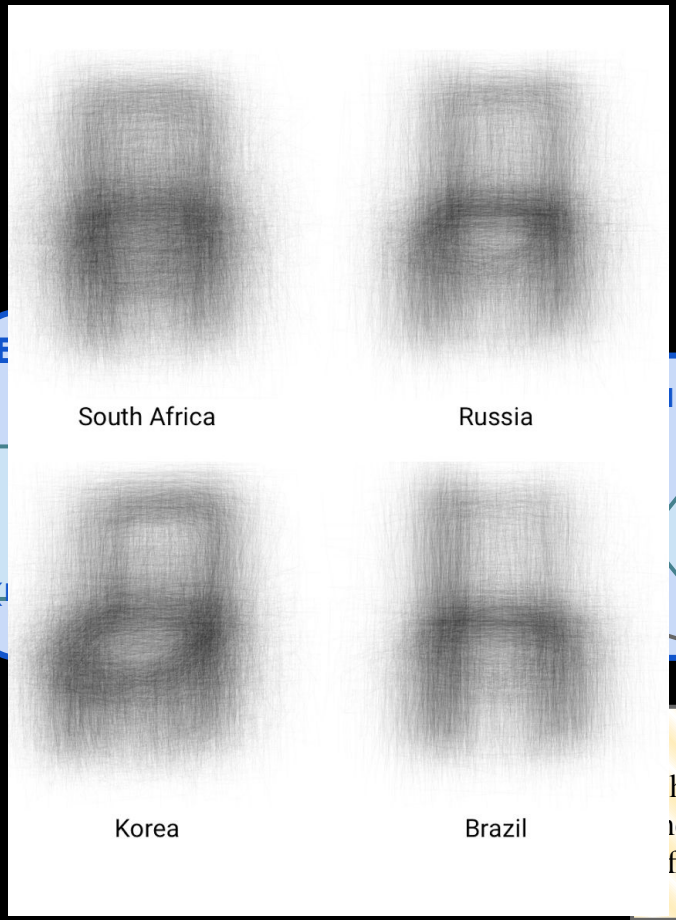
Label Bias - Example: Label word with drawing



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Devin Coldeway. 2017. TechCrunch: Google releases millions of bad drawings for you (and your AI) to paw through
https://techcrunch.com/2017/08/25/google-releases-millions-of-bad-drawings-for-you-and-your-ai-to-paw-through/

