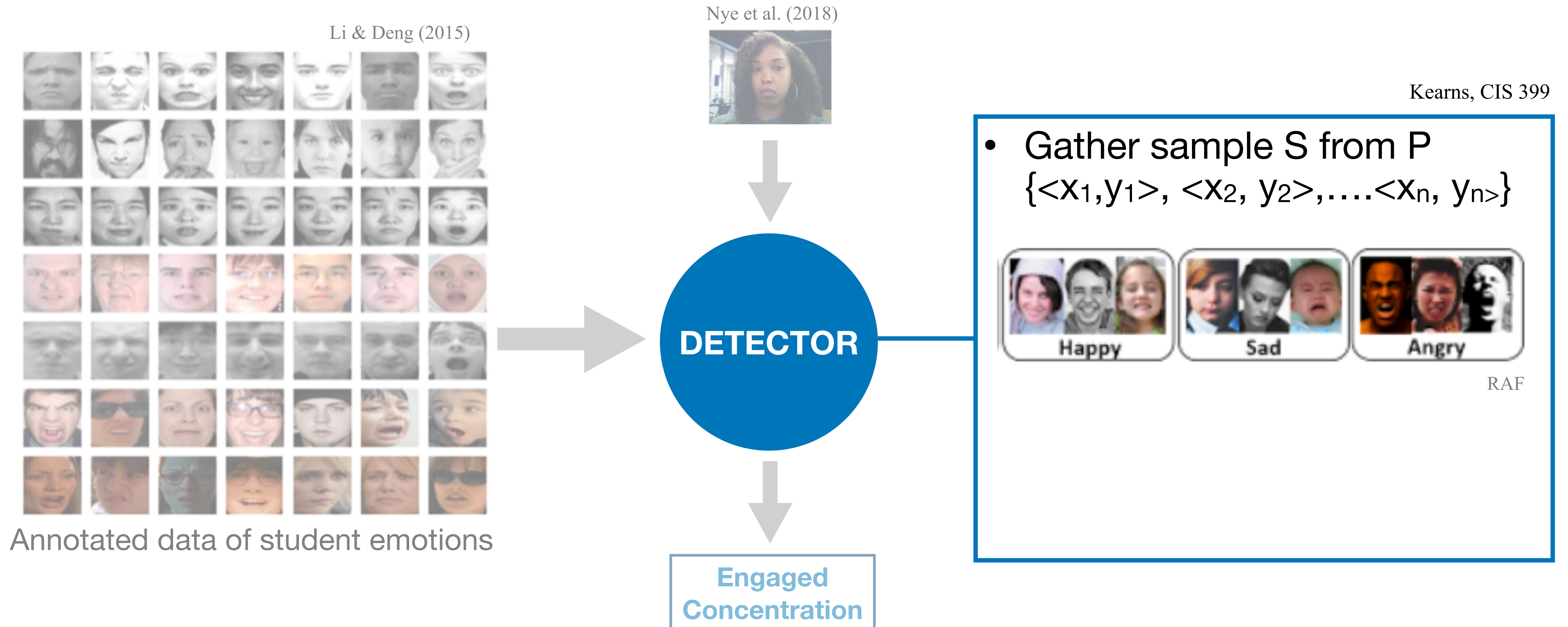
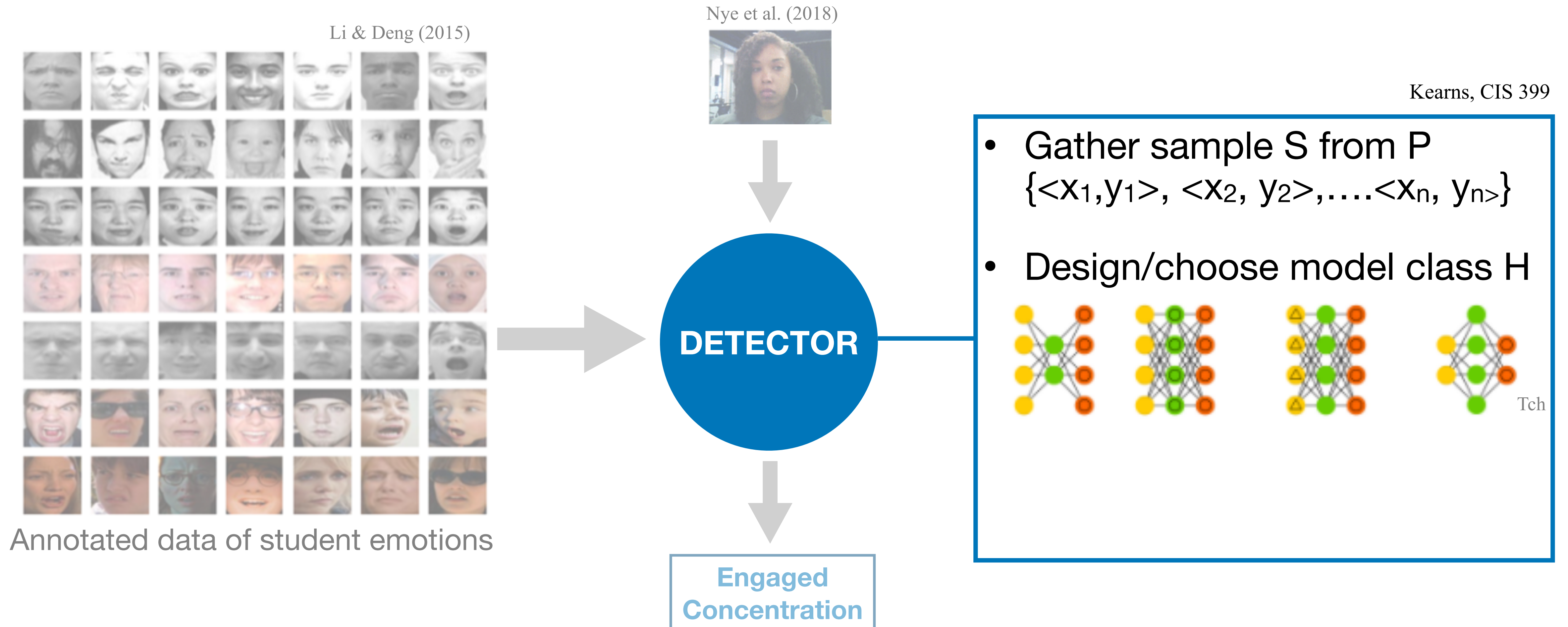


