Ethics in NLP

CSE 538

Ethics in NLP

Bias

Privacy

Ethical Research

Ethics in NLP - Bias

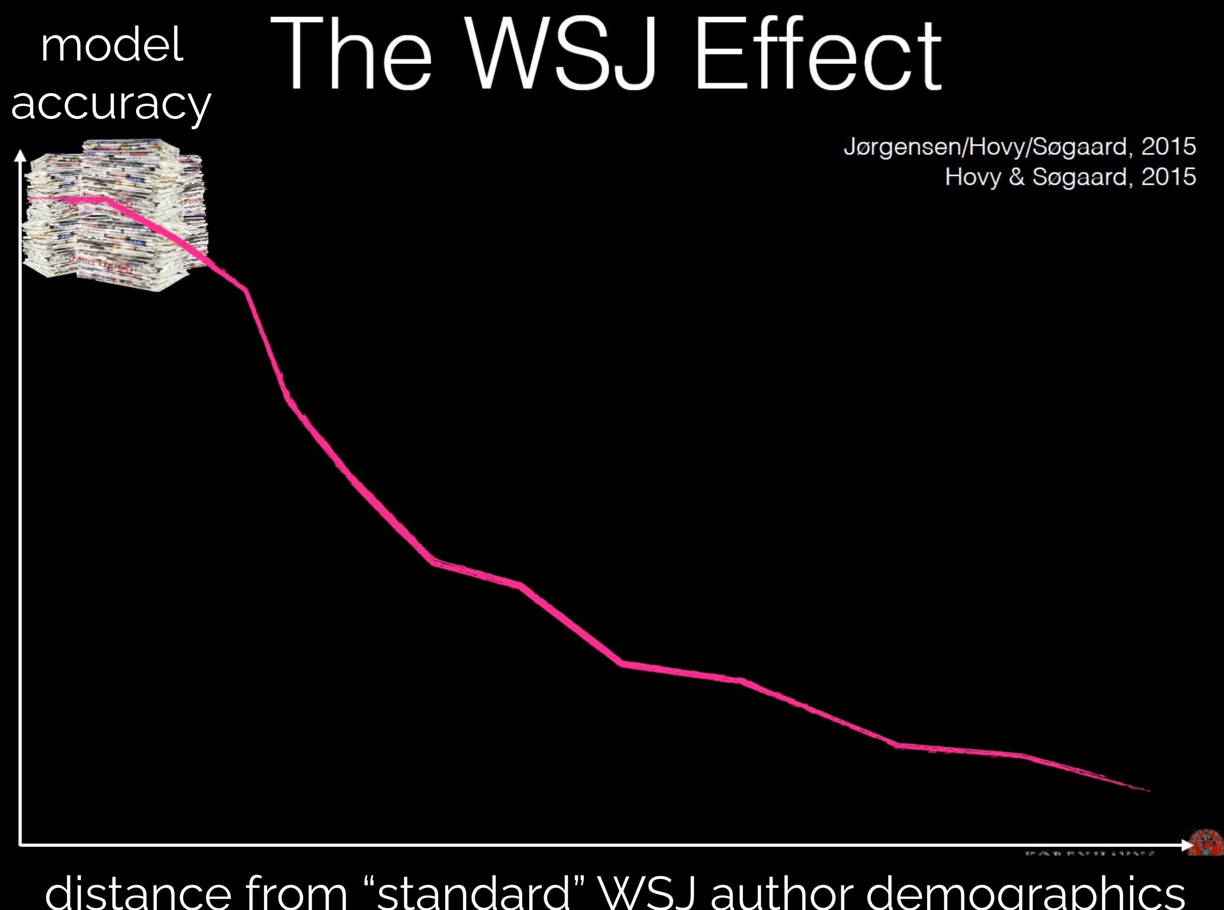
Consequences of Sociodemographic Bias in NLP Models:

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

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

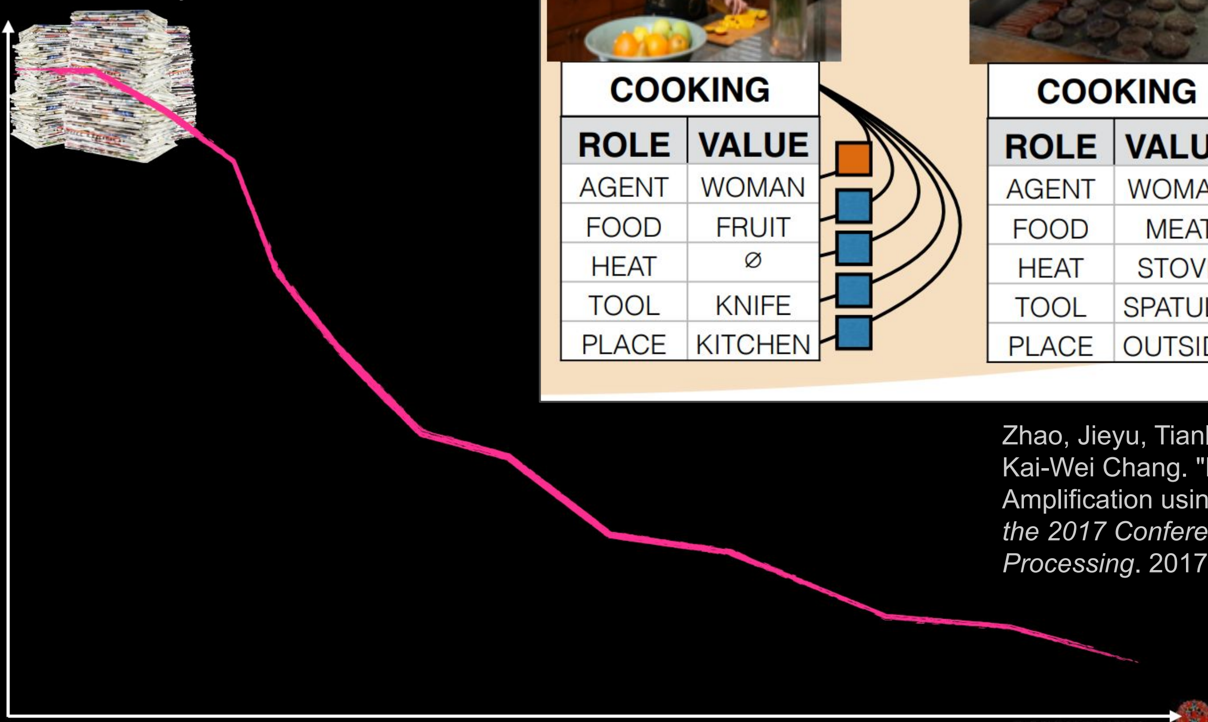
Shah, D., Schwartz, H. A., Hovy, D. (2020). Predictive Biases in Natural Language Processing Models: A Conceptual Framework and Overview. *In ACL-2020: Proceedings of the Association for Computational Linguistics.*

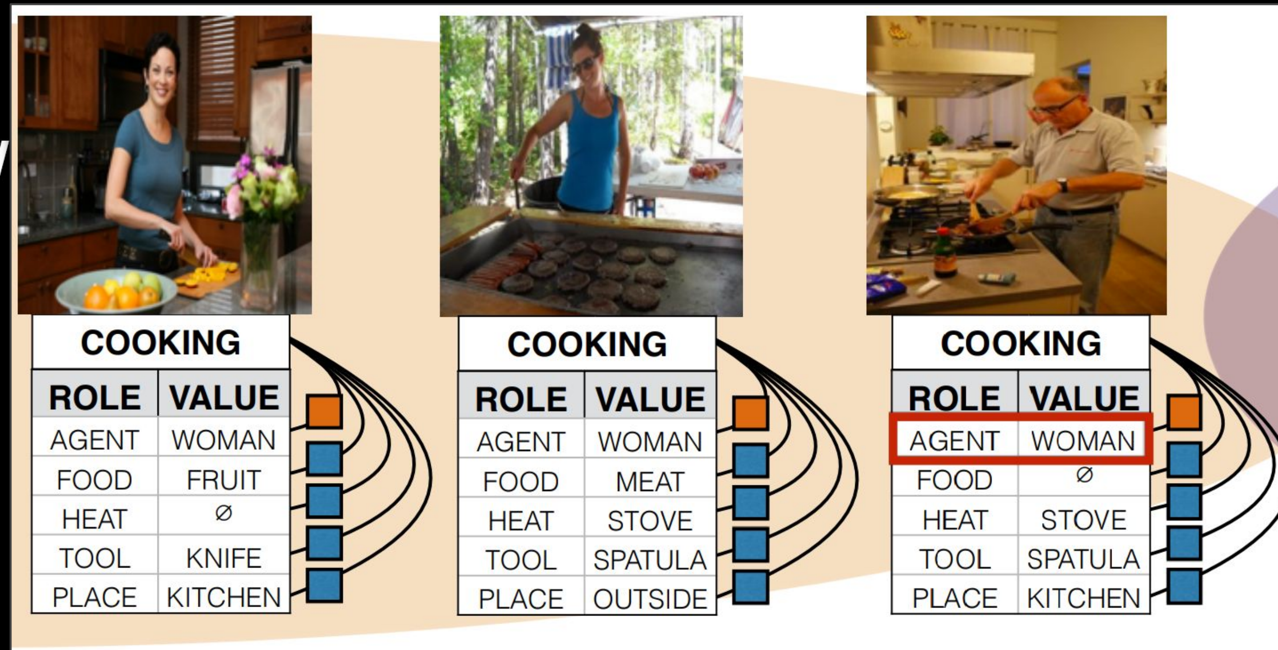
Two Examples



Two Examples

The W



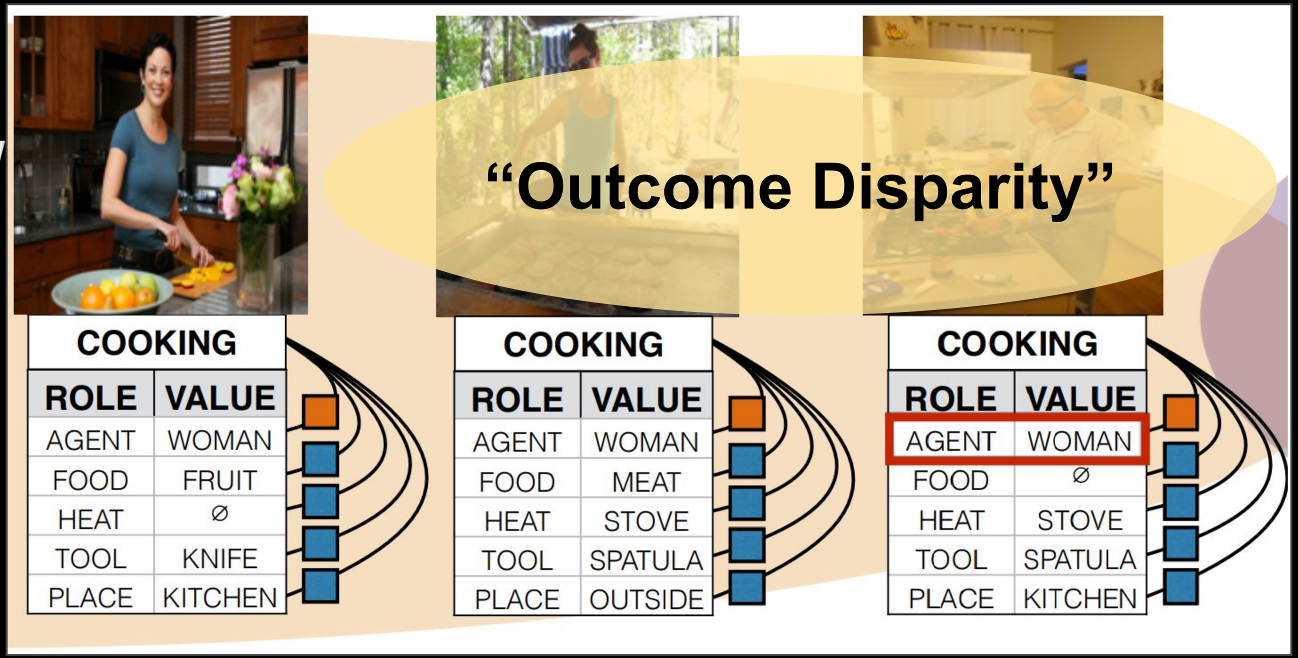


Zhao, Jieyu, Tianlu Wang, Mark Yatskar, Vicente Ordonez, and Kai-Wei Chang. "Men Also Like Shopping: Reducing Gender Bias Amplification using Corpus-level Constraints." In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*. 2017.