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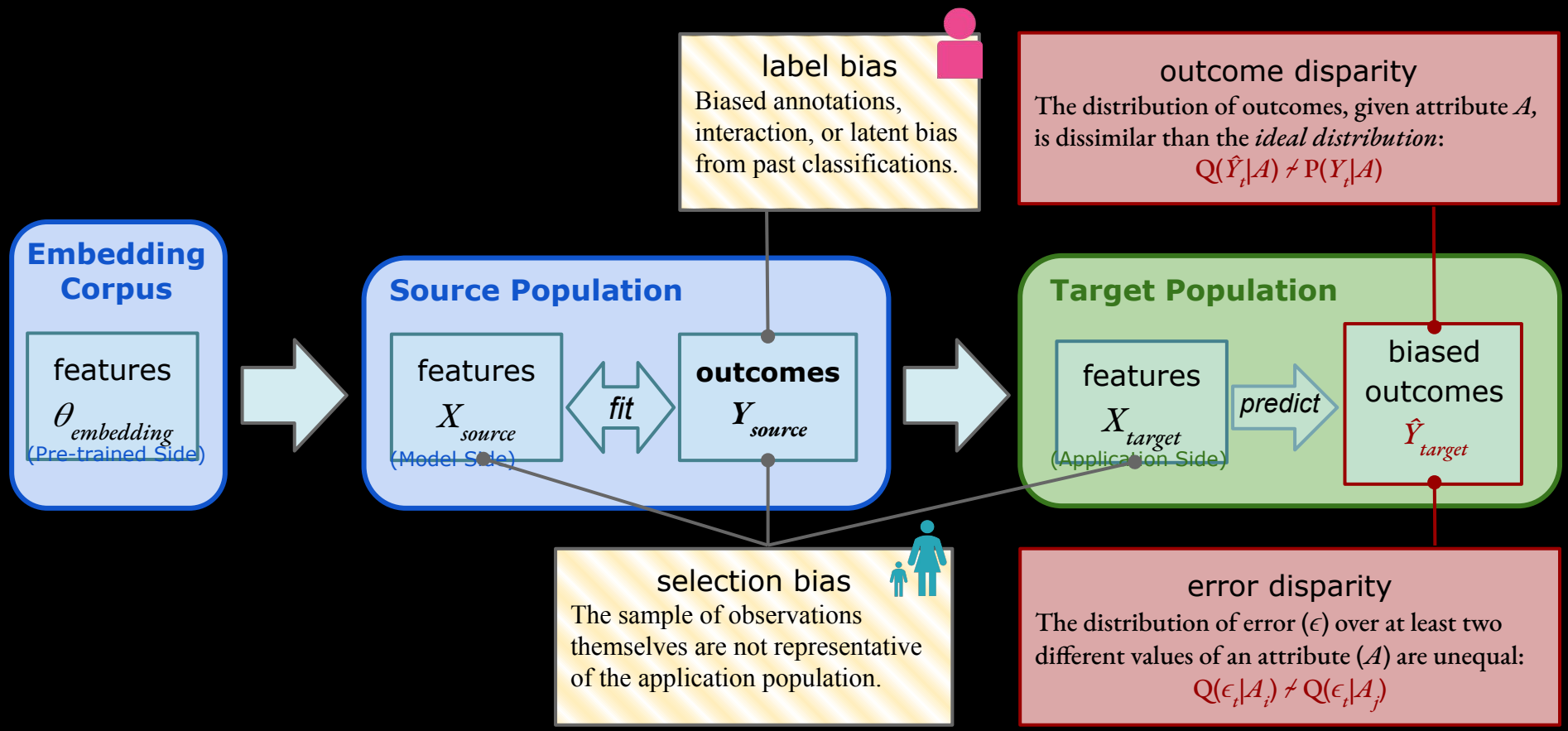
