

# **When Machine Learning meets Educational Science...**

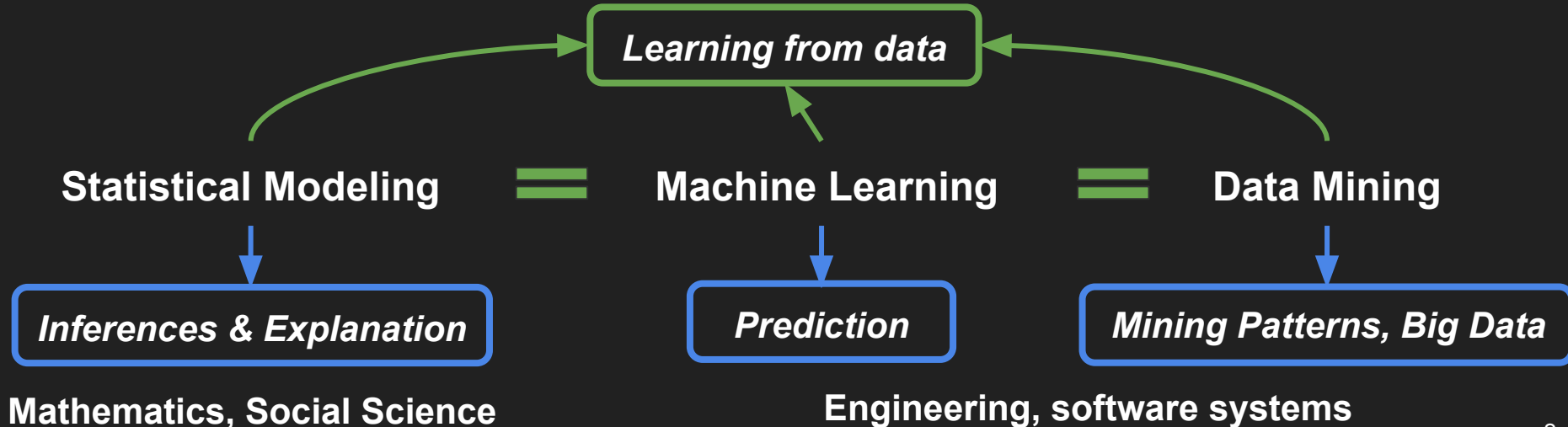
**An abstract of my Master's Thesis**

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Master of Artificial Intelligence**