Two Examples

model accuracy

The W



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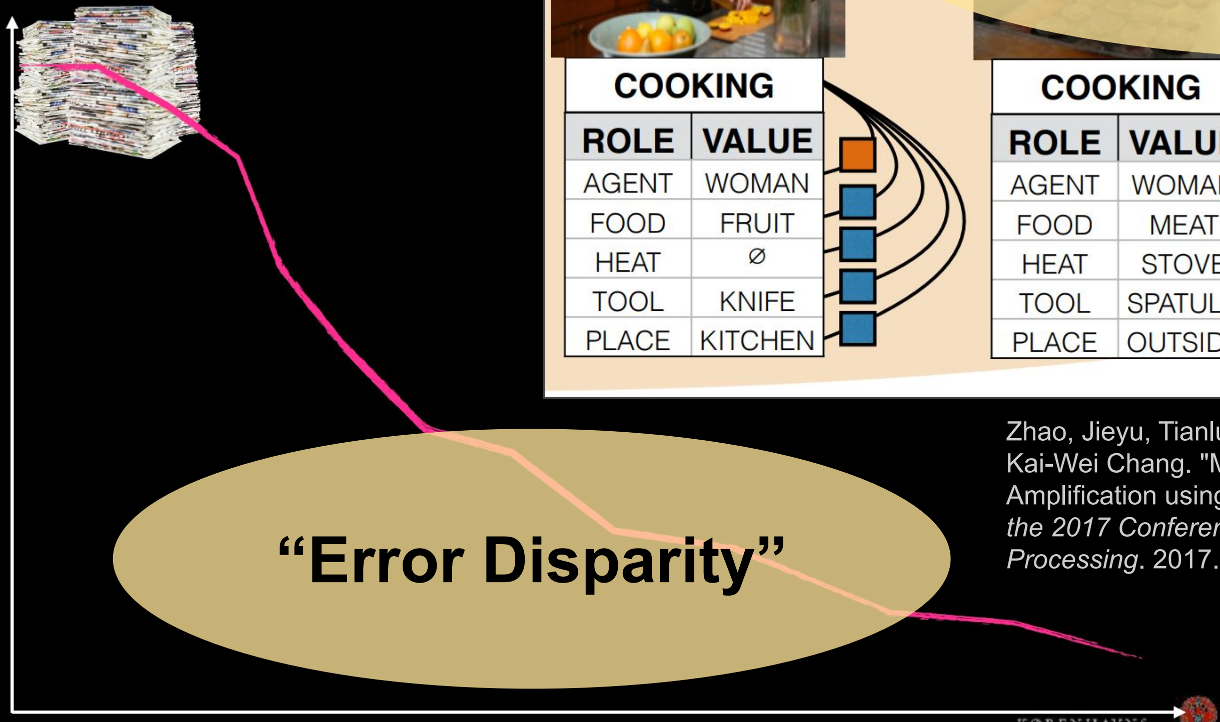

distance from “standard” WSJ author demographics

Our data and models are (human) biased.

“Outcome Disparity”

Person-level

attribute = 1

attribute = 2

“Error Disparity”

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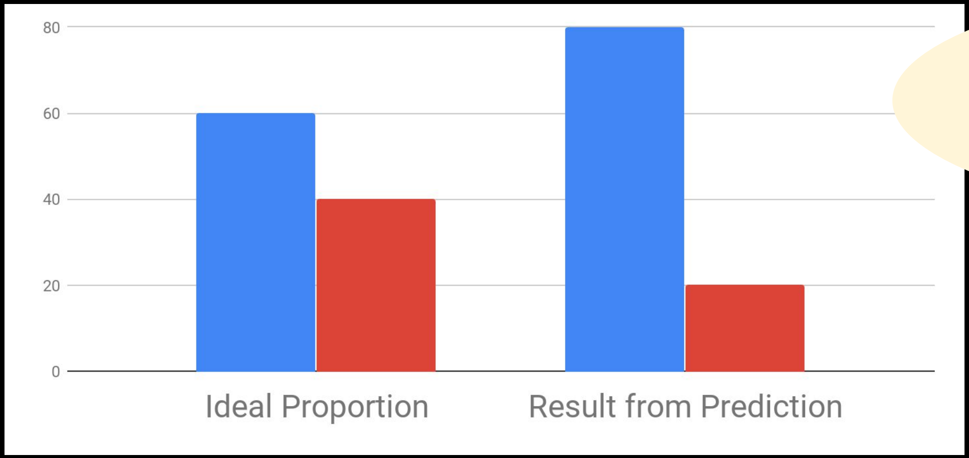

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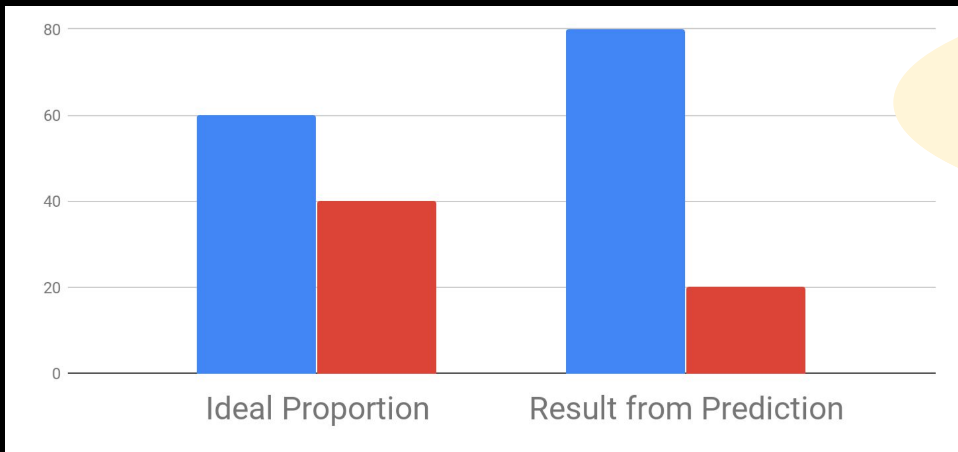
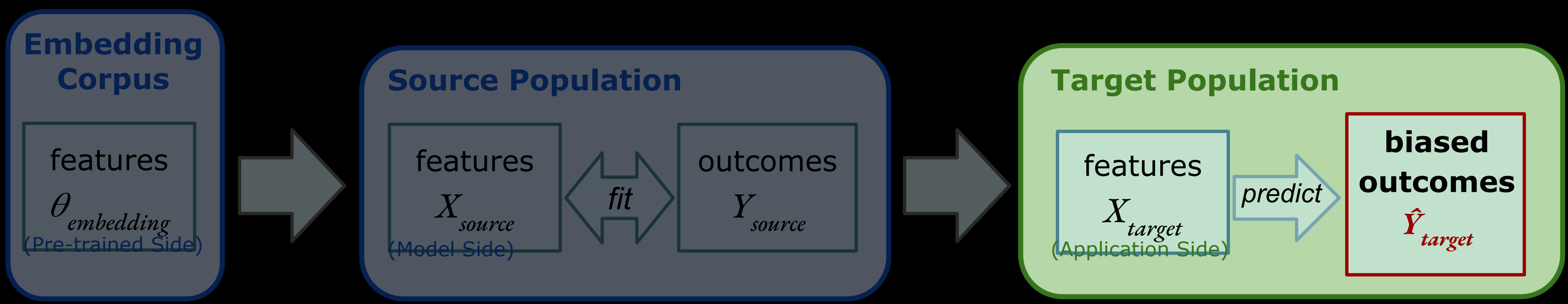


"Outcome Disparity"

Person-level
attribute = 1
attribute = 2

"Error Disparity"

Conceptual Framework:



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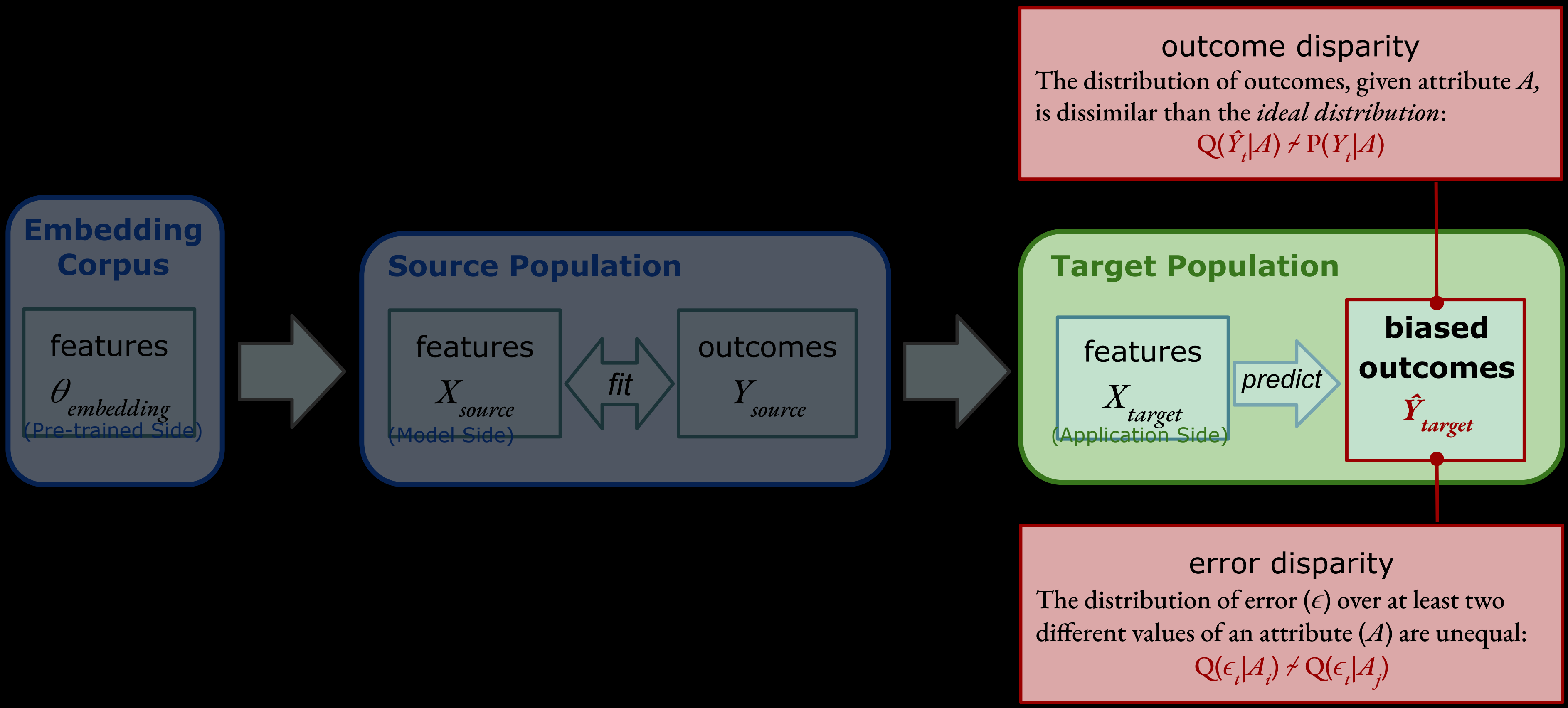
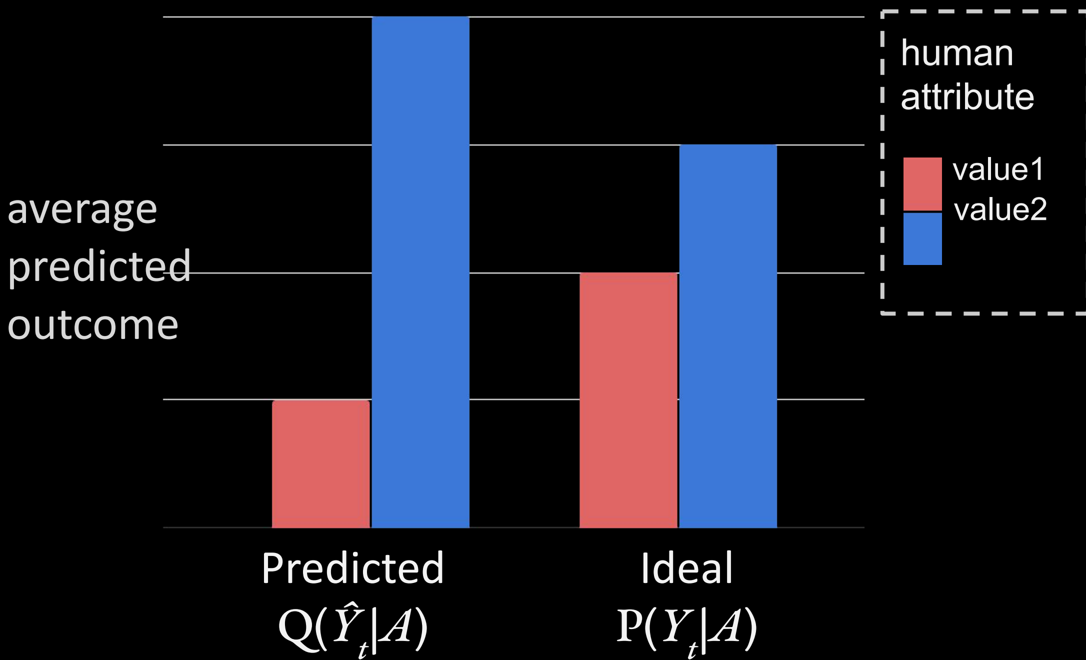
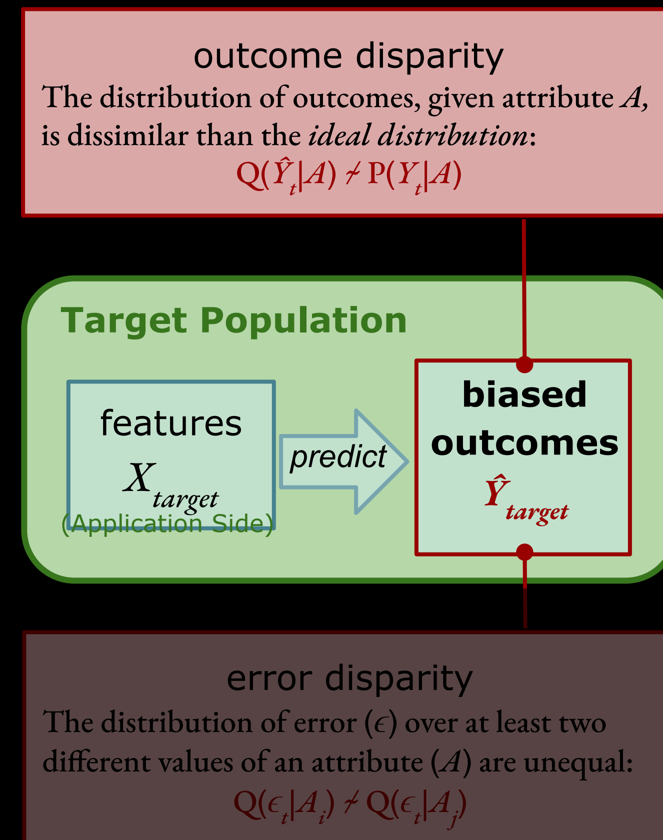
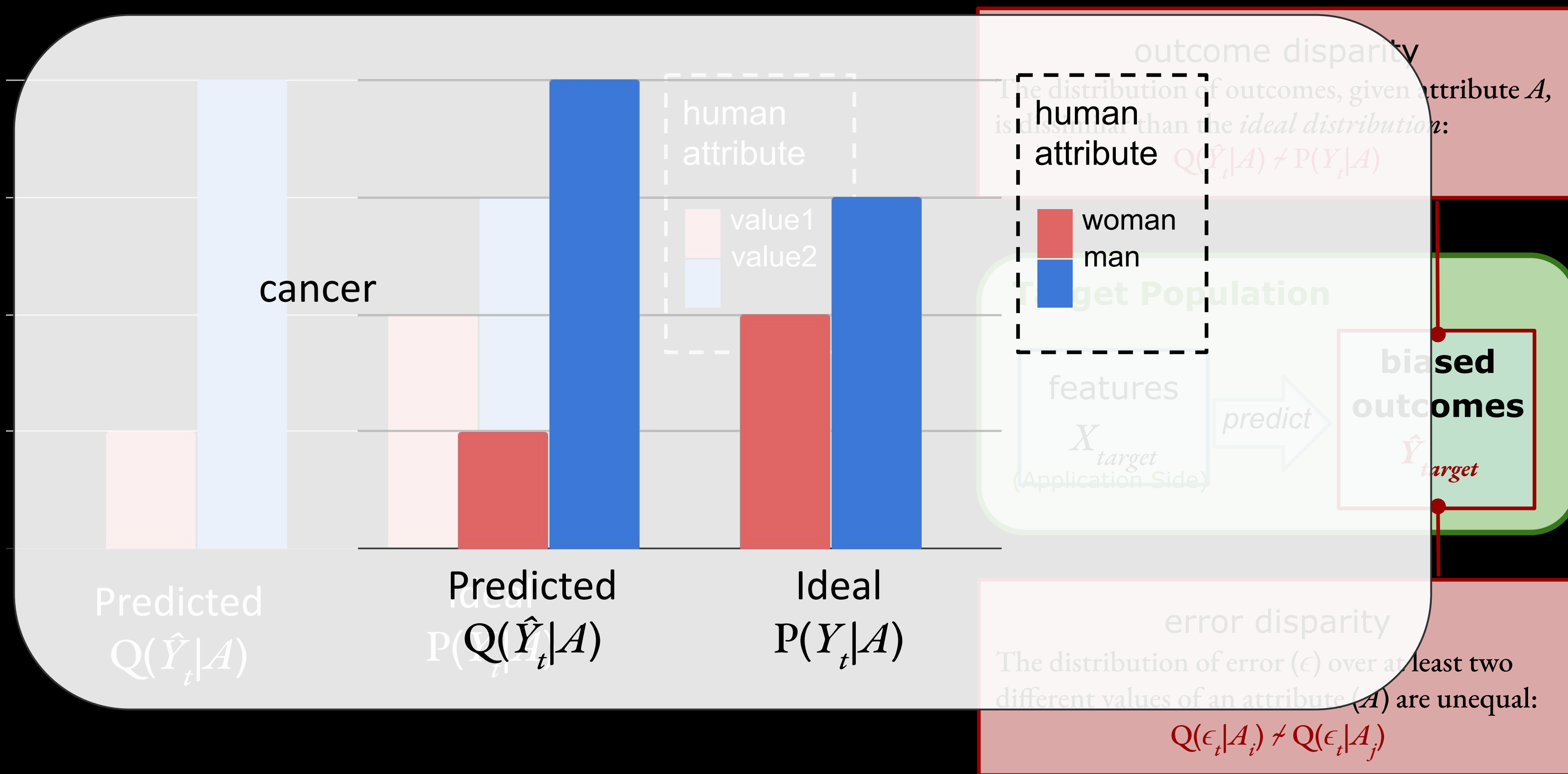