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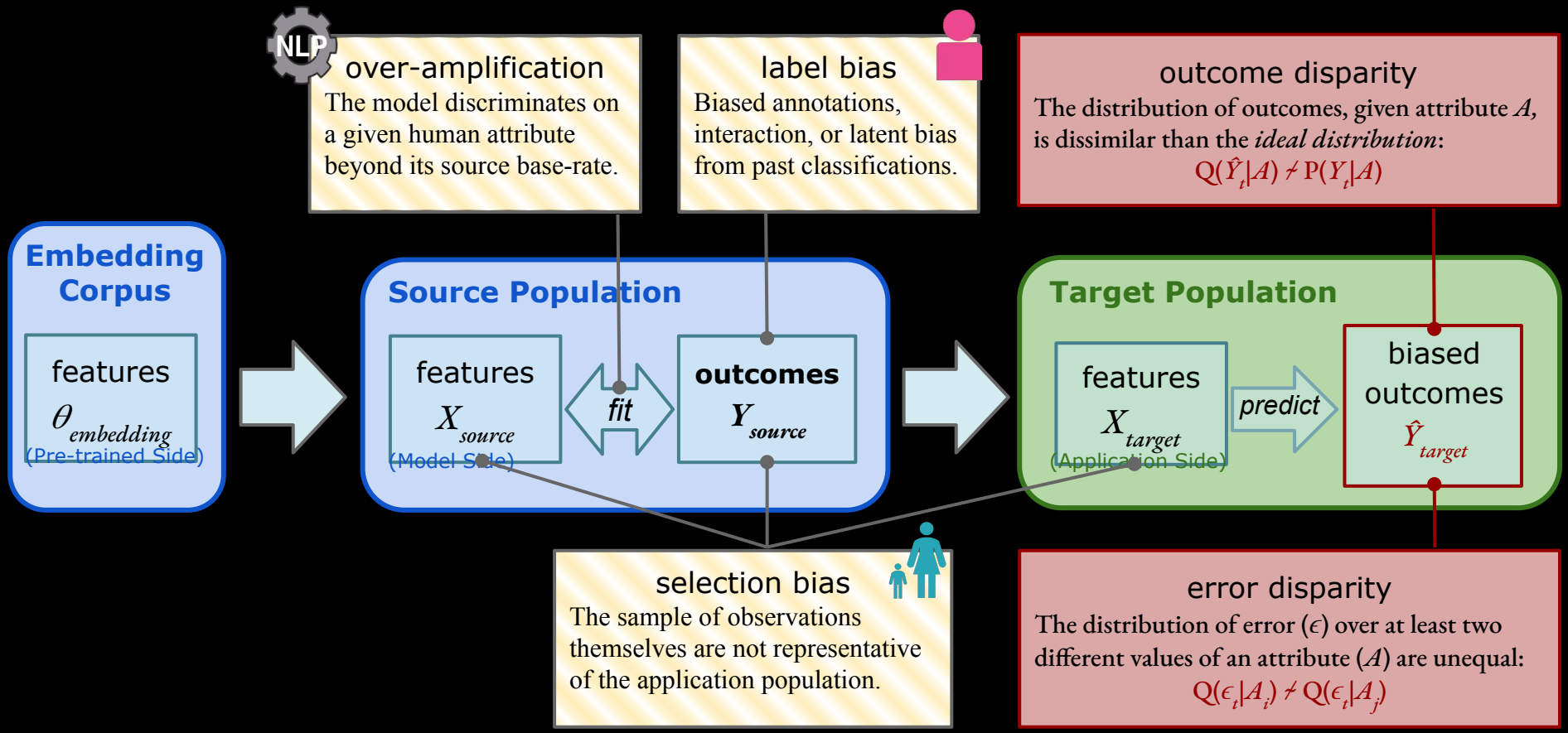