# When Machine Learning meets Educational Science...

An abstract of my Master's Thesis

## Clarification of Terms



# When Machine Learning meets Educational Science...

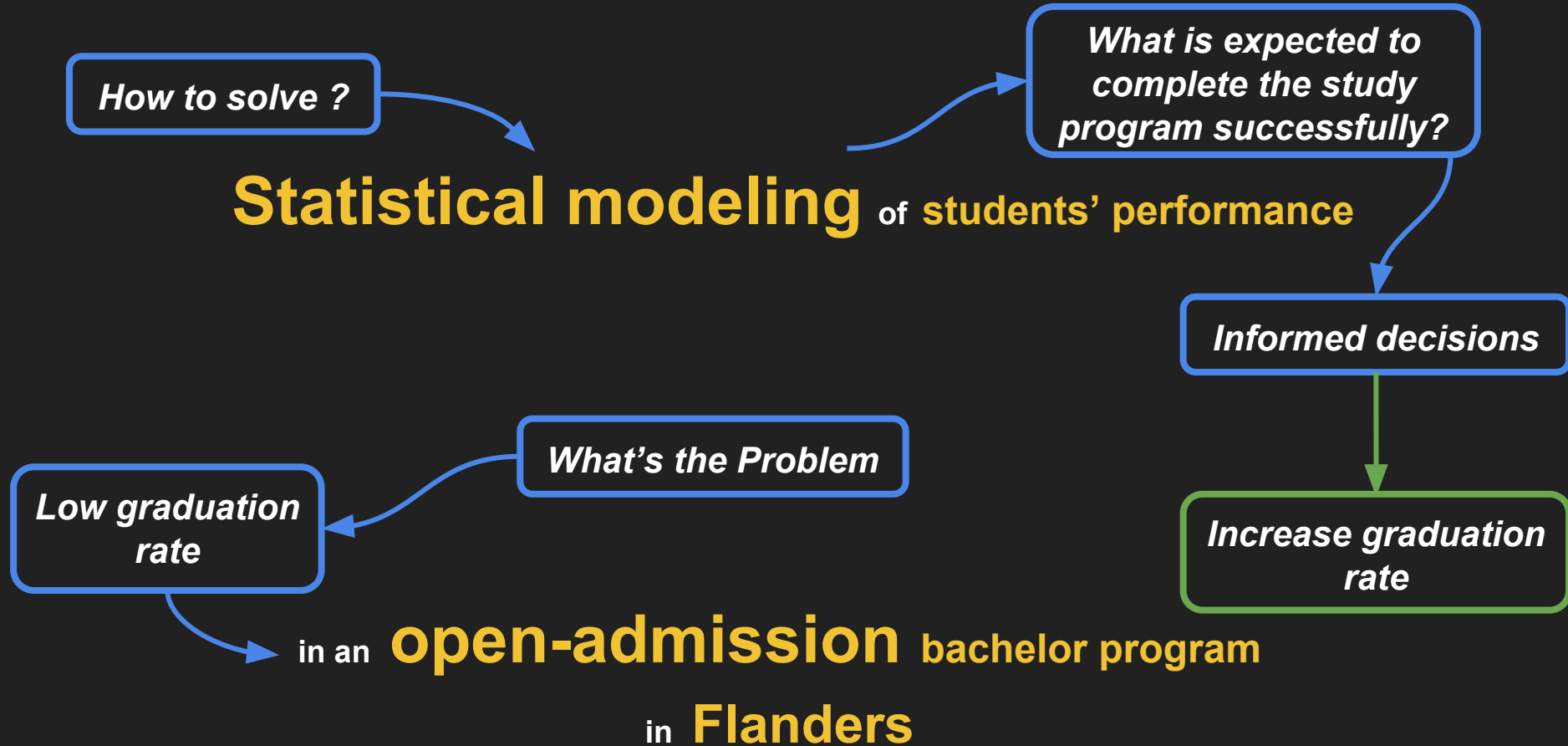
An abstract of my Master's Thesis



**Statistical modeling of students' performance in an open-admission bachelor program in Flanders**

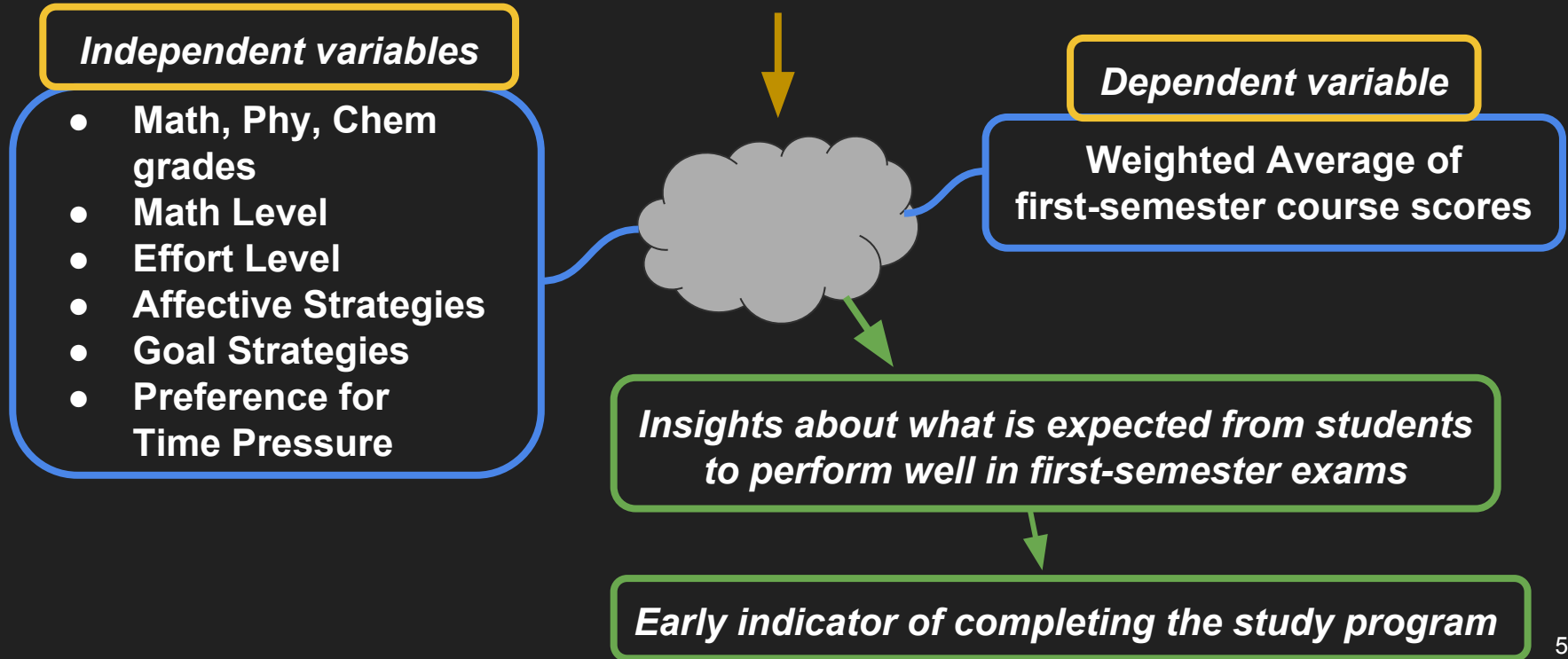
The need to discriminate between explanatory and predictive modeling