Outcome Disparity

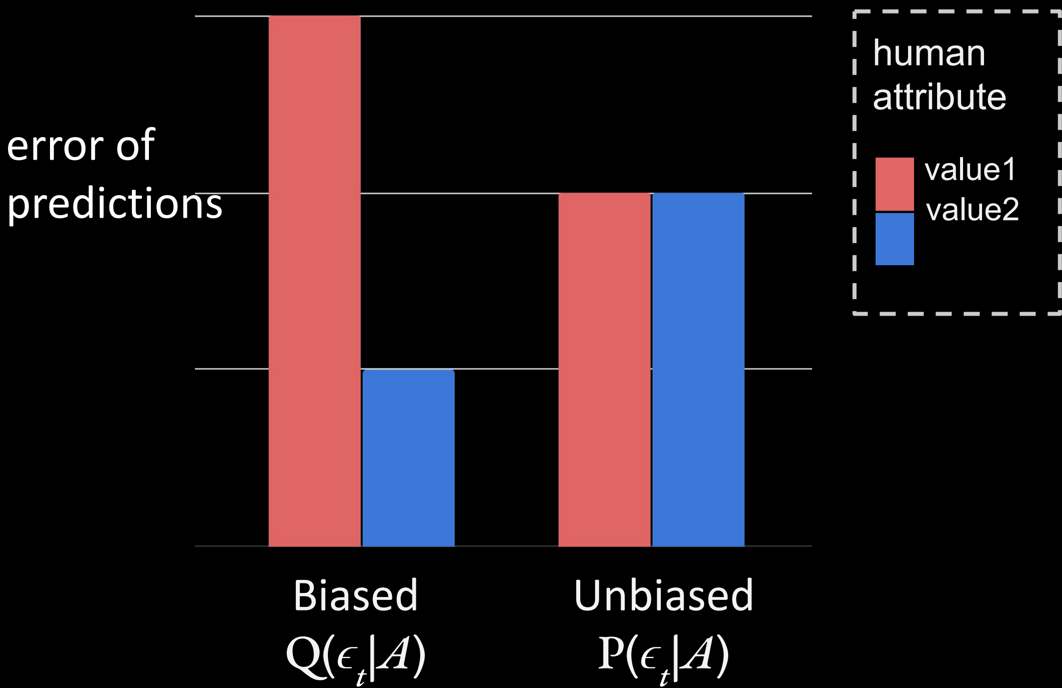


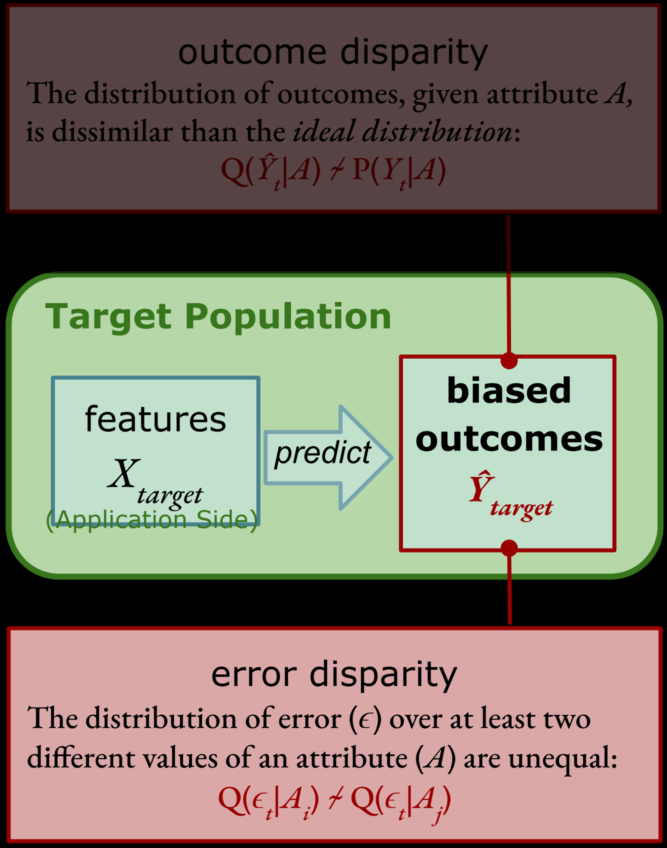


Outcome Disparity

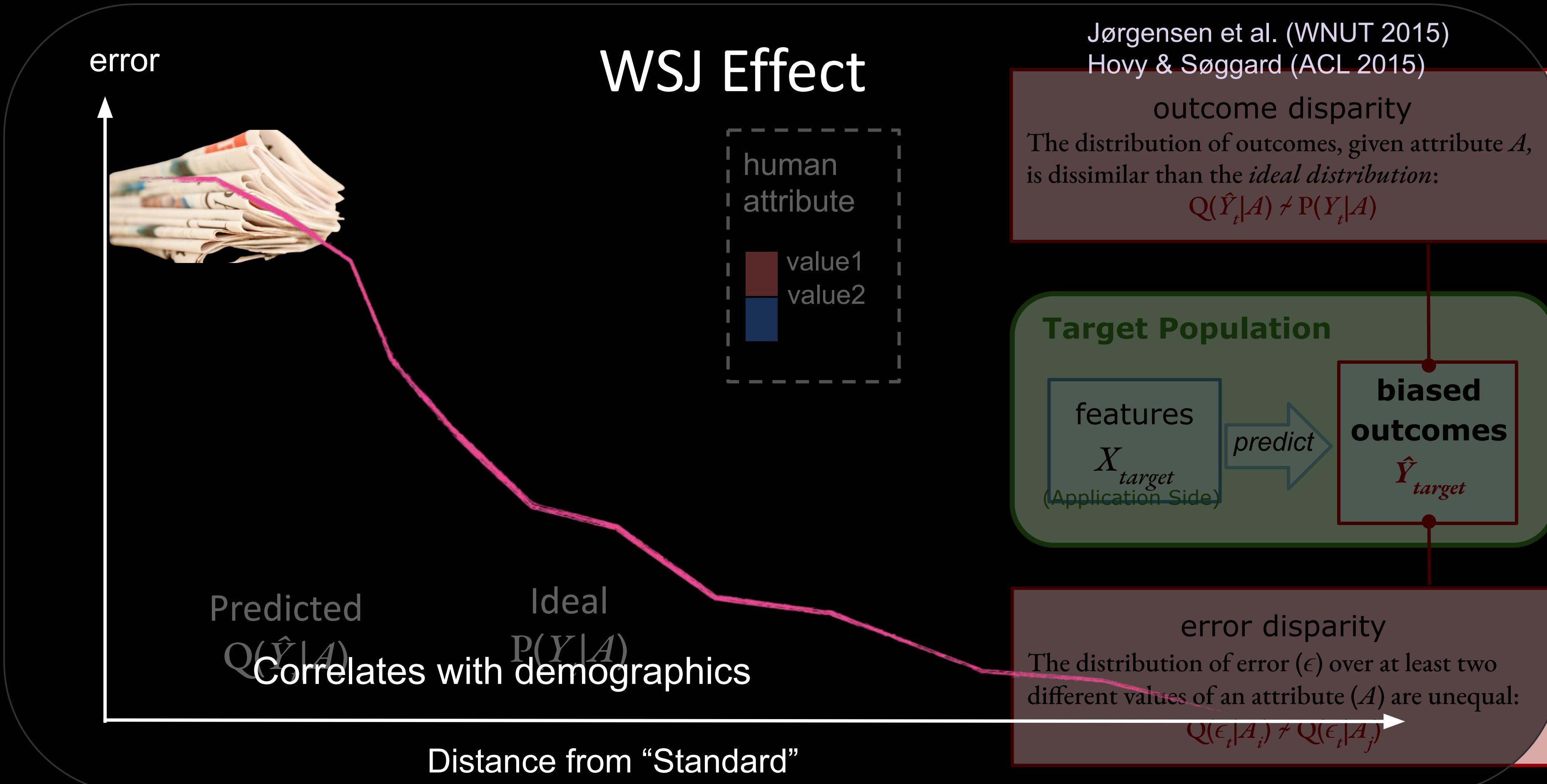


Error Disparity

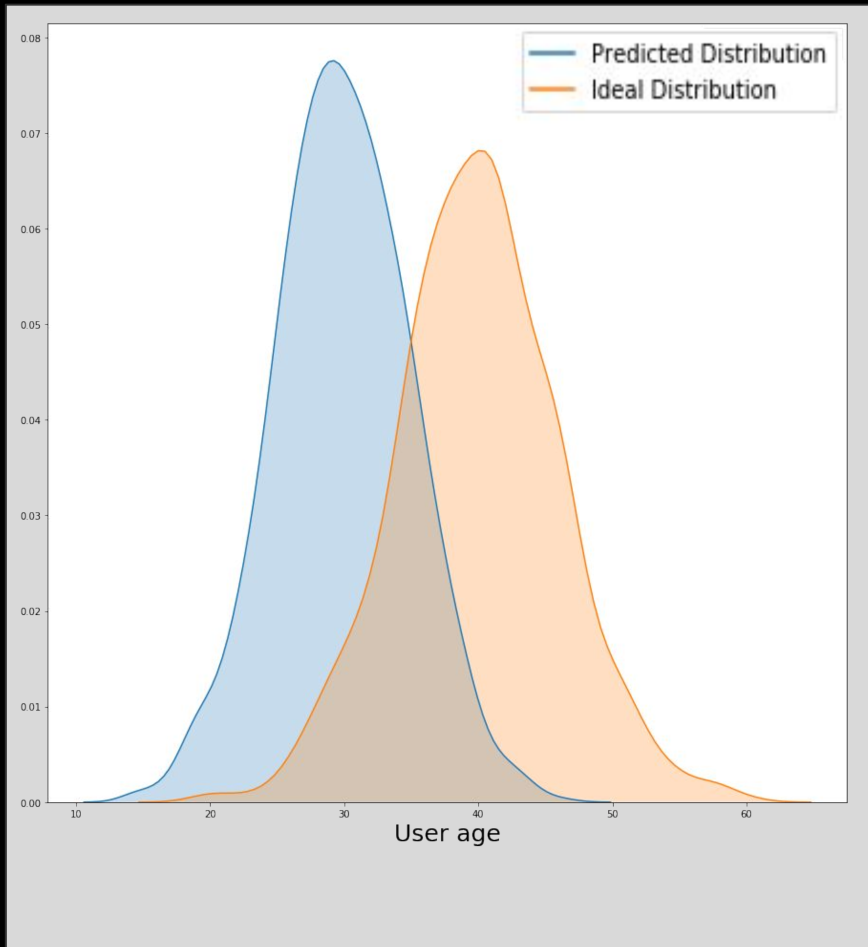




Error Disparity



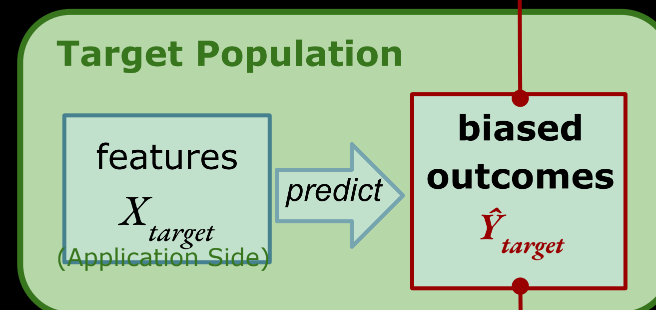
Disparities



outcome disparity