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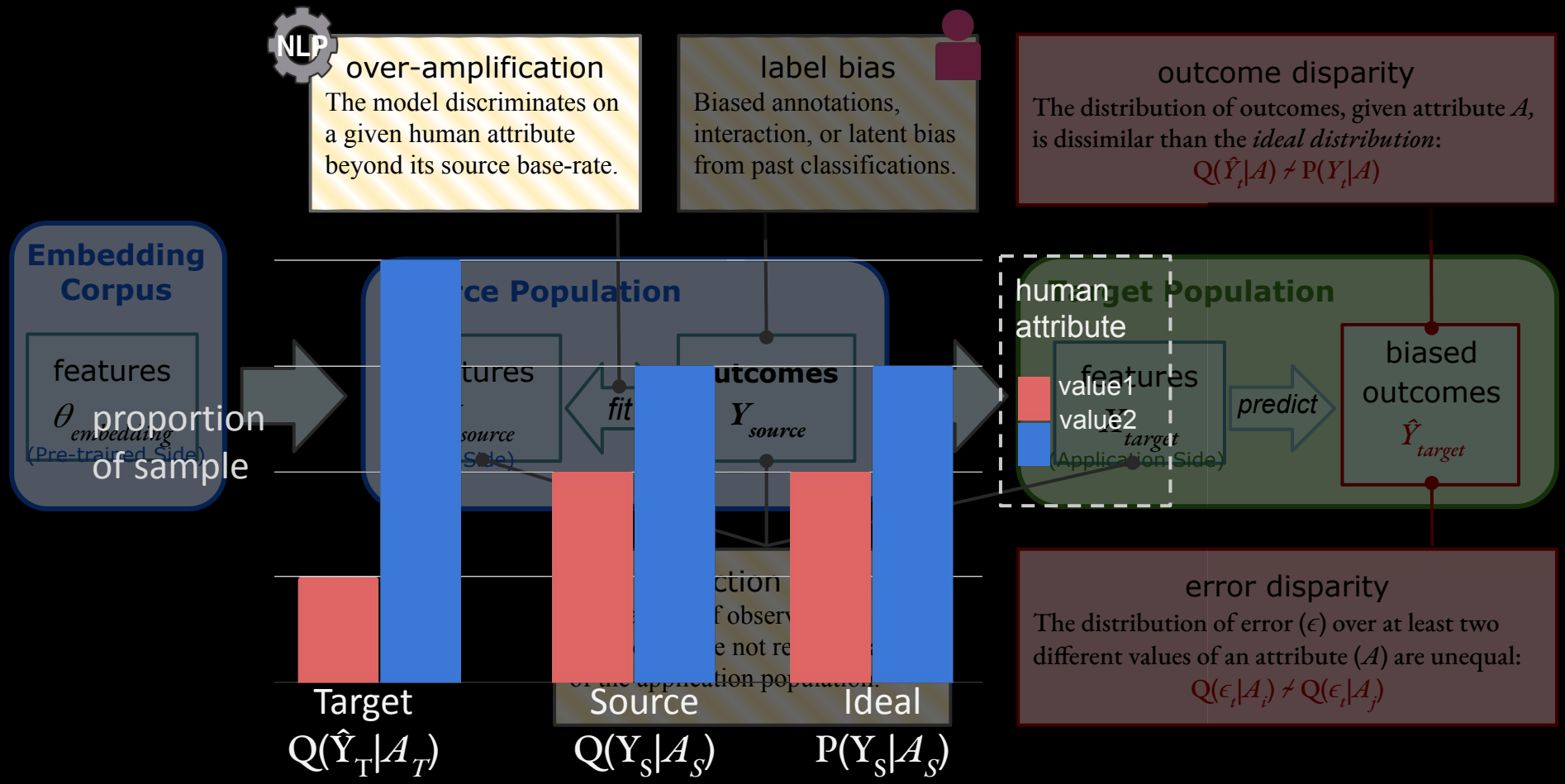