## An Overview:



# An Overview:

## Statistical modeling of students' performance



# An Overview:

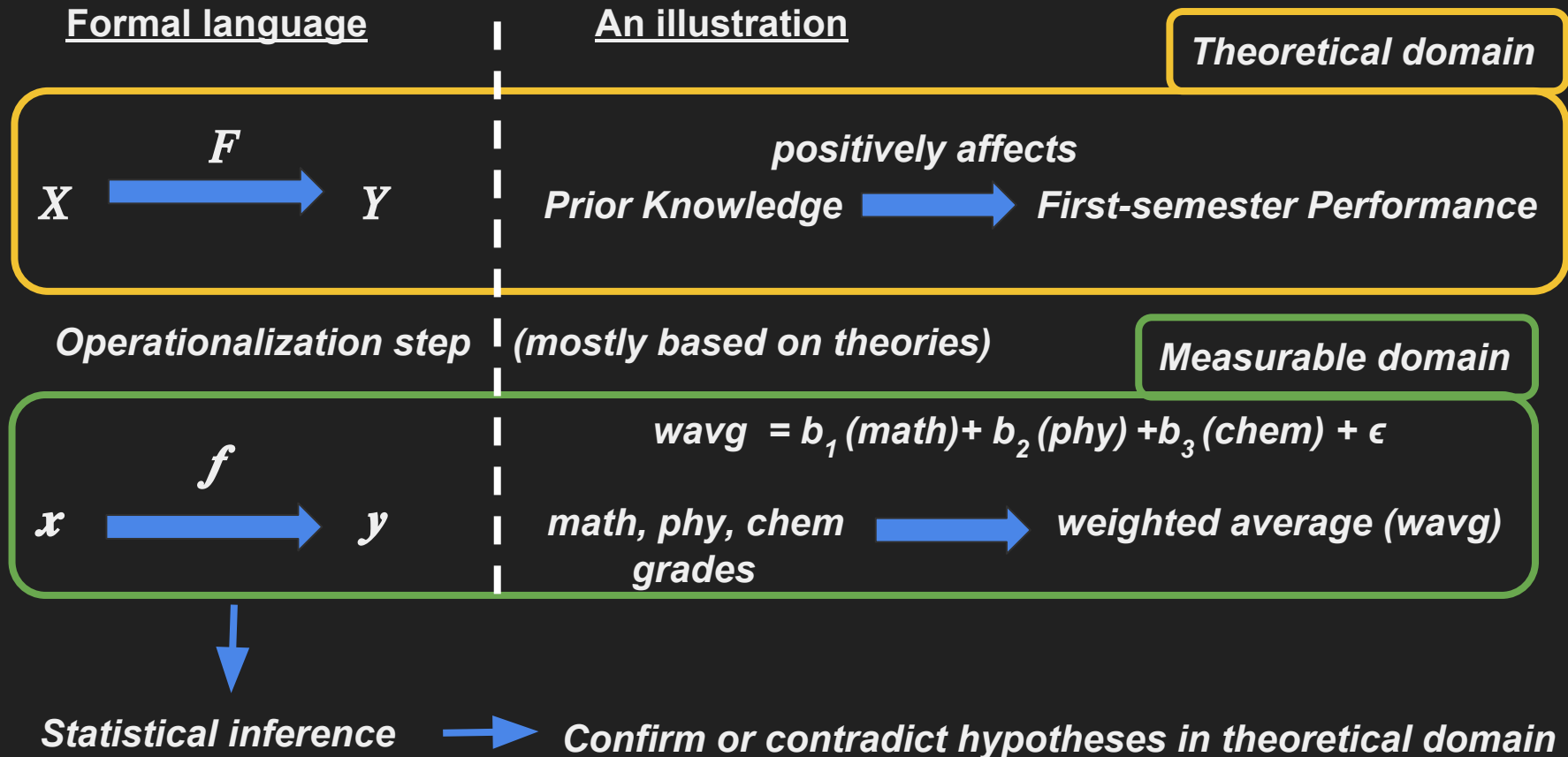
## Statistical modeling of students' performance