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

$$Q(\hat{Y}_t|A) \neq P(Y_t|A)$$



error disparity

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

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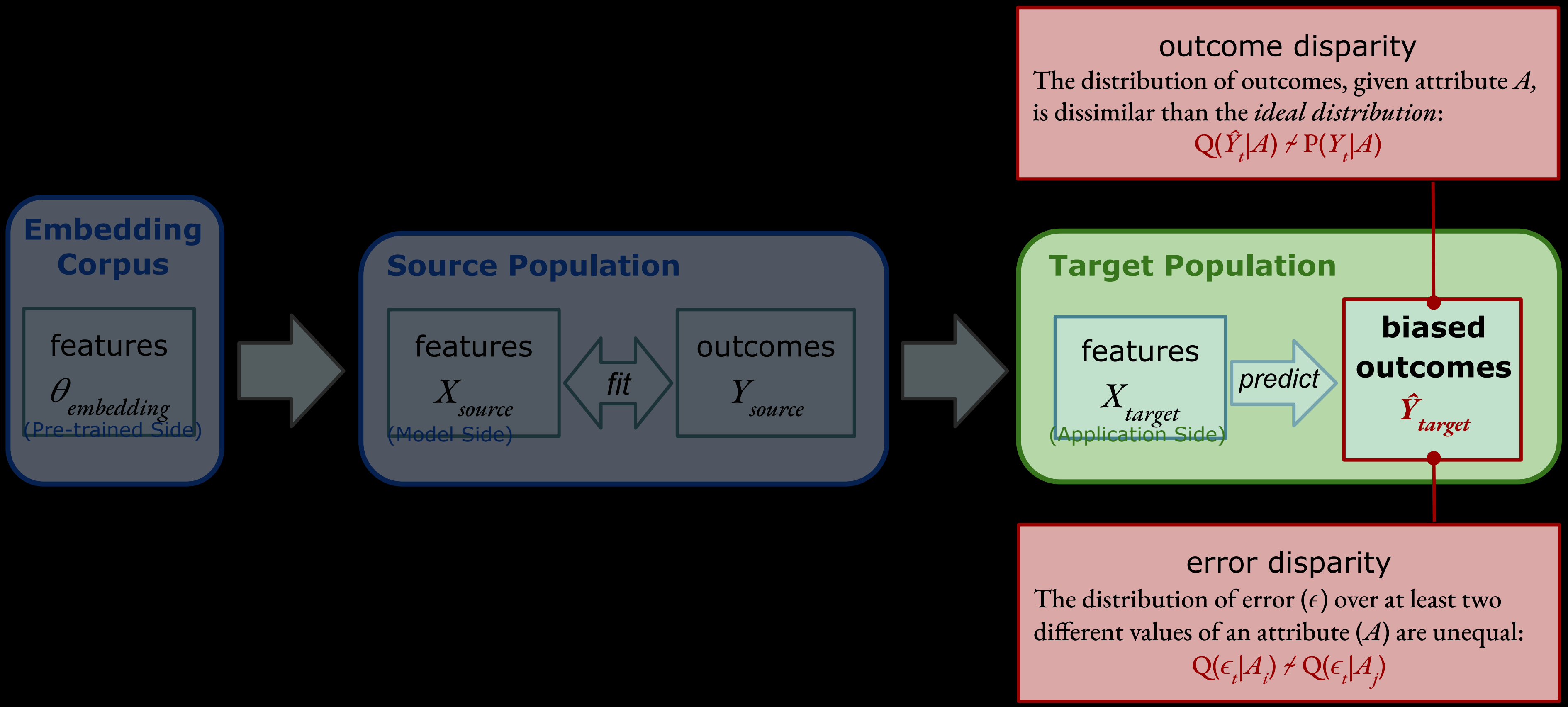
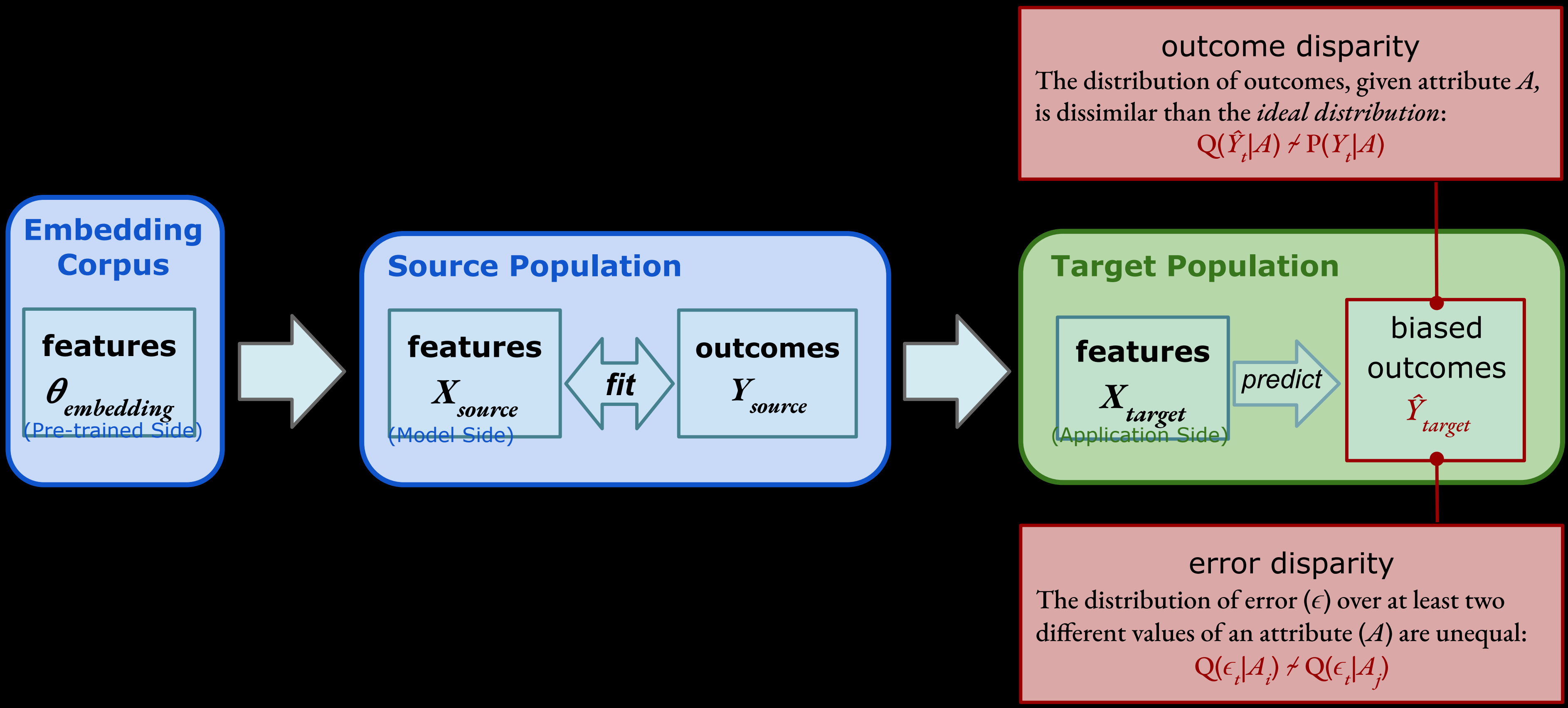
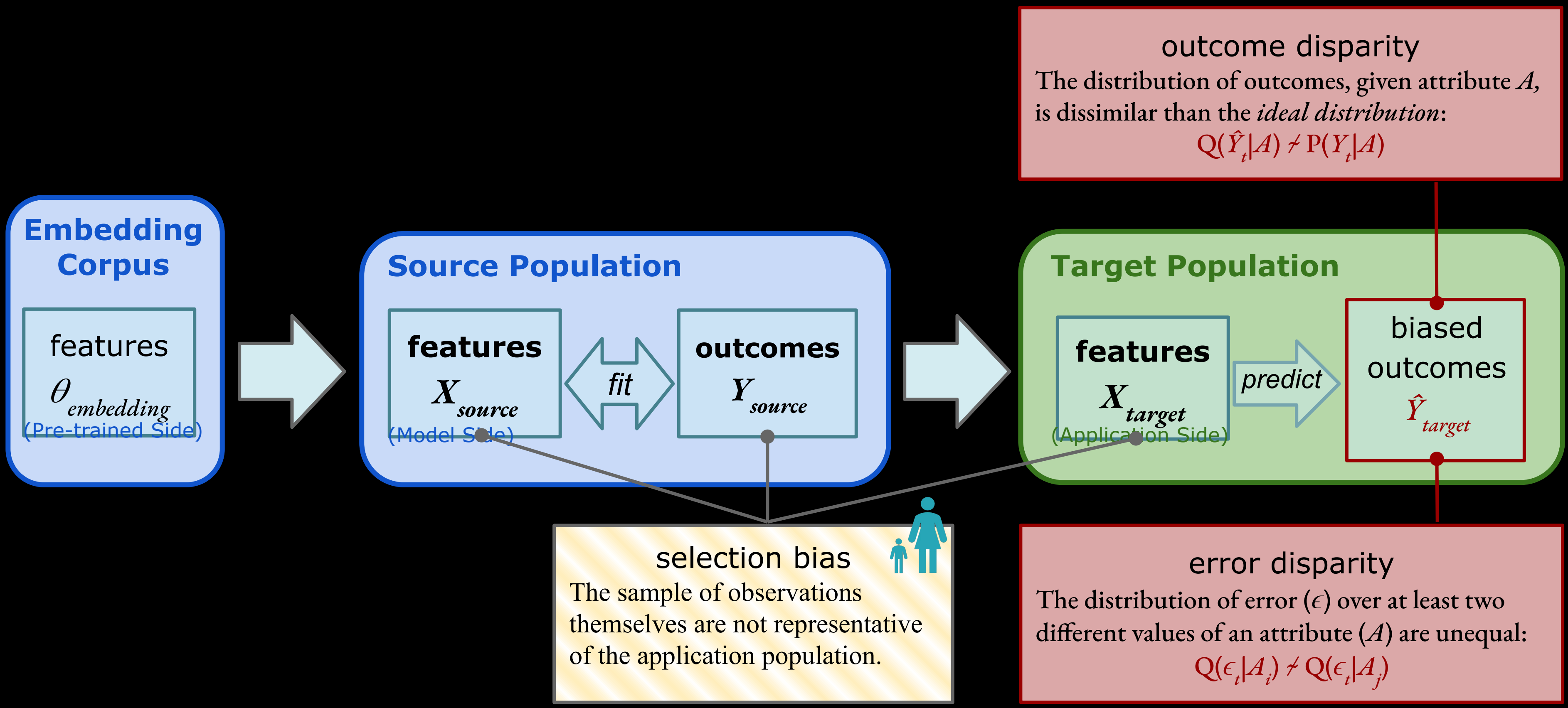
Disparities