Zhao et al. (ACL 2015)

Overamplifiction - Model Amplifies Bias

BIAS = 0.66

Agent: WOMAN

Agent: MAN

Agent: WOMAN

BIAS = 0.84

WOMAN

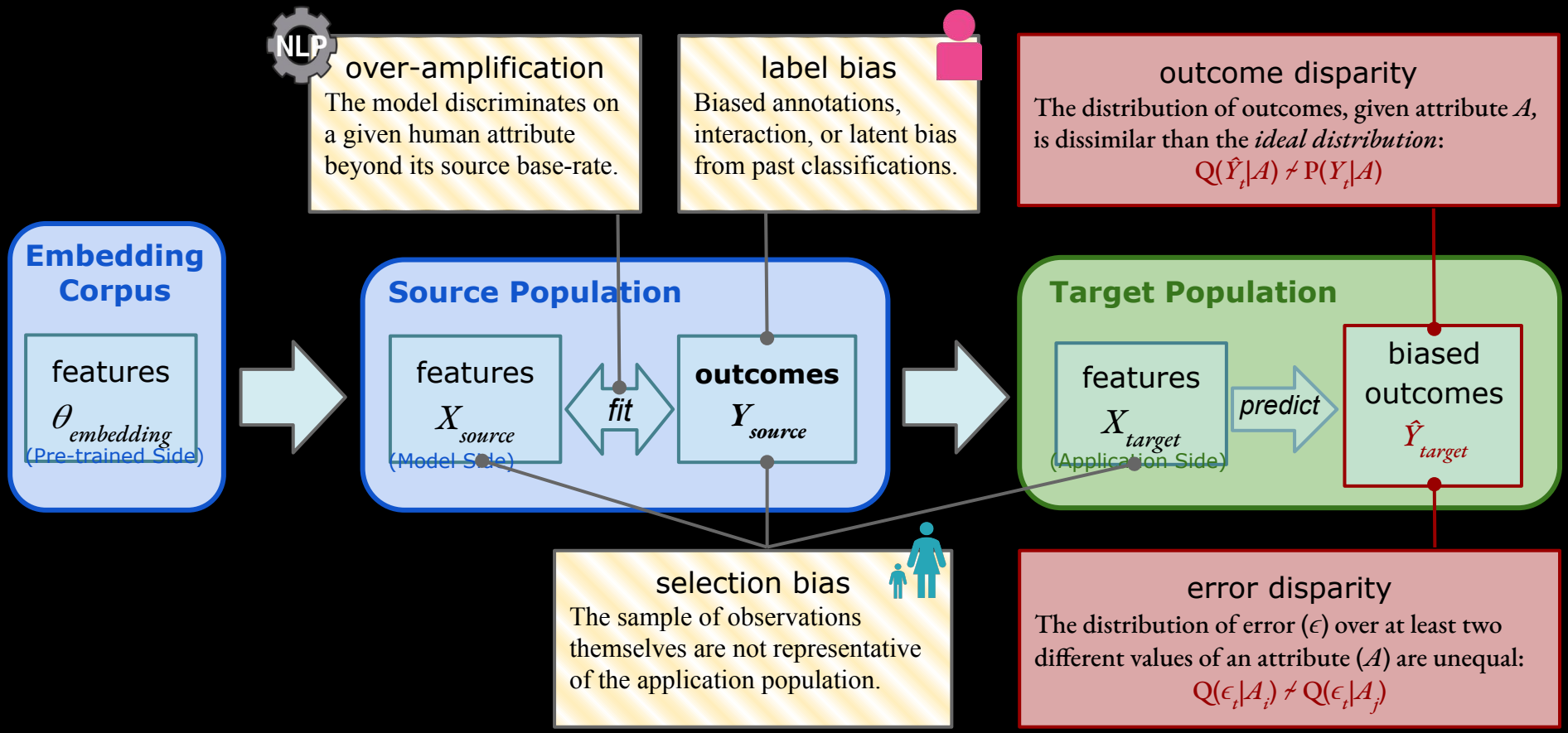
WOMAN

WOMAN

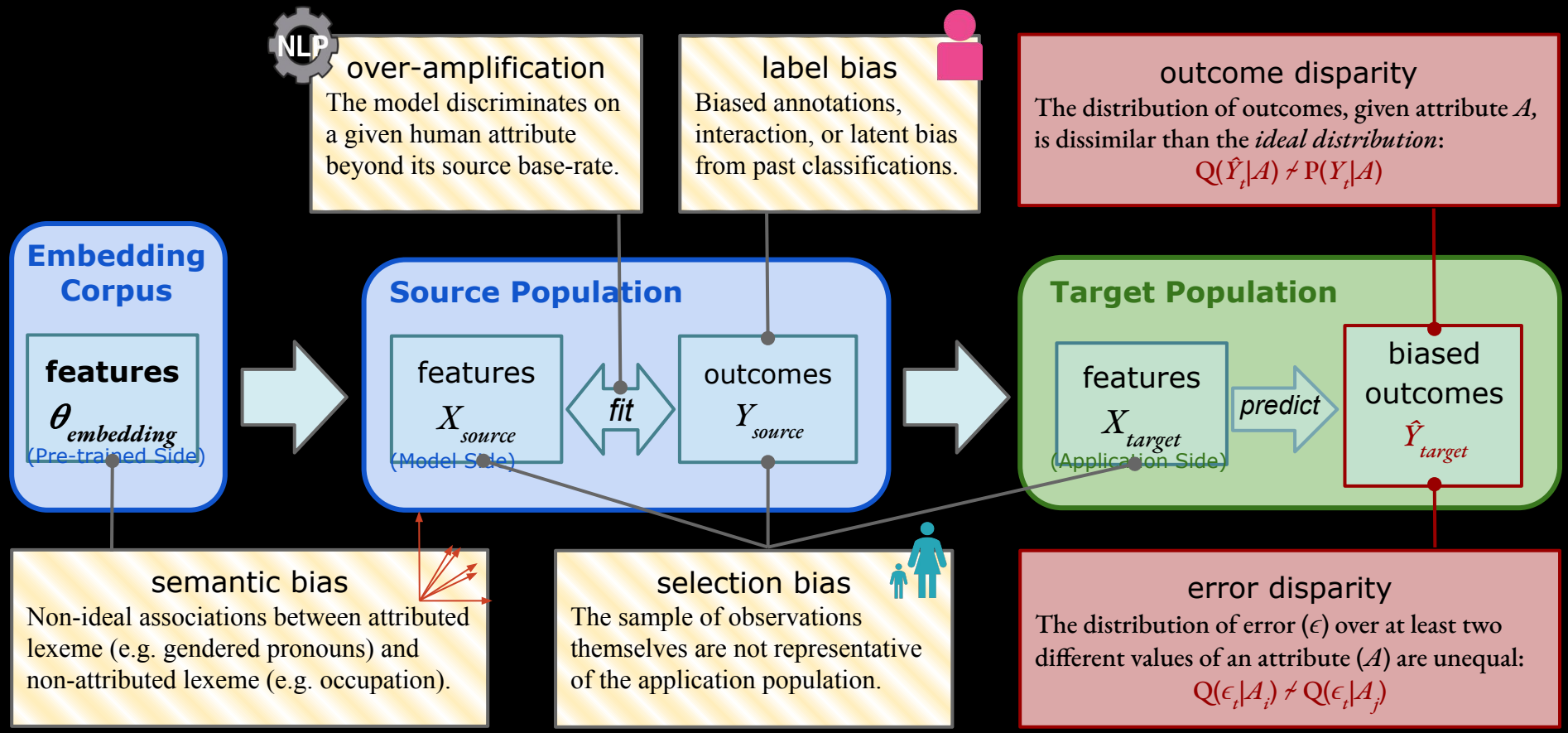
MAN

WOMAN

Overamplification