explanatory and predictive modeling

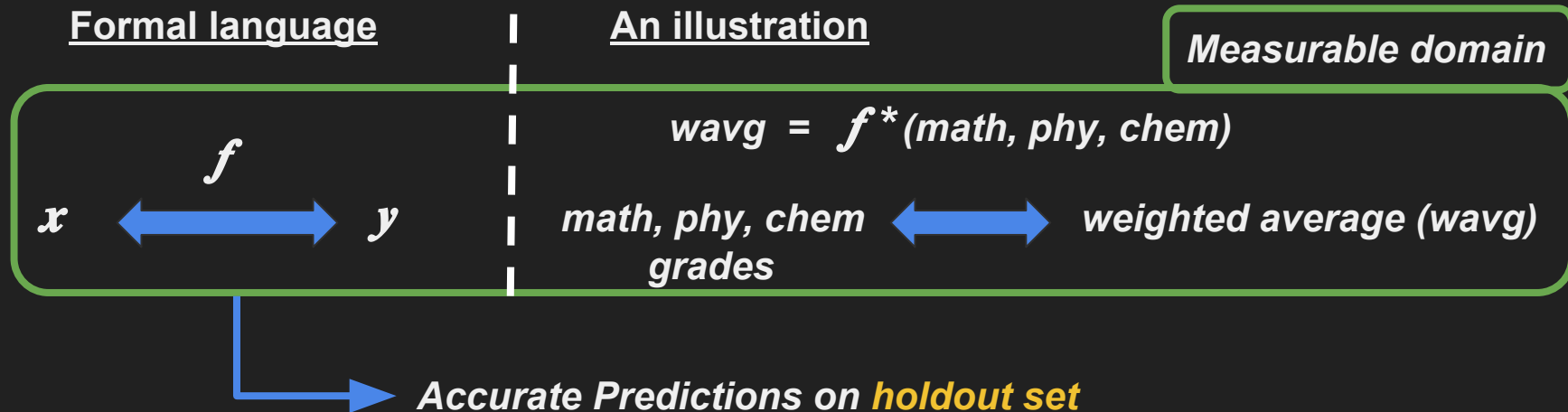
*Retrospective  
Causal explanations*

*Prospective  
Predictions*

# Explanatory Modeling - A Deeper Look



# Predictive Modeling - A Deeper Look



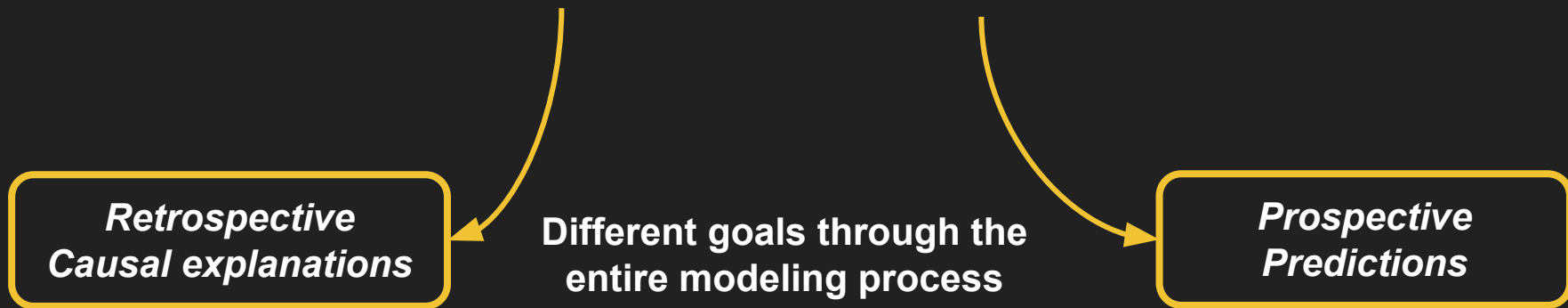
Not interested in explaining **causal relation**



# Explanatory and Predictive Modeling - A Deeper Look

## Statistical modeling of students' performance

The need to discriminate between  
explanatory and predictive modeling



But, confusion in related literature...

*Statistical goals, choice of methods, Evaluation criteria*  
( $R^2$  for predictive power)

***Appreciating the Differences between  
explanatory and predictive modeling***

***Correct Scientific  
and Practical  
Conclusions***

***Reveals their  
Advantages and  
Disadvantages***

***Explanatory  
Modeling***

***Explanatory Modeling  
with Predictive Validity***

***Predictive Modeling  
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## Explanatory Modeling

## Explanatory Modeling with Predictive Validity

## Predictive Modeling and Comprehensible Approximation

### Outcomes:

Model: Multiple Linear Regression

Prior academic knowledge  
(*math, phy, chem* and *hrs*)

positively affects  
36%

First-semester performance  
(*wavg*)

Affective and Goal strategies  
(*affe* and *goal*)

positively affects  
4%

First-semester performance  
(*wavg*)

Preference for Time pressure  
(*press*)

does not influence  


First-semester performance  
(*wavg*)

Average-case statistical patterns

*Appreciating the Differences between  
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*Explanatory  
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*Explanatory Modeling  
with Predictive Validity*

*Predictive Modeling  
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Why Optimize both explanatory and predictive goals?