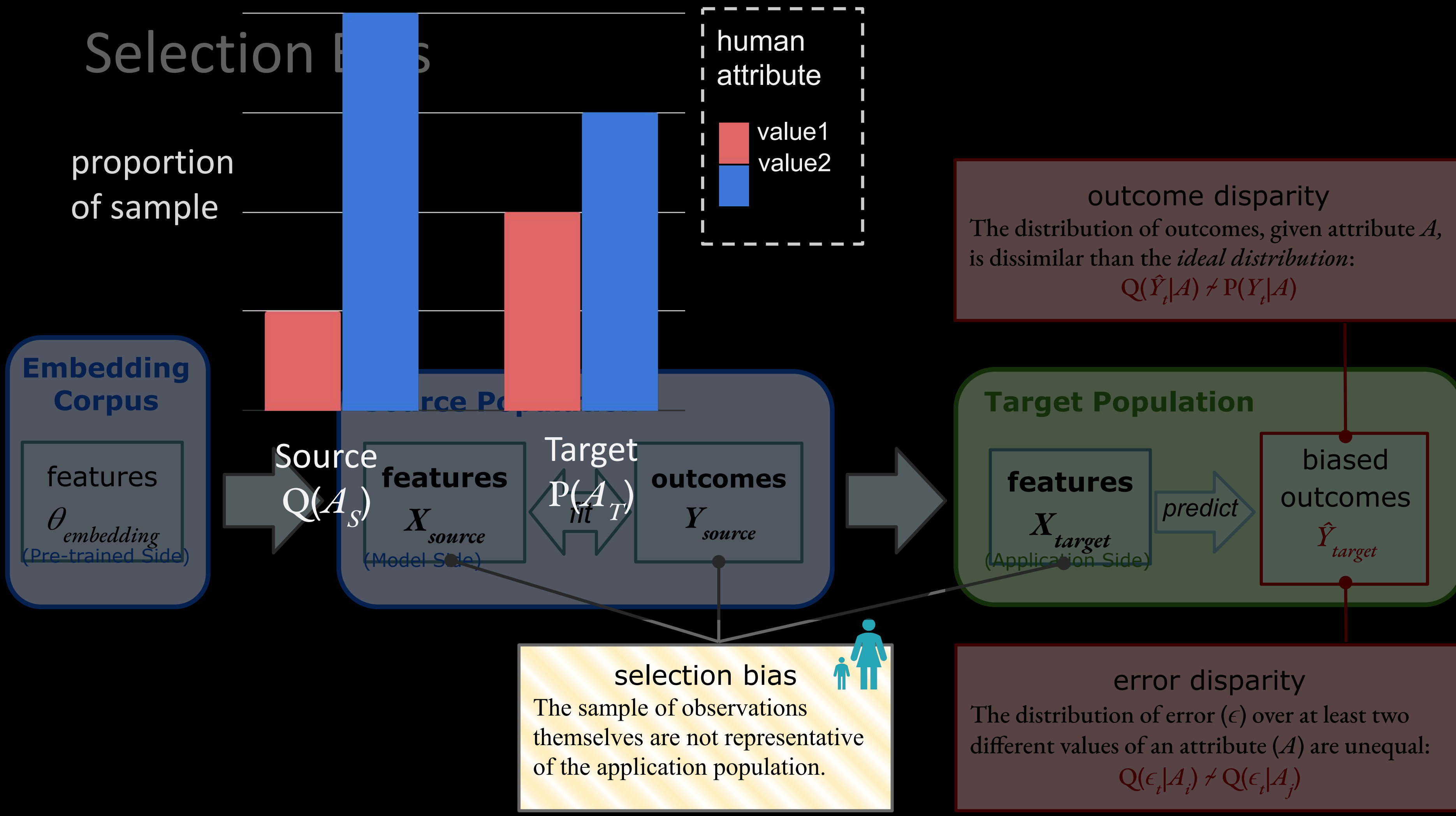


Origins of Bias



Selection Bias





Selection
proportion of sample
human attribute
value1
value2
Embedding Corpus
features
$\theta_{embedding}$
(Pre-trained Side)
Source
$Q(A_S)$
features
X_{source}
(Model Side)
Target
$P(A_T)$
outcomes
Y_{source}
Target Population
features
X_{target}
(Application Side)
predict
biased outcomes
$\hat{Y}_{target}$
outcome disparity
The distribution of outcomes, given attribute A, is dissimilar than the *ideal distribution*:
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selection bias
The sample of observations themselves are not representative of the application population.
error disparity
The distribution of error (ϵ) over at least two different values of an attribute (A) are unequal:
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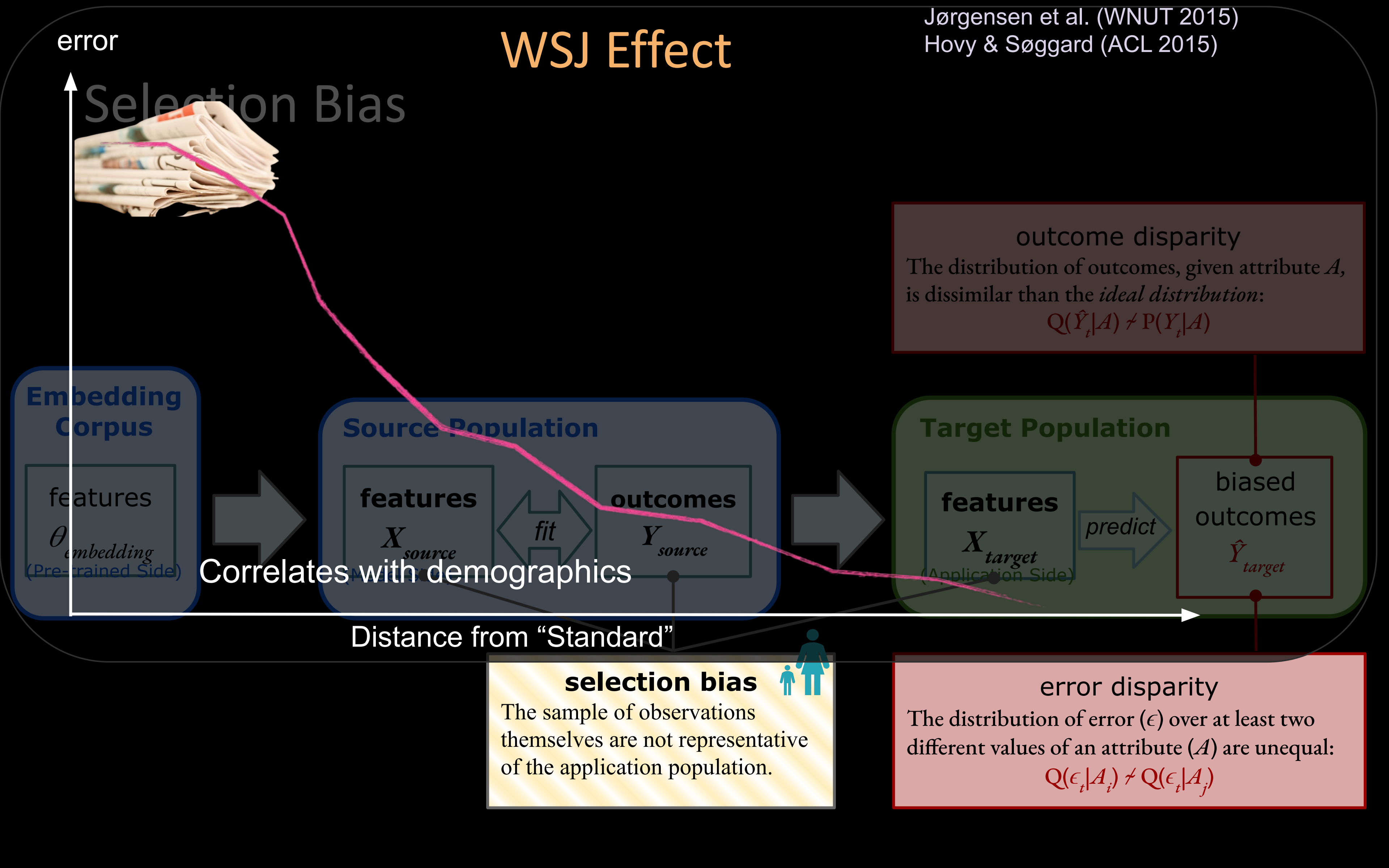

WSJ Effect
Jørgensen et al. (WNUT 2015)
Hovy & Søggard (ACL 2015)
error
Selection Bias
Distance from "Standard"
Correlates with demographics
Embedding Corpus
features
$\theta_{embedding}$
(Pre-trained Side)
Source Population
features
X_{source}
fit
outcomes
Y_{source}
Target Population
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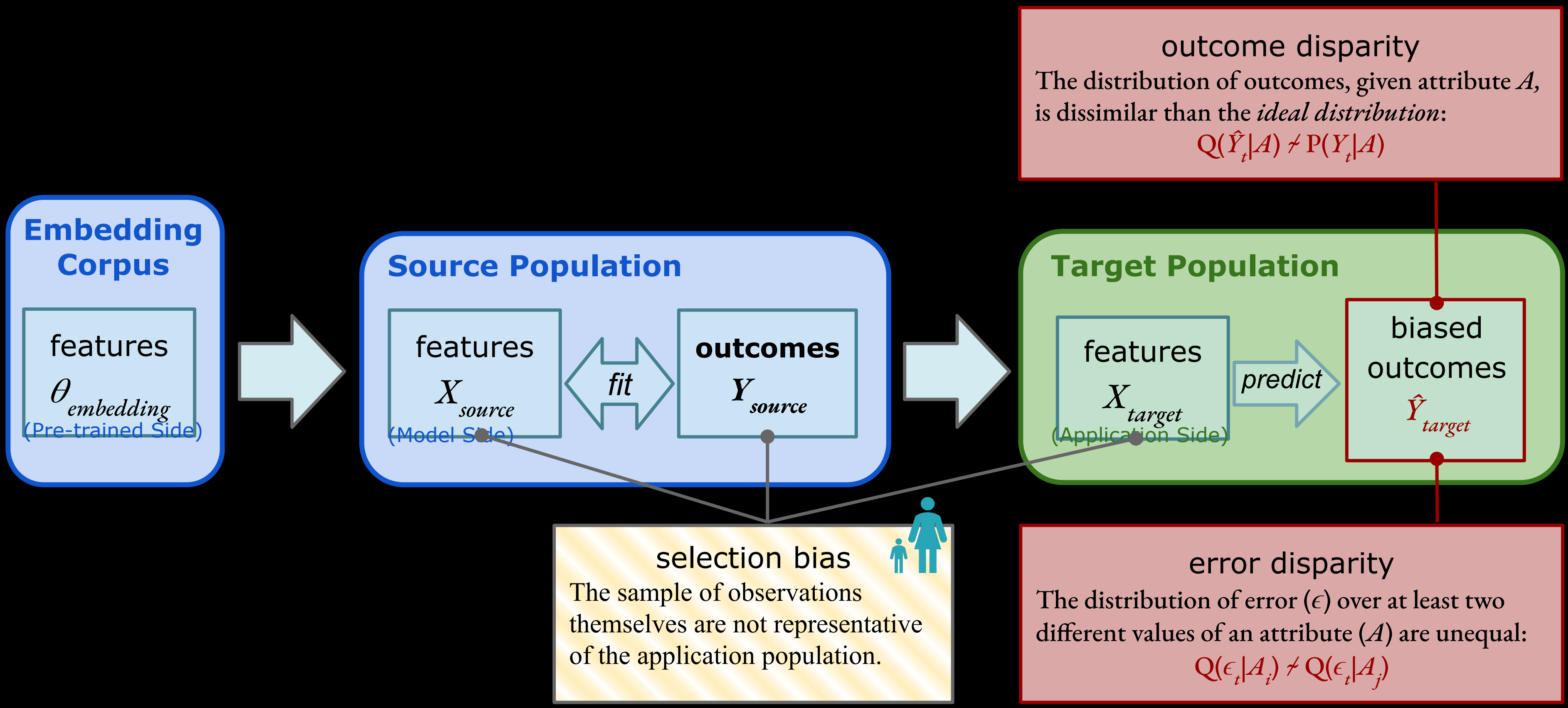
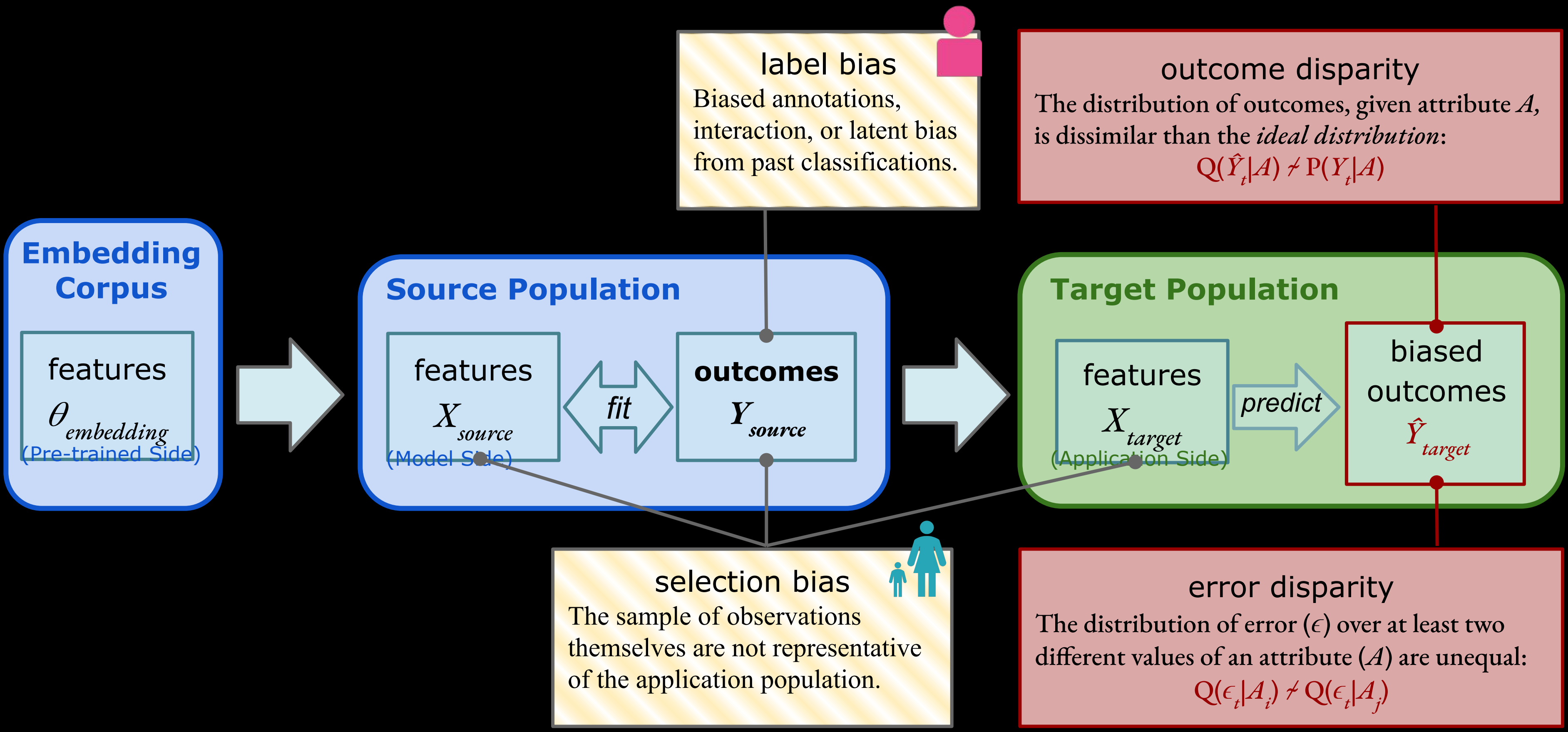