Semantic Bias



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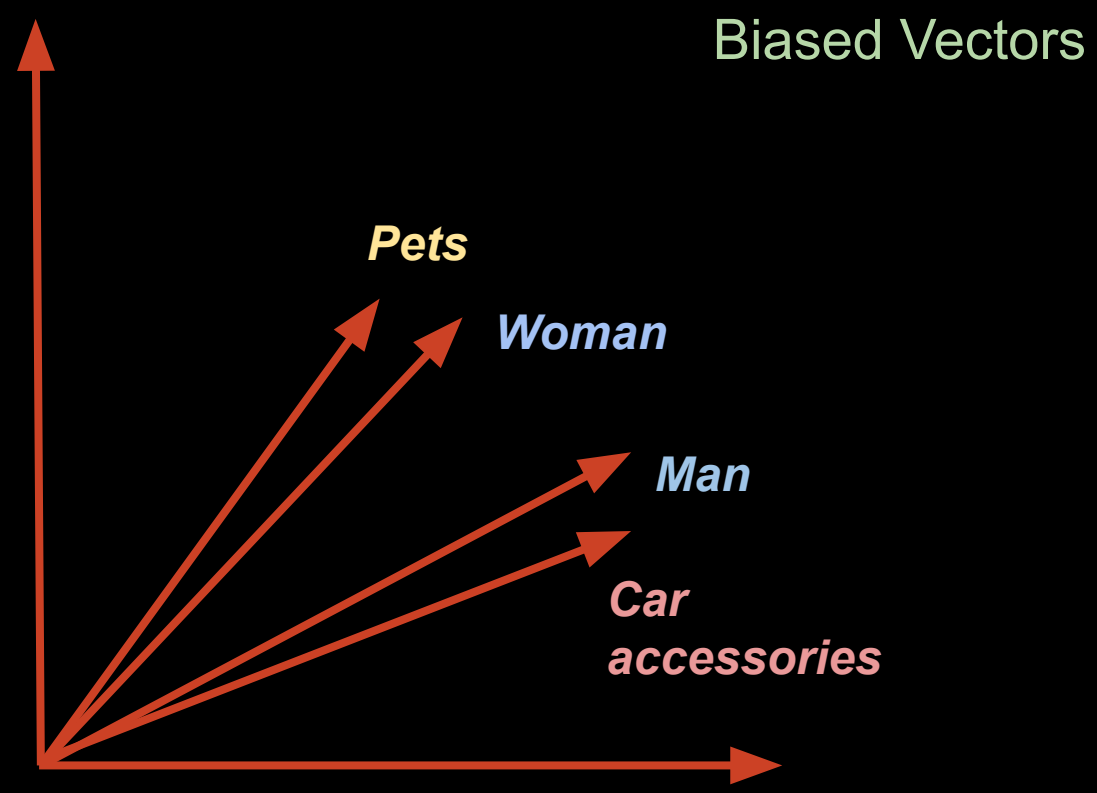

E.g. Coreference resolution:
connecting entities to references (i.e. pronouns).

"The doctor told Mary that she had run some blood tests."