- Explanations are **retrospective**
  - Need to **Generalize** statistical inferences to “unseen” incoming students

Explanatory Path:

Similar statistical inferences

Model: Ordinal Logistic Regression

Predictive Validity:

Low predictive power



Cannot **generalize** statistical inferences to “unseen” incoming students

- Predicts **only 60%** students in the “**at-risk**” zones
- **Wrongly** predicts **too many** students (**around 60%**) as “**no-risk**”

Important Inference...

models trying to optimize both  
explanatory and predictive goals



No

Making it  
complex

Yes



Poor predictive power



Presence of **complex patterns**  
that are hard to hypothesize



Complicate the explanation of  
association between variables

*Appreciating the Differences between  
explanatory and predictive modeling*

*Correct Scientific  
and Practical  
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*Reveals their  
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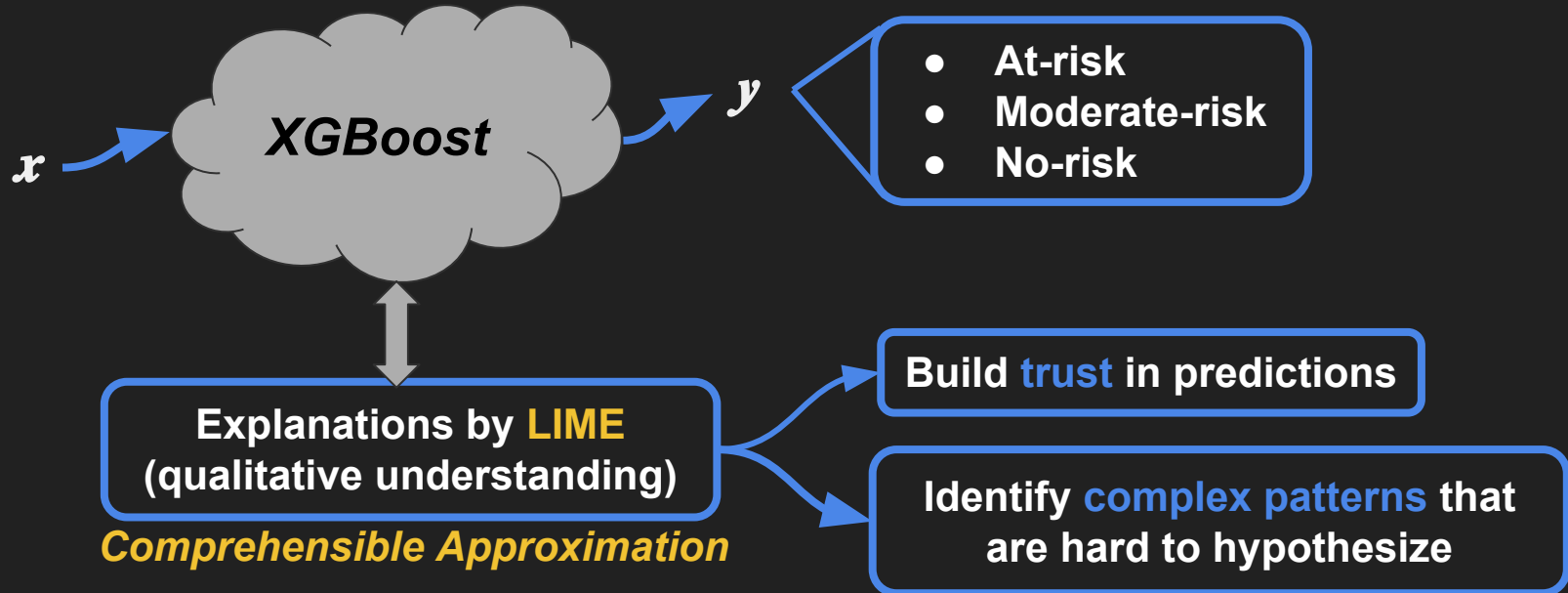
*Explanatory Modeling  
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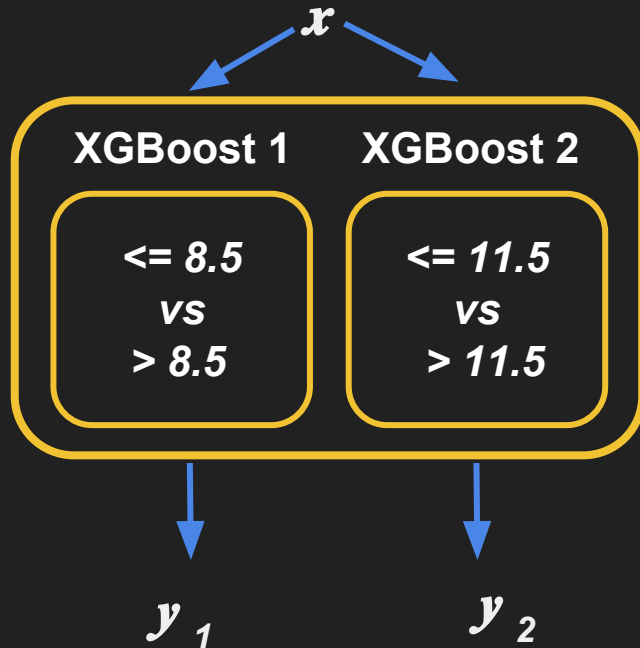