Label Bias



label bias
Biased annotations, interaction, or latent bias from past classifications.
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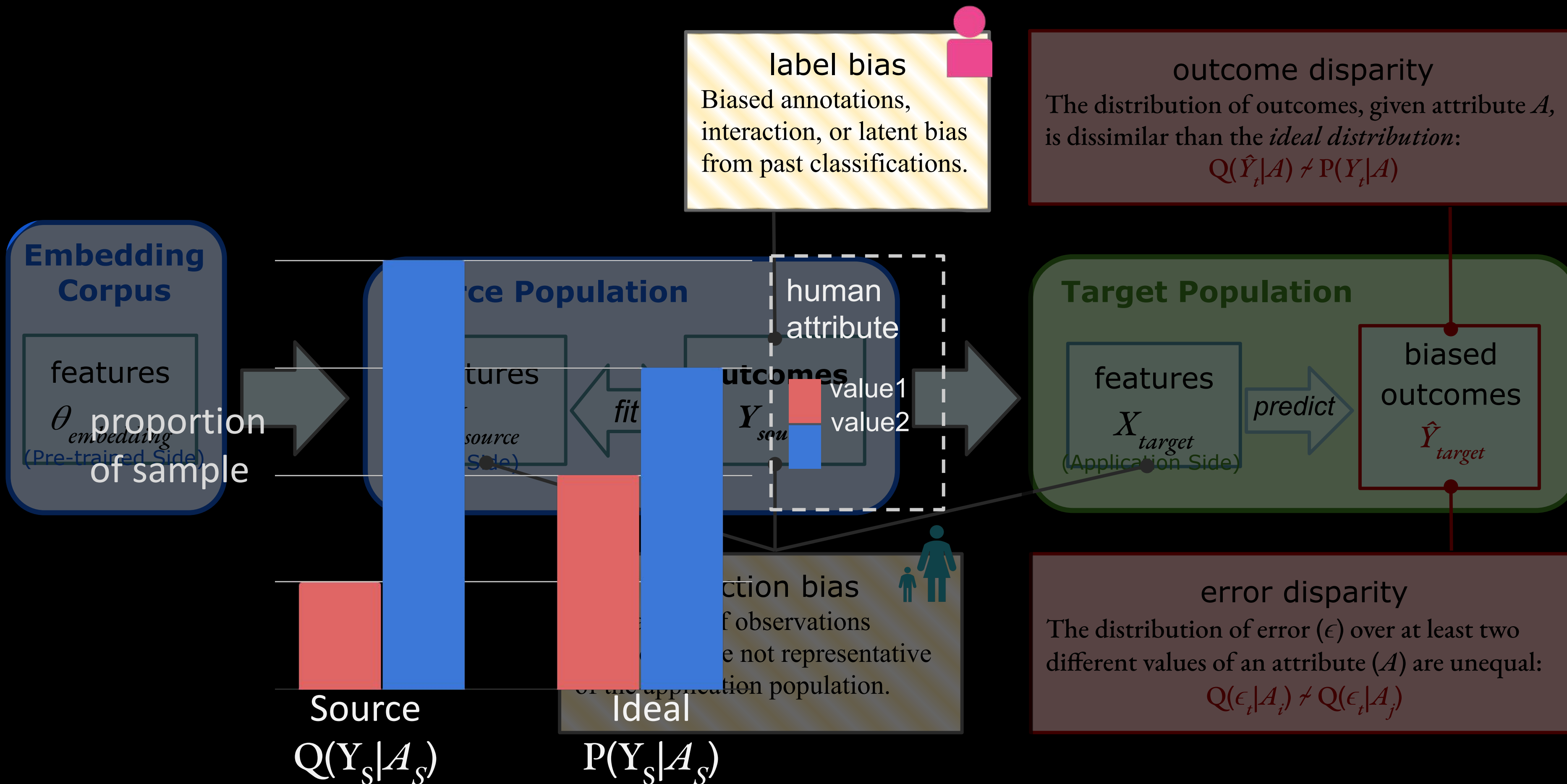
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Ŷ target
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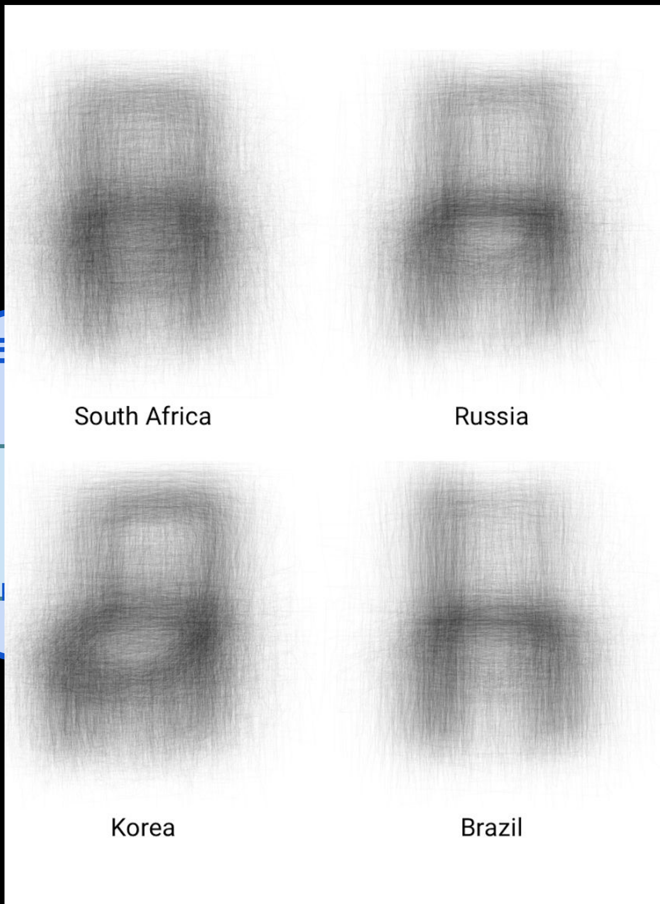
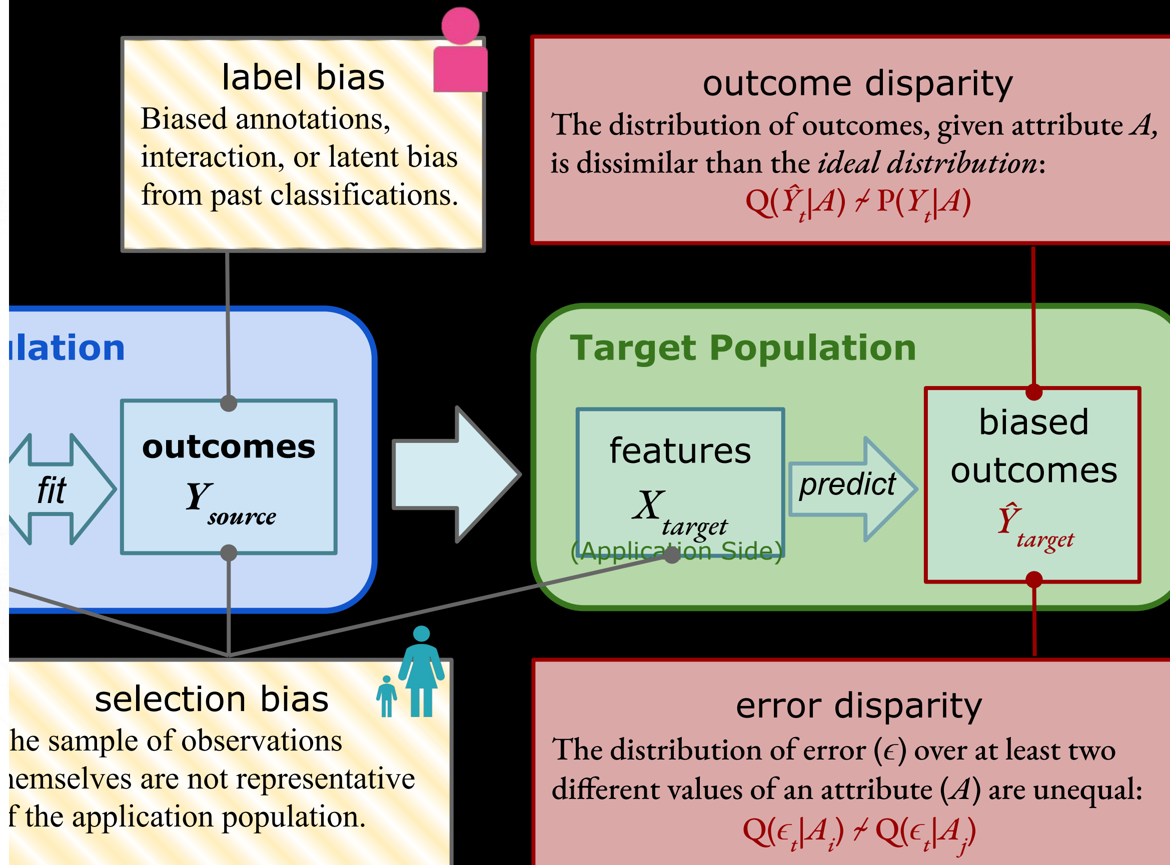
Q(ϵt|Ai) ≠ Q(ϵt|Aj)
Source
Q(YS|AS)
Ideal
P(YS|AS)

Label Bias - Example: Label word with drawing





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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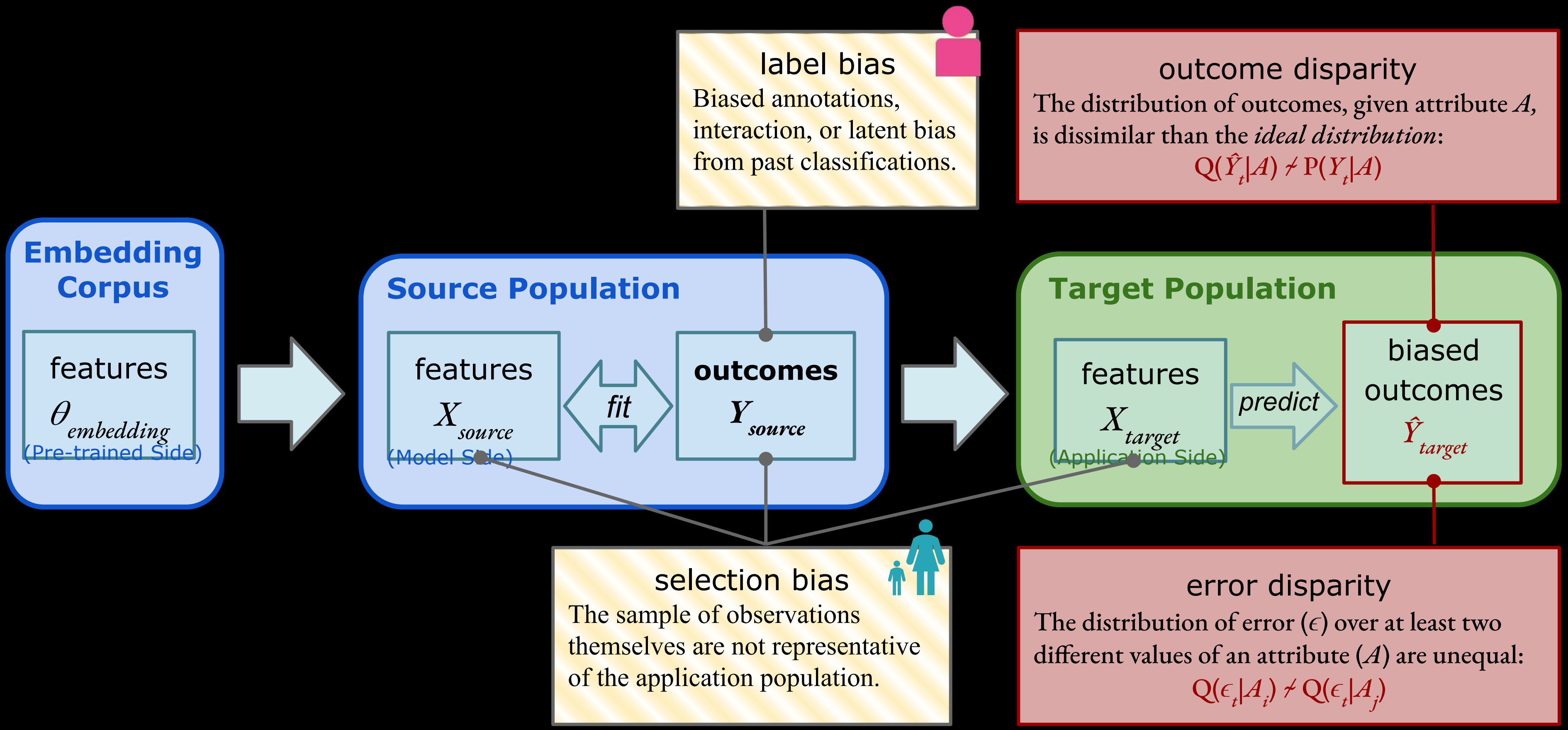