Limitations of Current Approaches

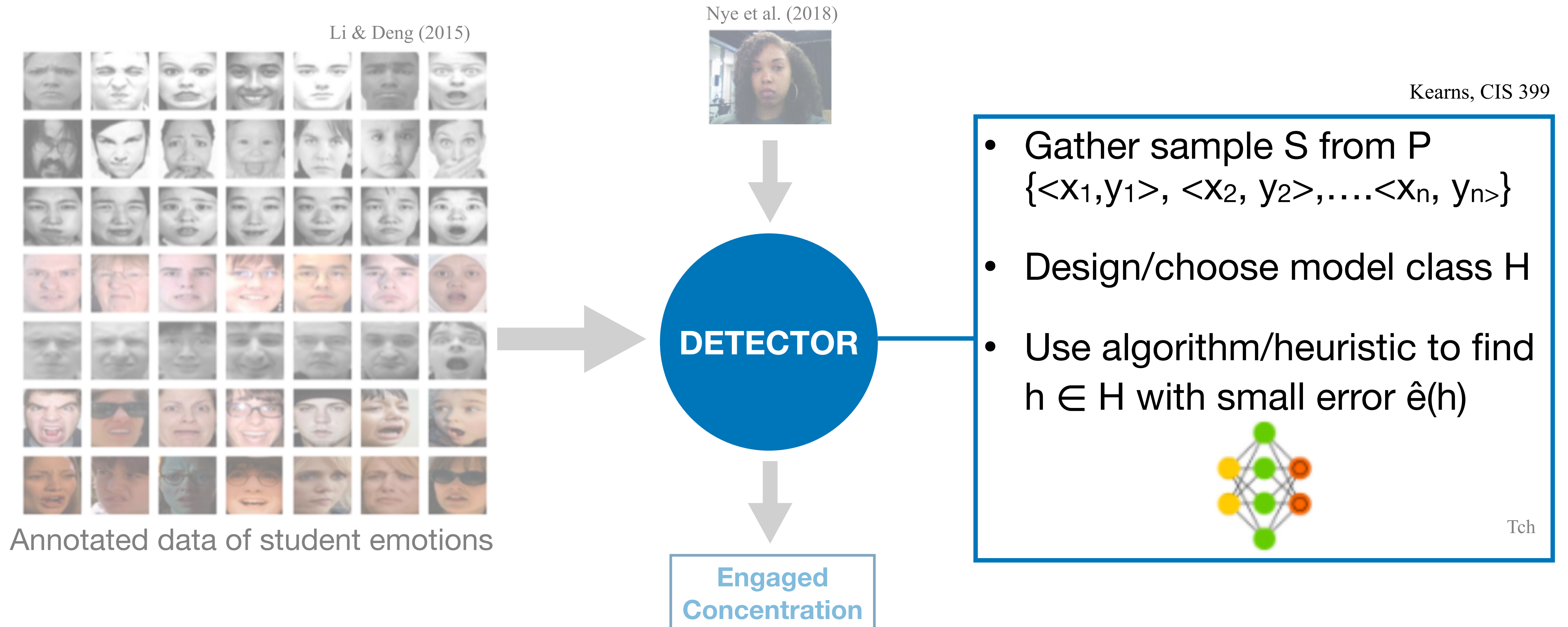
Machine Learning Workflow



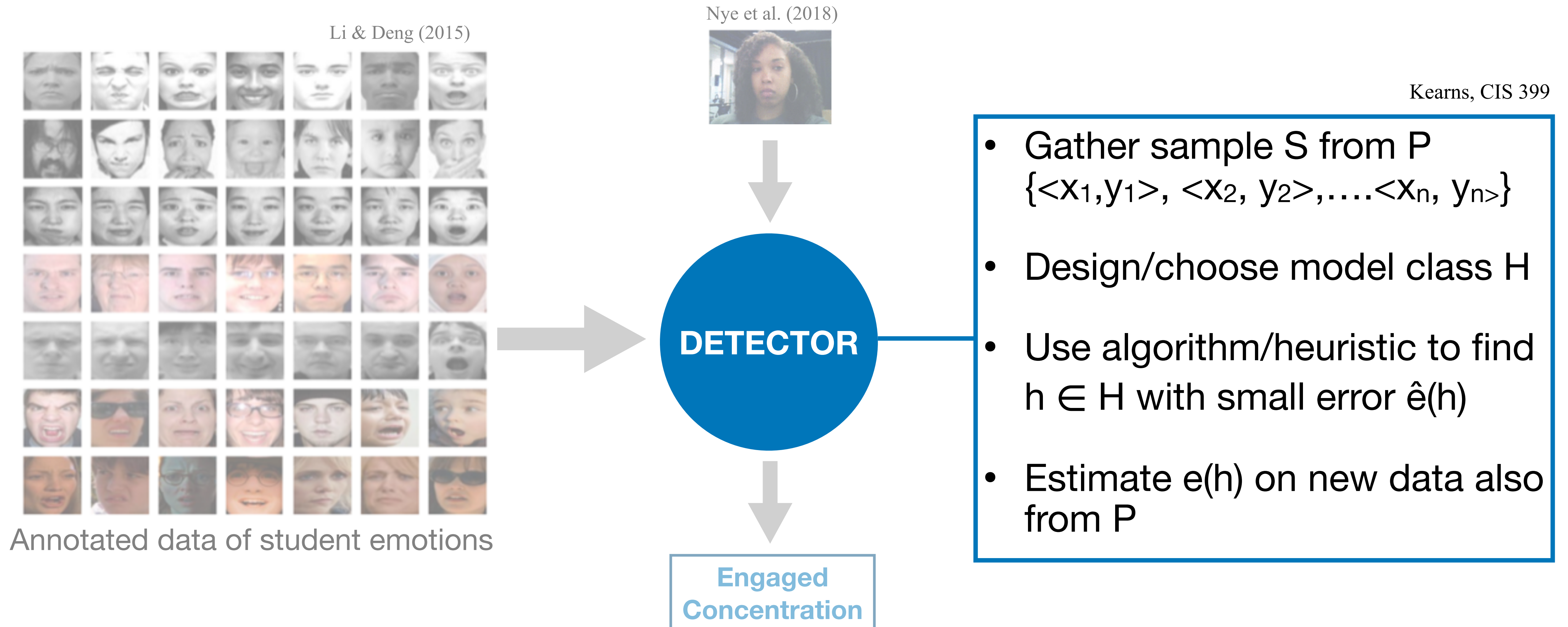
Machine Learning Workflow



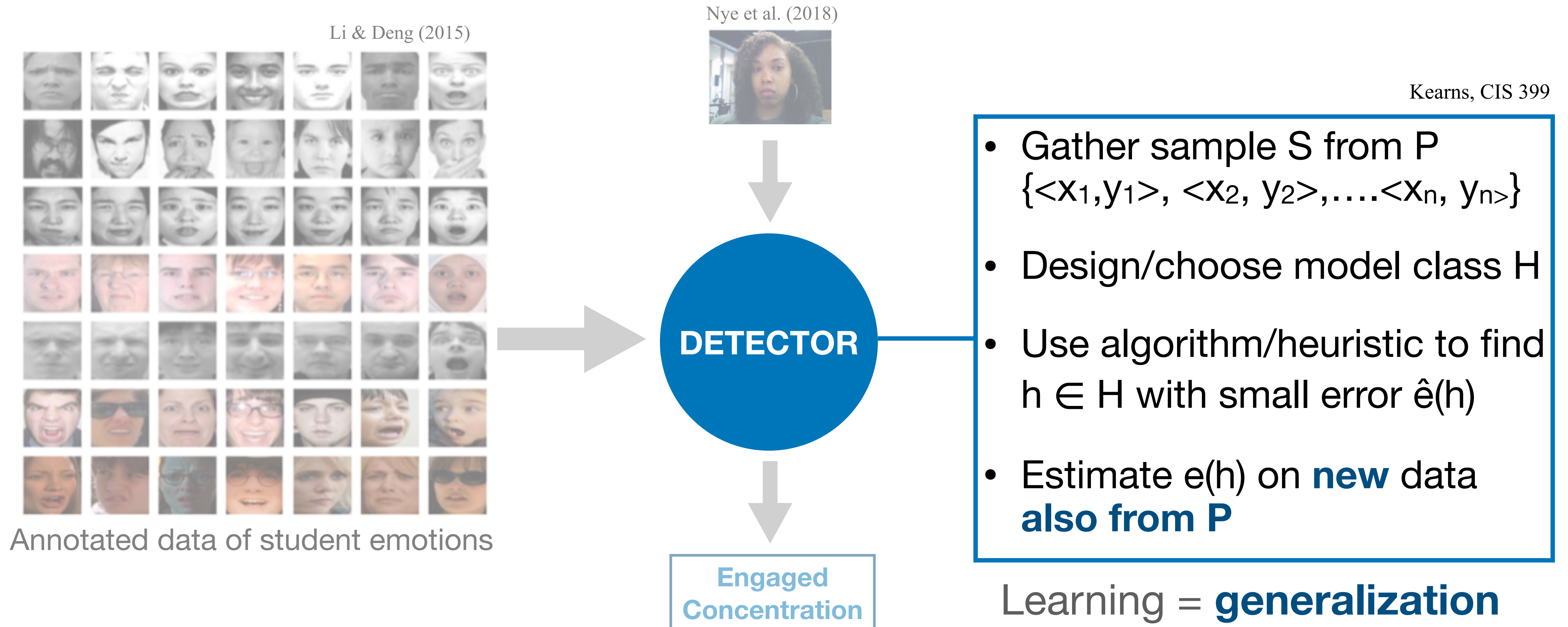
Machine Learning Workflow



Machine Learning Workflow



Machine Learning Workflow



Fundamental Theorem of Machine Learning

Learning = **generalization**

Kearns, CIS 399

No matter what P looks like...

...and for any reasonable H ...

...if we have **enough data** S ...

...then for **every** $h \in H$, we have

$$\hat{e}_S(h) \approx e_P(h)$$



DETECTOR

- Gather sample S from P
 $\{ \langle X_1, y_1 \rangle, \langle X_2, y_2 \rangle, \dots, \langle X_n, y_n \rangle \}$
- Design/choose model class H
- Use algorithm/heuristic to find $h \in H$ with small error $\hat{e}(h)$
- Estimate $e(h)$ on **new** data **also from P**

But Learning Context Varies Widely

Generalization to Student Subgroups

Kearns, CIS 399

No matter what P looks like...
...and for any reasonable H ...
...if we have enough data S ...
...then for every $h \in H$, we have

minimizing error on **data**
 \approx
minimizing **true/future** error

DETECTOR

- Gather sample S from P
 $\{\langle X_1, y_1 \rangle, \langle X_2, y_2 \rangle, \dots, \langle X_n, y_n \rangle\}$
- Design/choose model class H
- Use algorithm/heuristic to find $h \in H$ with small error $\hat{e}(h)$
- Estimate $e(h)$ on new data also from P

Student population not reported with generalization estimates (Paquette et al., 2020)

The Problem of Bias

No matter what P looks like...