## Why Predictive Modeling and Comprehensible Approximation?

**Generalize** ~~statistical inferences to “unseen” incoming students~~ **predictive performance**



## Model Design :



| $y_1$      | $y_2$       | <u>Interpretation</u> |
|------------|-------------|-----------------------|
| $\leq 8.5$ | $\leq 11.5$ | at-risk               |
| $> 8.5$    | $\leq 11.5$ | moderate-risk         |
| $> 8.5$    | $> 11.5$    | no-risk               |

## Why two-binary-classifiers model ?

- difficult to identify students in the “moderate-risk” zone
- easy to train and optimize

## ✓ Overall Good Predictive Performance

Low misclassification of “at-risk” students

| XGBoost 1 | Precision | Recall |
|-----------|-----------|--------|
| <= 8.5    | 0.64      | 0.80   |
| > 8.5     | 0.88      | 0.77   |
| w. avg    | 0.80      | 0.78   |

Accurately predicts “at-risk” and “moderate-risk” students

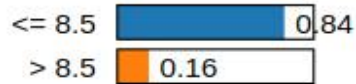
Significant misclassification of “moderate-risk” students

| XGBoost 2 | Precision | Recall |
|-----------|-----------|--------|
| <= 11.5   | 0.87      | 0.85   |
| > 11.5    | 0.68      | 0.70   |
| w. avg    | 0.81      | 0.81   |

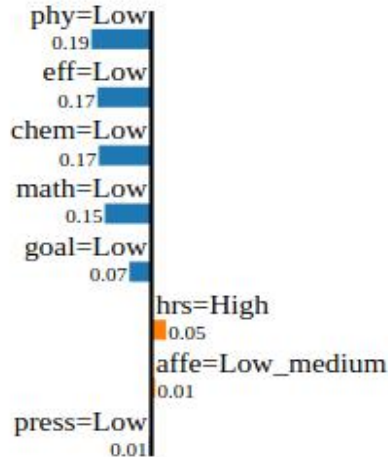
Trusting **correct identification** of “at-risk” students - **LIME Explanations**

## Example 1

Prediction probabilities



<= 8.5 > 8.5



A Low background in **math, phy, chem** contributes  $19 + 17 + 15 = 51\%$  of  $P(<= 8.5)$

## Observation:

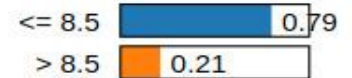
“**Low**” value for most of the IVs contributes heavily to class “<= 8.5” (at-risk students)