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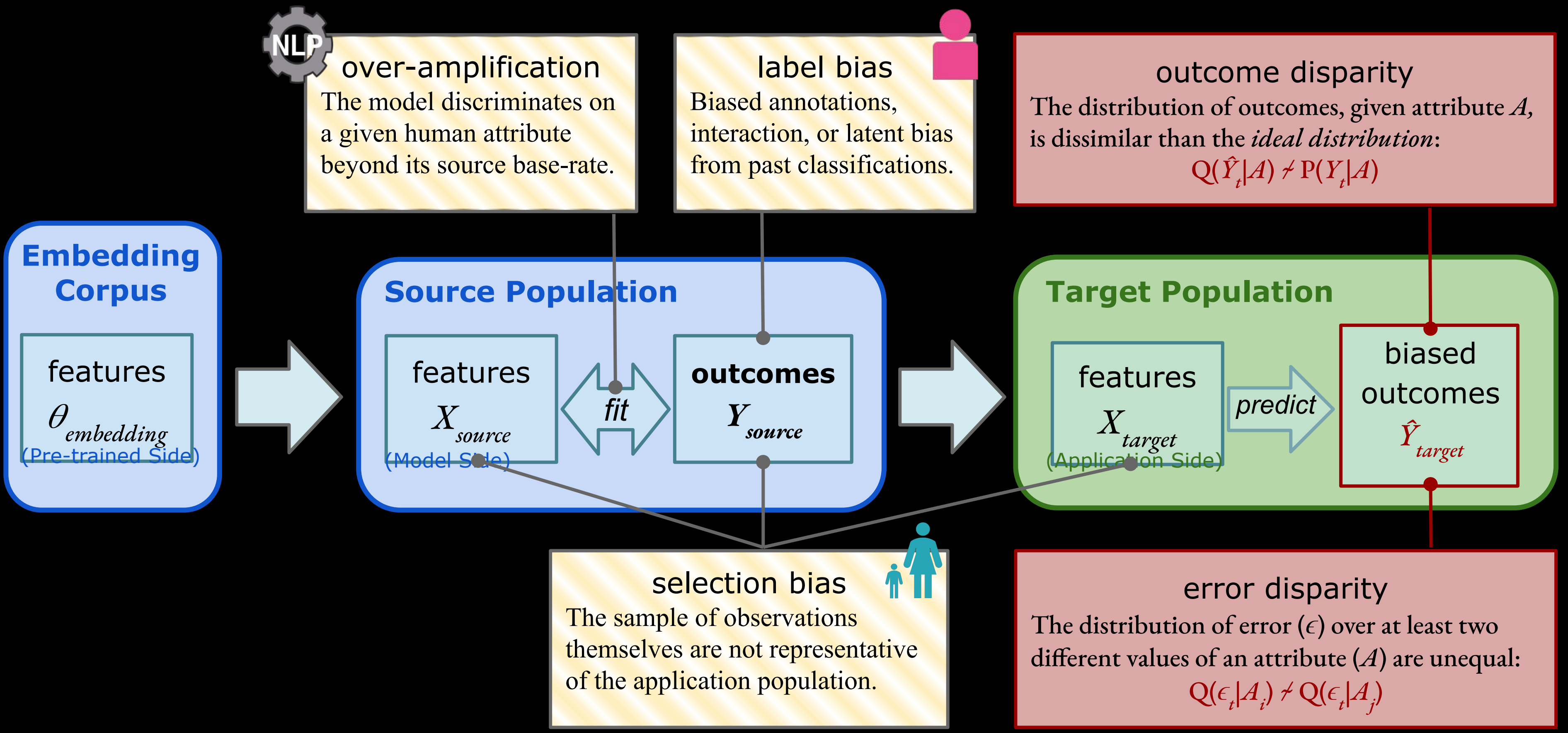
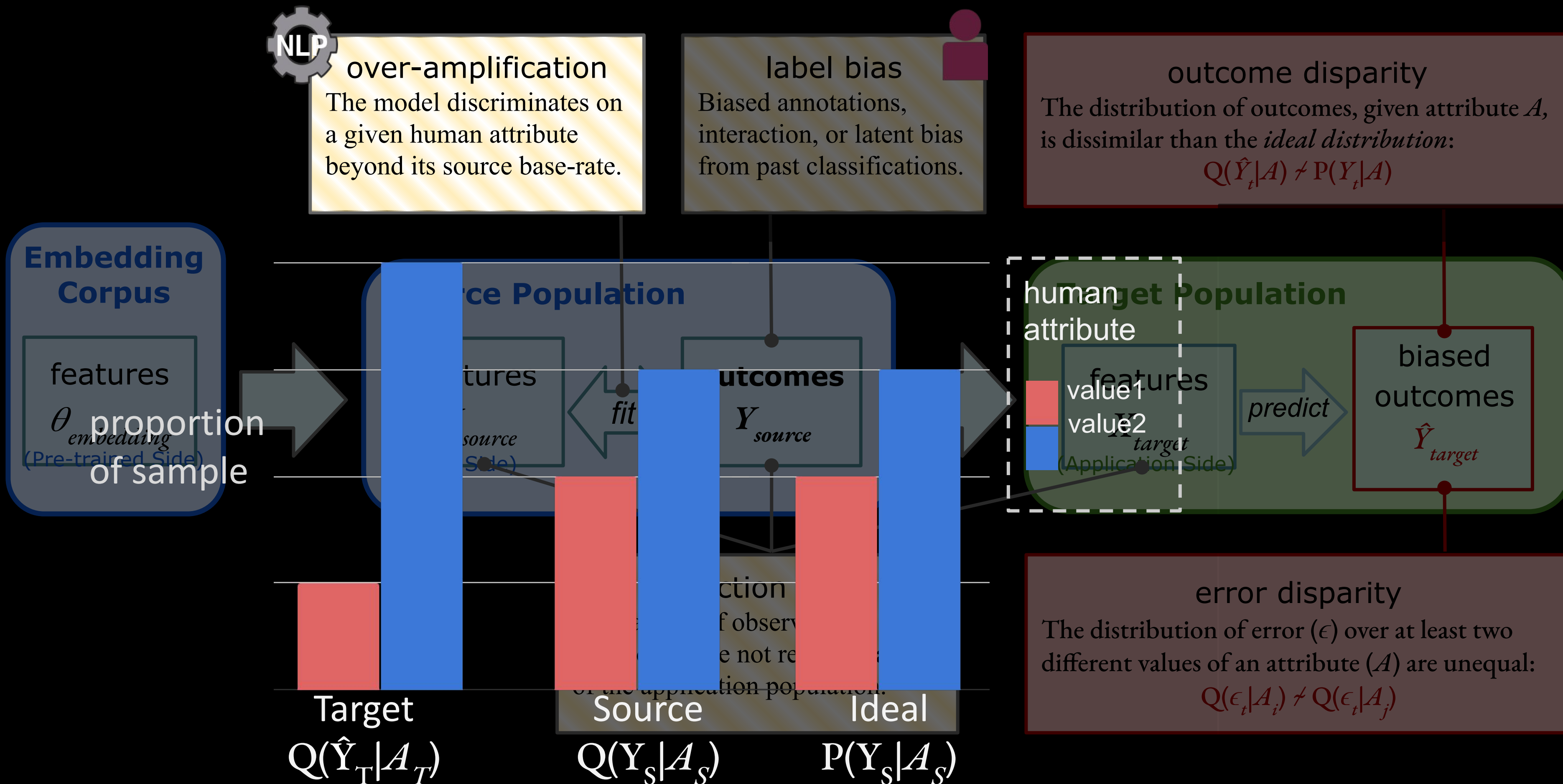
Overamplification