...and for any reasonable H ...

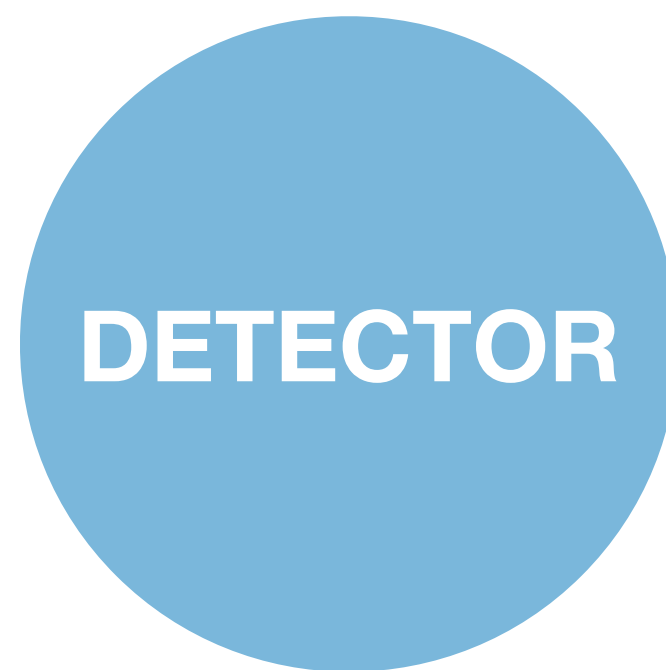
...if we have enough data S ...

...then for every $h \in H$, we have

minimizing error on **data**

\approx

minimizing **true/future** error



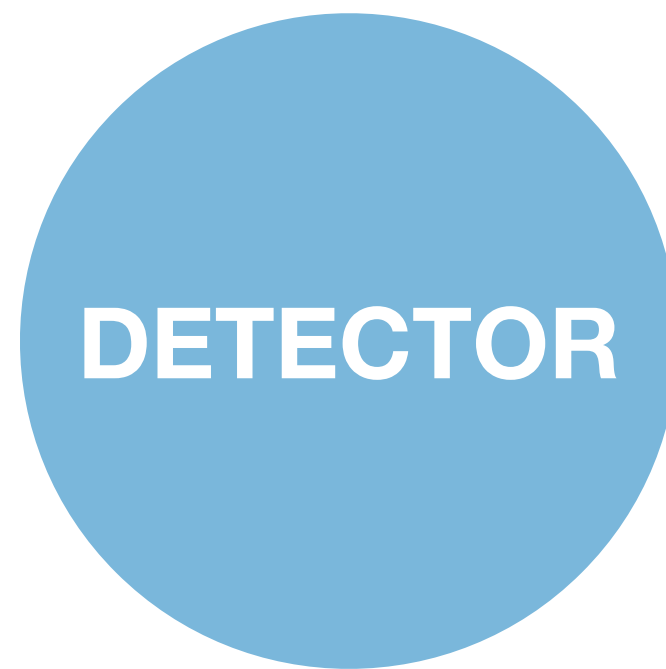
“All models are wrong
but some are useful”
- George Box

The Problem of Bias

No matter what P looks like...
...and for any reasonable H ...
...if we have enough data S ...
...then for every $h \in H$, we have

minimizing error on **data**
 \approx
minimizing **true/future** error

Karumbaiah, S., & Brooks, J. (2021) How Colonial Continuities Underlie Algorithmic Injustices in Education. [IEEE RESPECT21]



Haley Falcon

The Wire

Current Downstream Efforts

Focus on Model Development and Evaluation

No matter what P looks like...

...and for any reasonable H ...

...if we have **enough data** S ...

...then for **every** $h \in H$, we have

minimizing error on **data**

\approx

minimizing **true/future** error

DETECTOR

Study	Subgroups	Prediction Task
Hu & Rangwala, 2020	Gender, Race	At-Risk (course)
Yu et al., 2020	Gender, Race	College success
Lee & Kizilcec, 2020	Gender, Race	Course grade
Anderson et al., 2019	Gender, Race	Graduation
Kai et al., 2017	Gender, Race	Online college retention
Bridgeman et al., 2009, 2012	Gender, Nationality	Essay scoring
Ogan et al., 2015	Nationality	Learning Outcome

Need to Move Upstream



No matter what P looks like...