## Practical Implication:

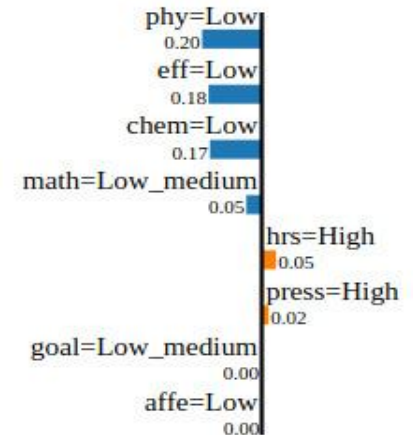
**Individual** counselling

## Example 2

Prediction probabilities

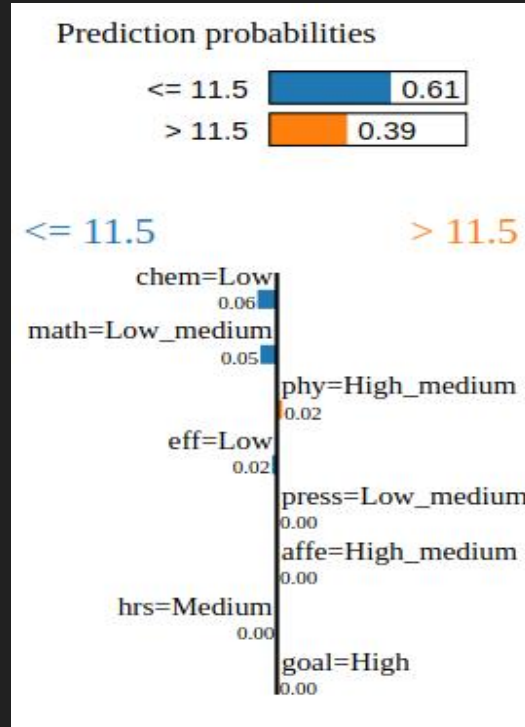
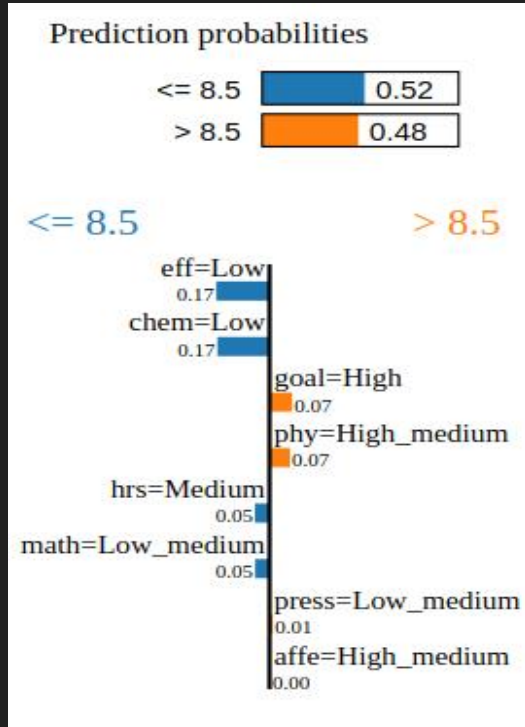


<= 8.5 > 8.5



## Trusting correct identification of “at-risk” students - LIME Explanations

### Example 3



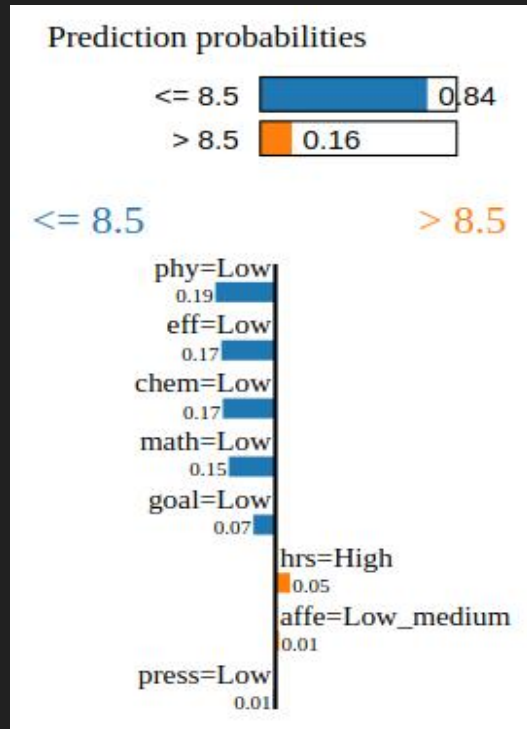
### Observation:

Moving towards the **higher** levels of an IV increases the chances of being **not** classified as “at-risk” (i.e., “ $>8.5$ ”)

### Practical Implication:

**Individual** counselling

## Further exploitation of LIME Explanations...



Type I

The frequencies of different values taken by an input variable

Type II

The frequencies of an input variable displayed at different positions in the lists of contribution

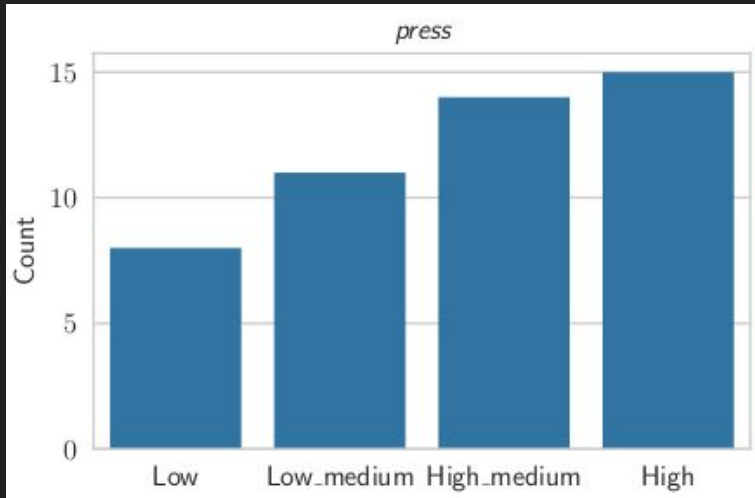
Identify **complex patterns** that are hard to hypothesize