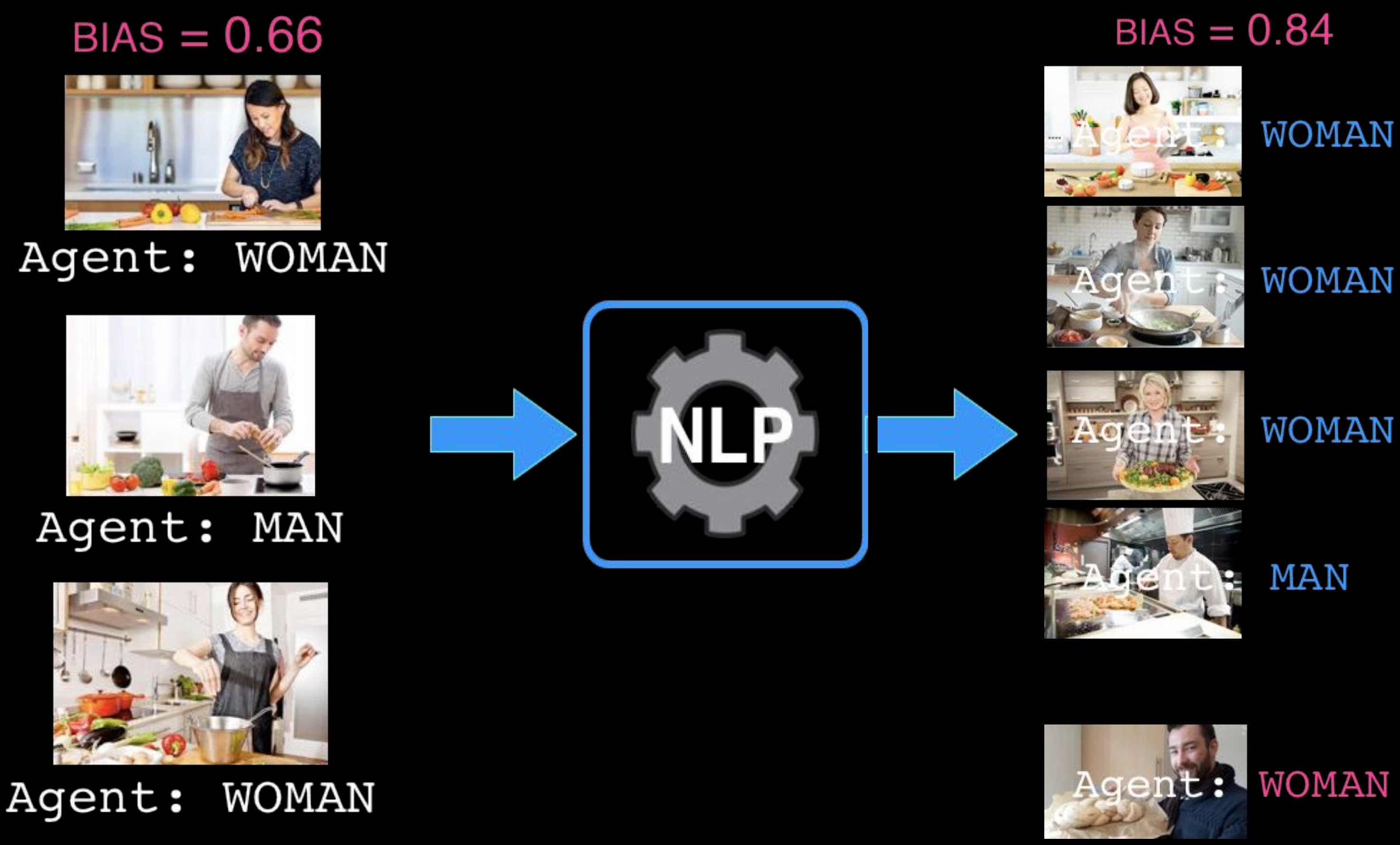


Overamplification

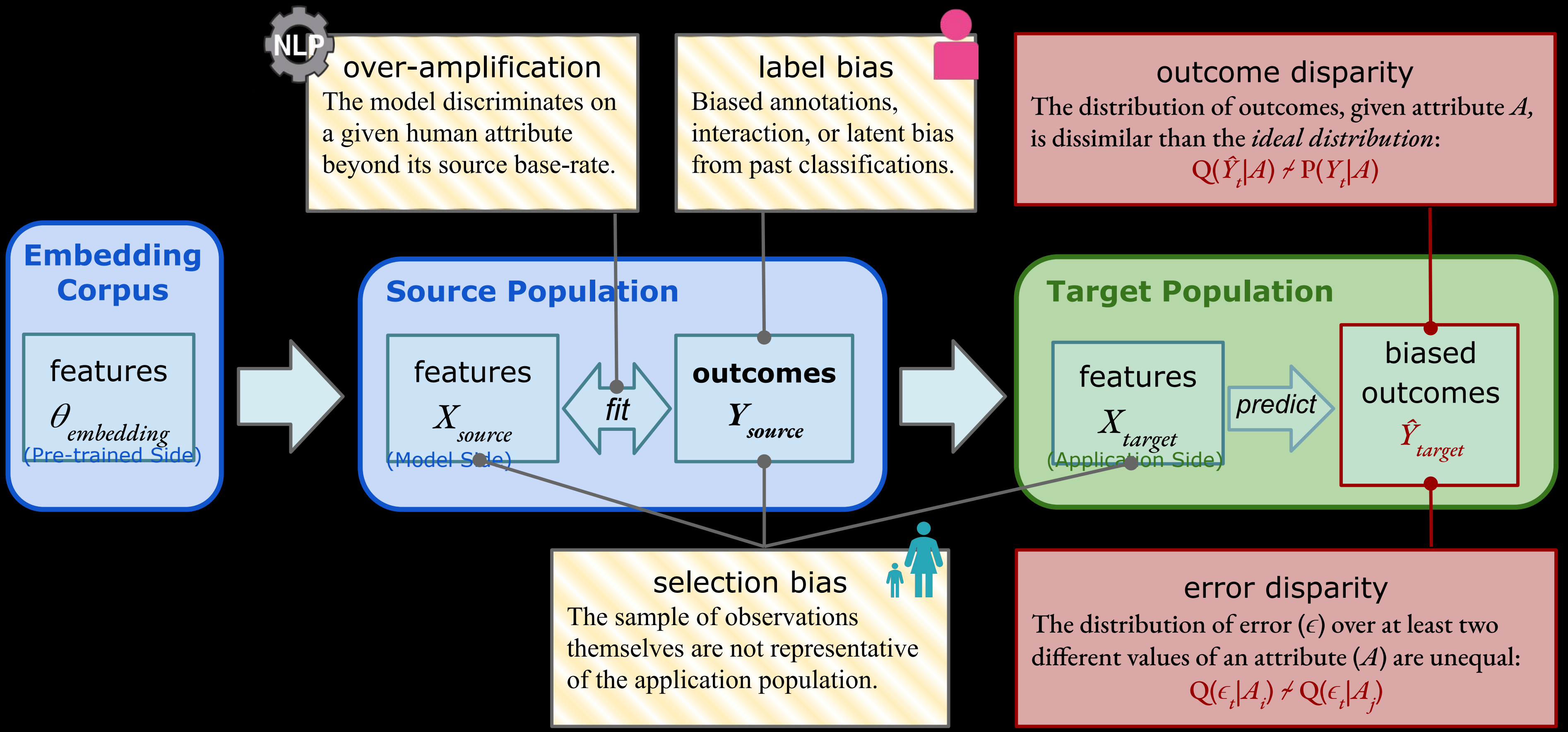


Zhao et al. (ACL 2015)

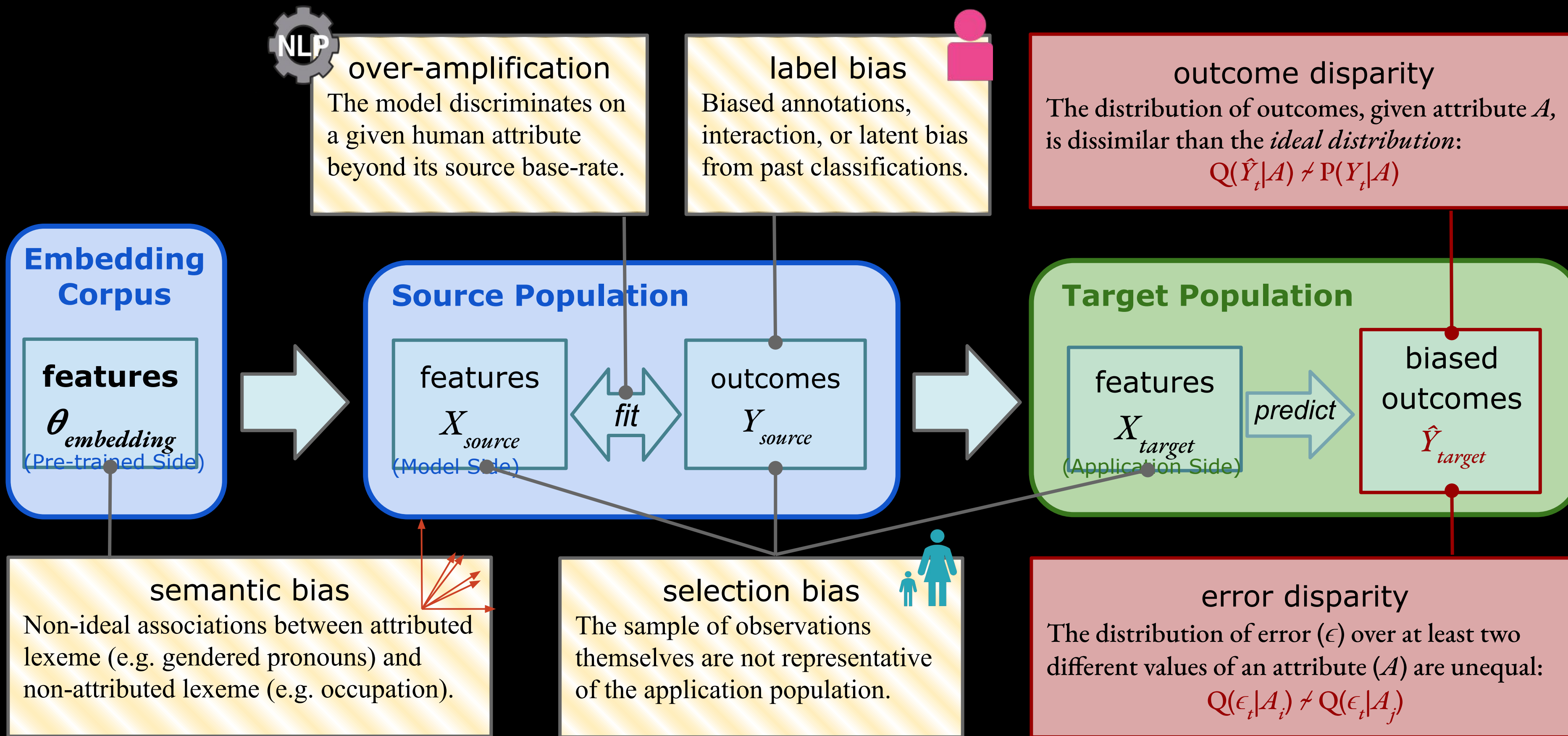
Overamplifiction - Model Amplifies Bias



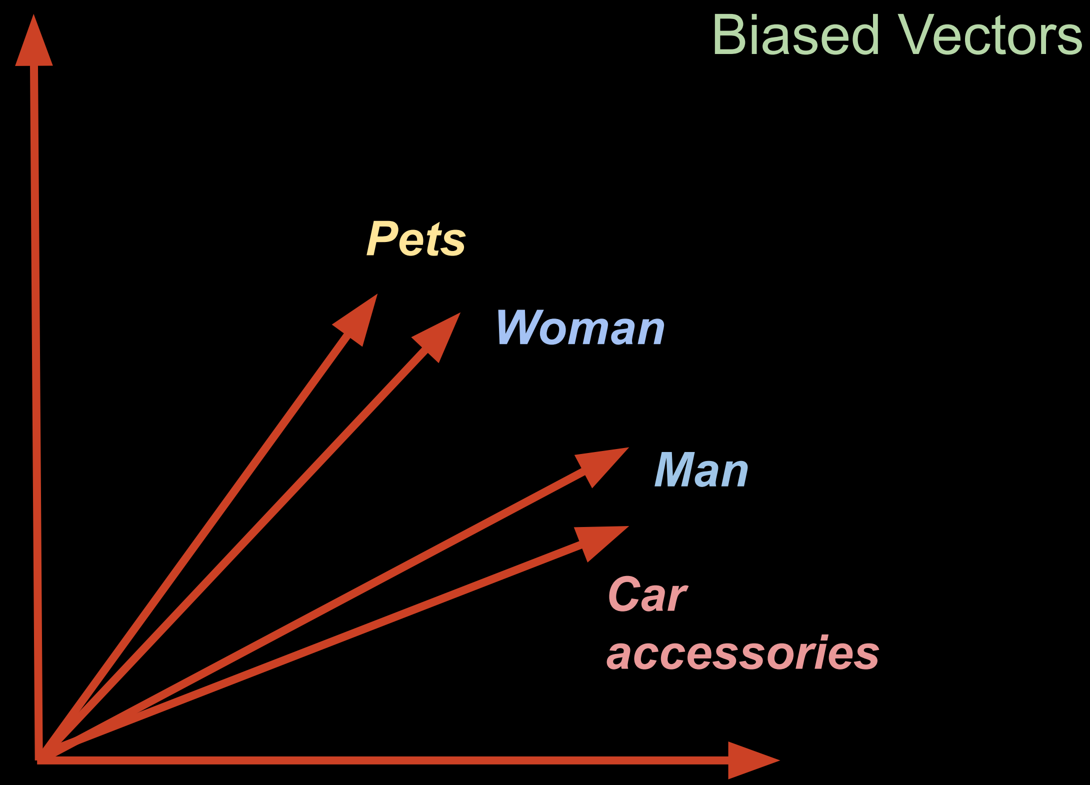
Overamplification



Semantic Bias



Semantic Bias



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).

selection bias

The sample of observations themselves are not representative of the application population.

error disparity

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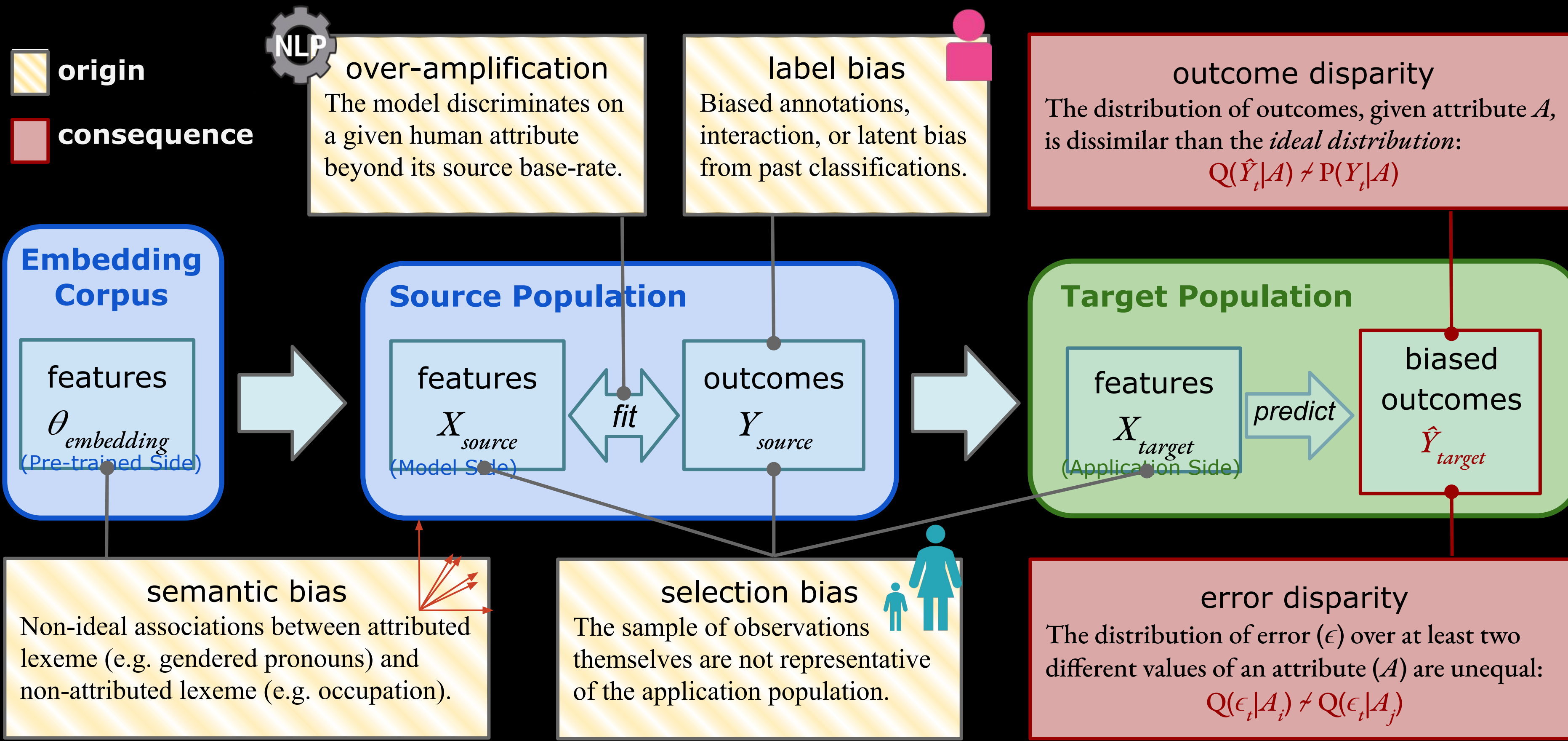
Predictive Bias Framework for NLP



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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Ethics in NLP

Privacy

- Risk Categories:
  - Revealing unintended private information
  - Targeted persuasion

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- Mitigation strategies:

Ethics in NLP

Privacy

- Risk Categories:
  - Revealing unintended private information
  - Targeted persuasion
- Mitigation strategies:
  - Informed consent -- let participants know and opportunity to opt-in/-out
  - Do not share / secure storage
  - *Federated learning* -- obfuscate to the point of preserving privacy
  - Transparency in information targeting

    "You are being shown this ad because ..."

Ethics in NLP

Bias

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Ethical Research

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

Ethics in NLP Research

ACM Code of Ethics; General Ethical Principles:

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- Avoid harm.

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- 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.

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

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).