...and for any reasonable H ...

...if we have **enough data** S ...

...then for **every** $h \in H$, we have

minimizing error on **data**

\approx

minimizing **true/future** error



DETECTOR

What upstream sources
shape data collection,
modeling, and adaptive
decision making?
Are they context aware?

Upstream Sources of Bias

Focus on Data Collection Method, System Design, and Theory

No matter what P looks like...

...and for any reasonable H ...

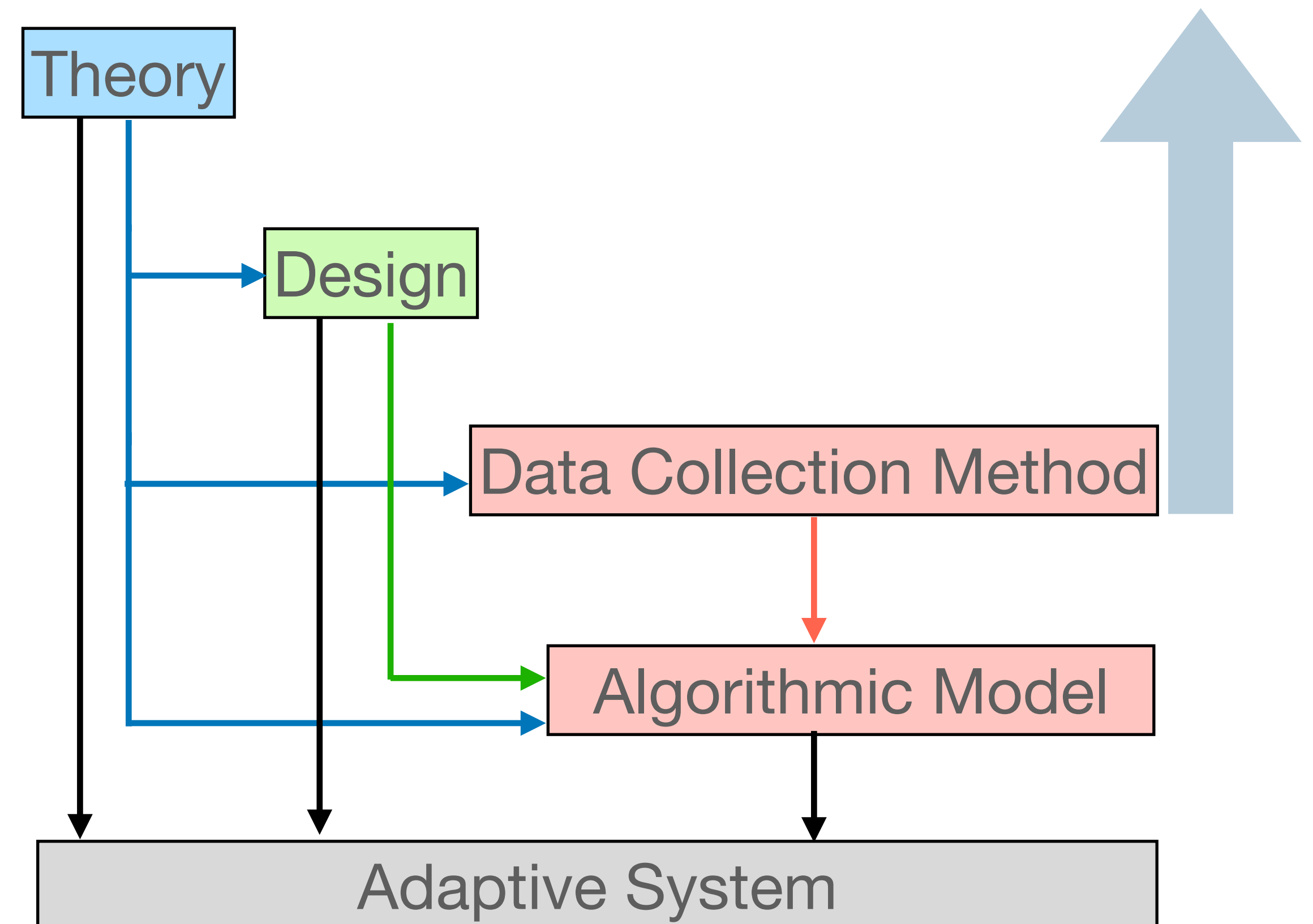
...if we have **enough data** S ...