semantic bias
Non-ideal associations between attributed lexeme (e.g. gendered pronouns) and non-attributed lexeme (e.g. occupation).

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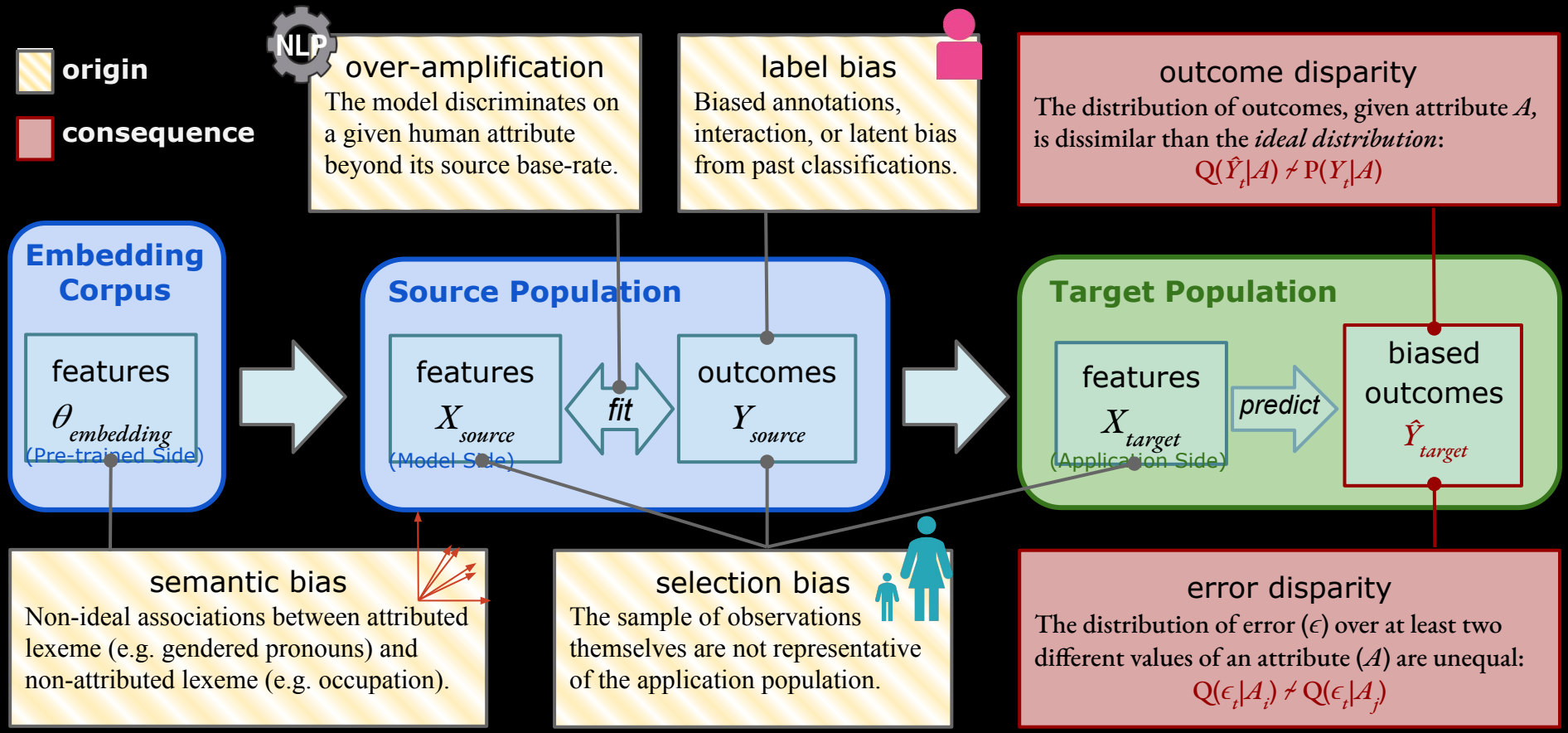
Predictive Bias Framework for NLP