Subtle average-case patterns

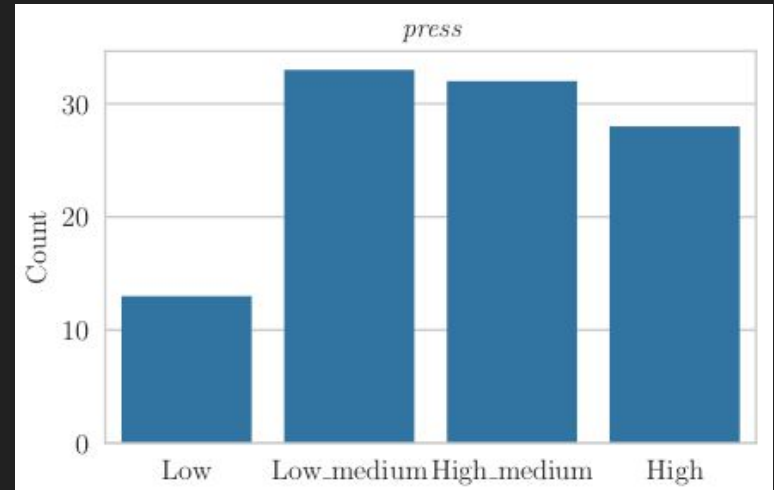
## Type I plot using LIME Explanations

High levels of “preference for time pressure” are associated with students in the “at-risk” and “moderate-risk” zones

*at-risk students (“ $\leq 8.5$ ”)*



*at-risk + moderate-risk students (“ $\leq 11.5$ ”)*

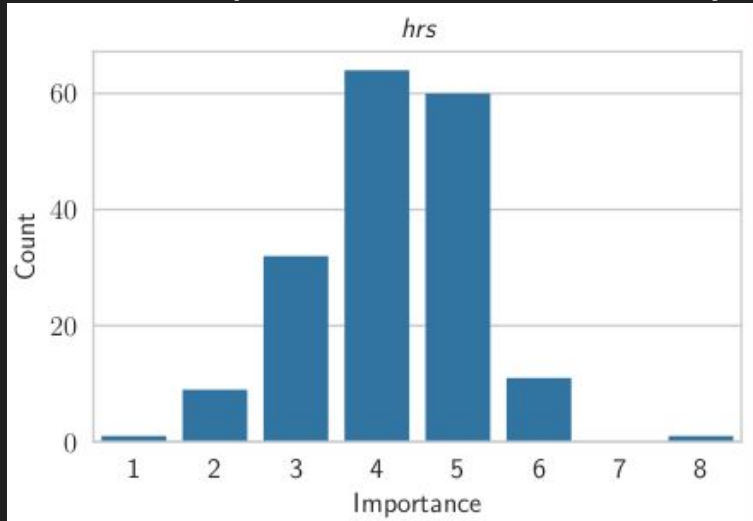


## Type II plot using LIME Explanations

Different effects of “Hours spent for Math per week” for different classification

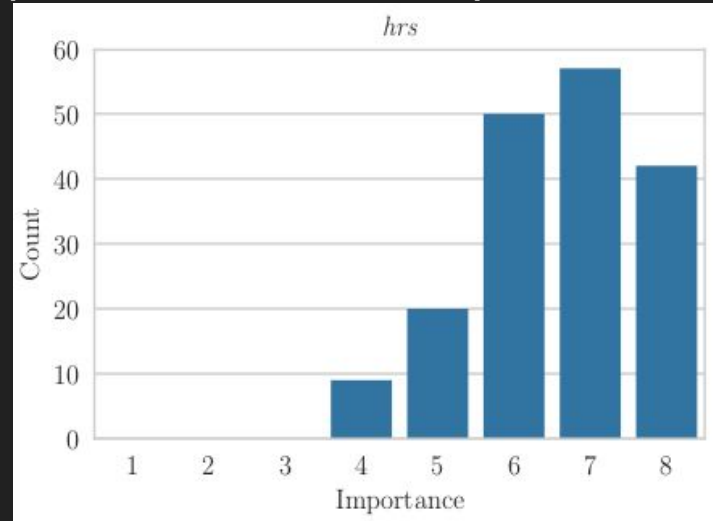
“ $\leq 8.5$ ” vs “ $> 8.5$ ”

at-risk vs (moderate-risk + no-risk)



“ $\leq 11.5$ ” vs “ $> 11.5$ ”

(at-risk + moderate-risk) vs no-risk





# TAKEAWAYS

- **Indiscrimination** between different statistical modeling approaches in related literature
- Three important approaches :

Explanatory

Explanatory  
+  
Predictive

Predictive  
+  
Some method  
to make predictions  
interpretable

- For the current problem, all three approach gave **many similar** results showing that our understanding of the phenomenon is **almost correct**
- However, some **subtle effects** were uncovered only in **predictive modeling**
- Finally, we should **not** get **settled** at explanatory modeling,  
But at the same time, we should **not** get **fascinated** by predictions