...then for **every** $h \in H$, we have

minimizing error on **data**

\approx

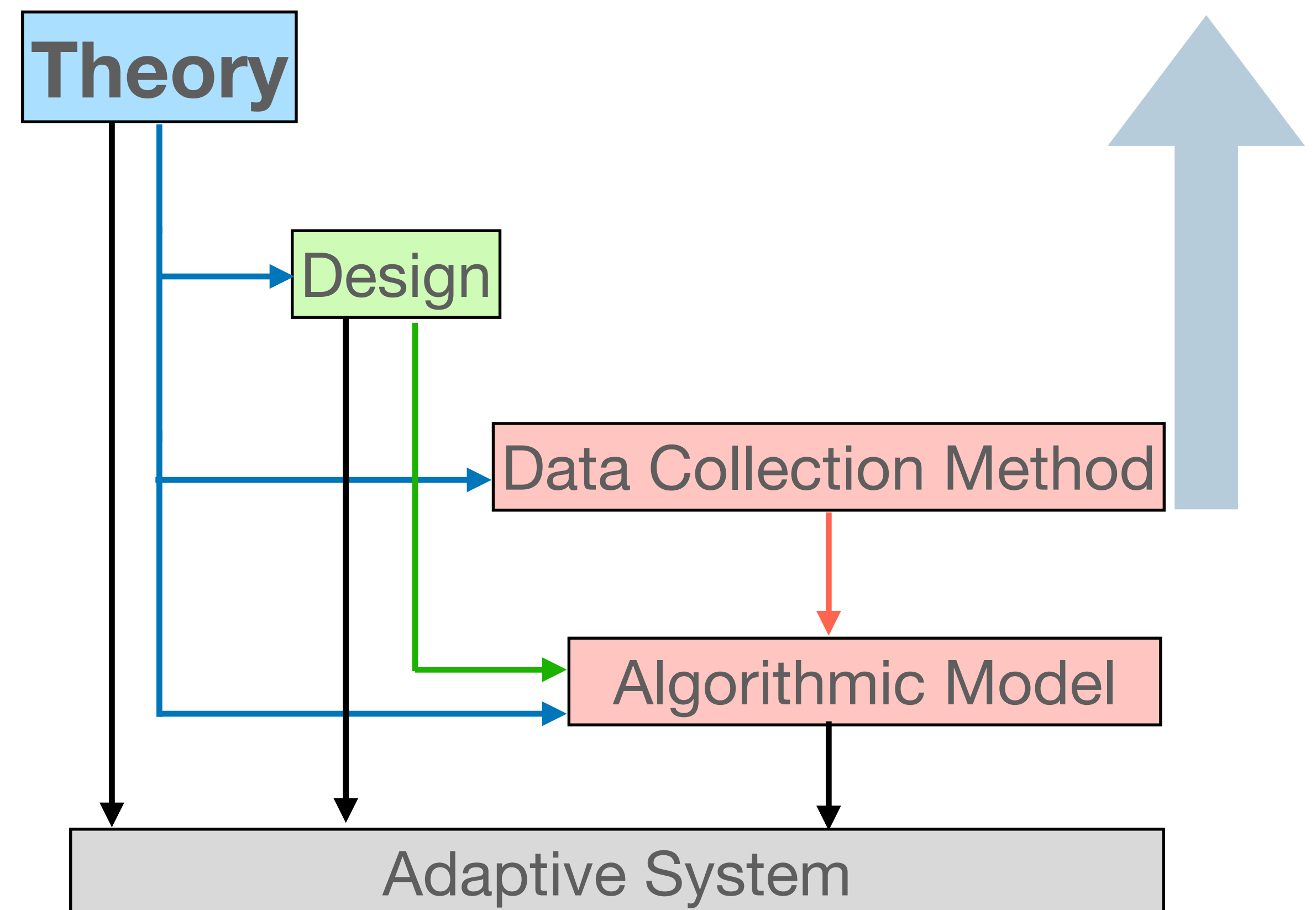
minimizing **true/future** error



Upstream Sources of Bias

Focus on Data Collection Method, System Design, and Theory

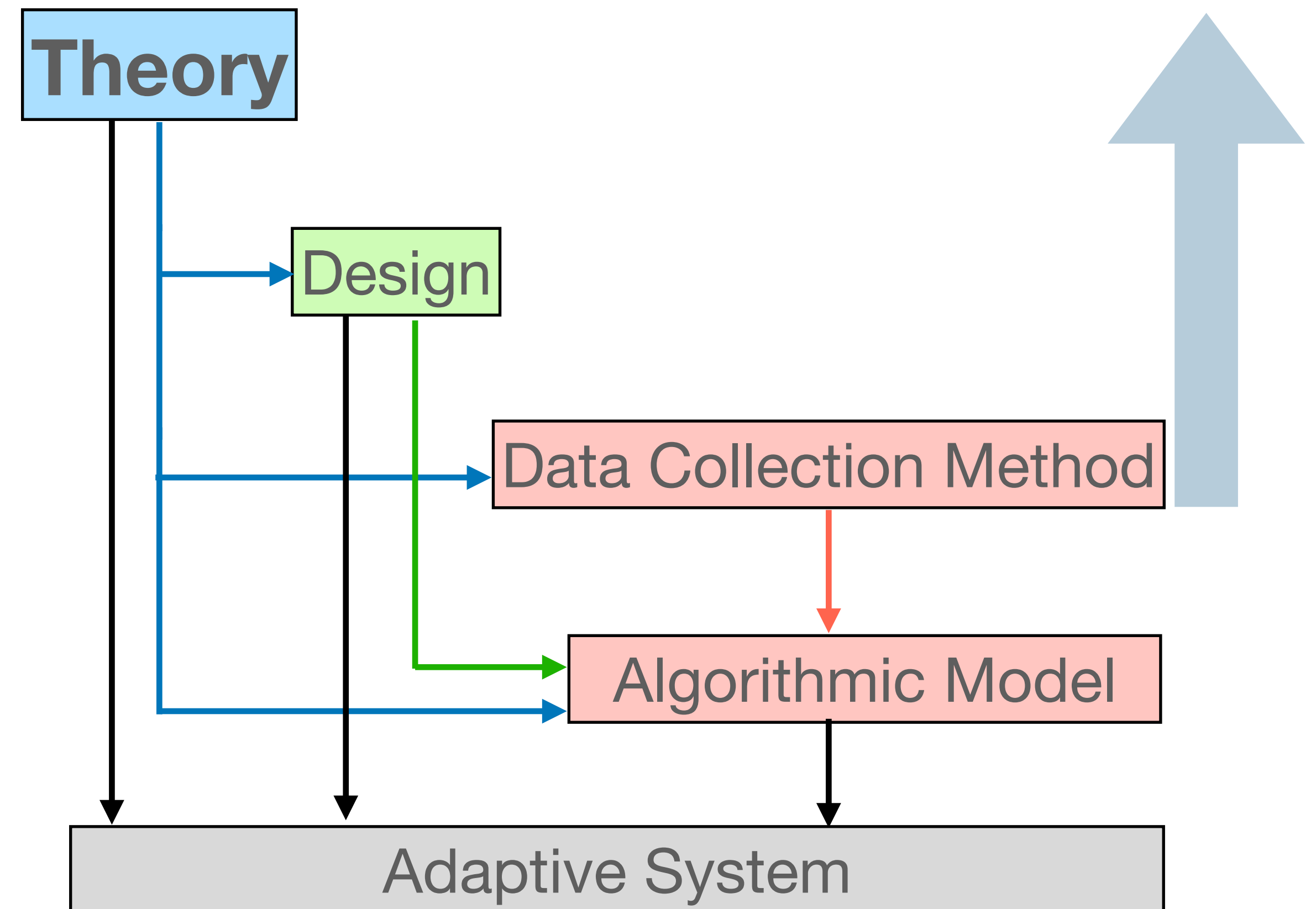
- Assumptions around the conceptualization of the construct
- Interpretation of student behaviors in the data collected
- Construction of variables used in predictive modeling
- Design of interventions in adaptive systems



Upstream Sources of Bias

Focus on Data Collection Method, System Design, and Theory

- Theory -> Design (e.g., culturally irrelevant rewards as extrinsic motivators)
- Theory -> Data Collection (e.g., choice of culturally irrelevant affective states to collect data for)
- Theory -> System (e.g., theory-driven rules of affective interventions that are culturally insensitive)
- Theory -> Algorithmic model (e.g., influencing a biased choice of predictors for boredom detection)



Sources of Bias

Focus on Data Collection Method, System Design, and Theory

For your example model, name some potential **sources** of bias (upstream or downstream). Try to be as specific as you can.

Discussion Board Question