Summary of Countermeasures

Source	Origin	Countermeasures
annotation	**Label Bias**	Post-stratification, Re-train annotators
data selection	**Selection Bias**	Stratified sampling, Post-stratification or Re-weighing techniques
NLP models	**Overamplification**	Synthetically match distributions, add outcome disparity to cost function
embeddings	**Semantic Bias**	Use above techniques and re-train embeddings

Bias - Takeaways

Bias, as outcome and error **disparities**, can result from many **origins**:

- the **embedding** model
- the feature **sample**
- the **fitting** process
- the **outcome** sample

Our understanding is evolving:

This is an active area of work, both theoretically and technically!

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  - Targeted persuasion

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    - Information targeting: "You are being shown this ad because ..."
  - Do not share / secure storage

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    - Information targeting: "You are being shown this ad because ..."
  - Do not share / secure storage
  - *Federated learning* -- obfuscate to the point of preserving privacy

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Ethics in NLP Research

ACM Code of Ethics; General Ethical Principles:

- Contribute to society and to human well-being, acknowledging that all people are stakeholders in computing.

https://www.acm.org/code-of-ethics

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- Avoid harm.

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- Be honest and trustworthy.
- Be fair and take action not to discriminate.
- Respect the work required to produce new ideas, inventions, creative works, and computing artifacts.
- Respect privacy.
- Honor confidentiality.

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Ethics in NLP

Human Subjects Research

Observational versus Interventional

Ethics in NLP

Human Subjects Research

Observational versus Interventional

(The Belmount Report, 1979)

(i) Distinction of research from practice.
(ii) Risk-Benefit criteria
(iii) Appropriate selection of human subjects for participation in research
(iv) Informed consent in various research settings.

Ethics in NLP

Human Subjects Research

Observational versus Interventional

(modeling) (models interact)

Ethics in NLP

Human Subjects Research

Observational versus Interventional
(modeling) (models interact)

Deploying a model within an application often shifts the works from being simply observational (privacy harms) to interventional (consideration for additional harms).

Ethics in NLP

Bias – Consider target application and population.

Privacy - Secure, do not share, and inform

Ethical Research and Development