Predicting first-year engineering student success:

from traditional statistics to machine learning

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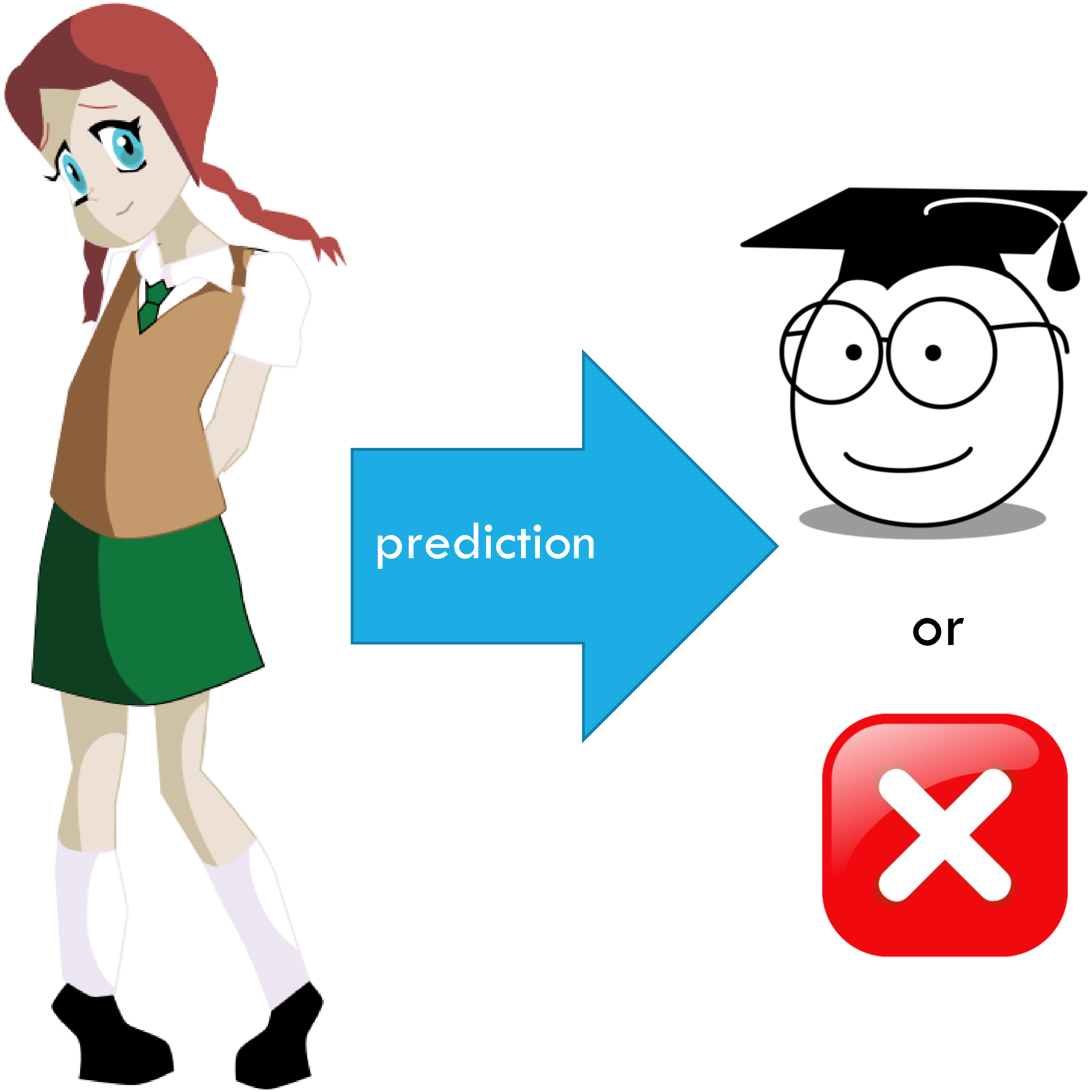
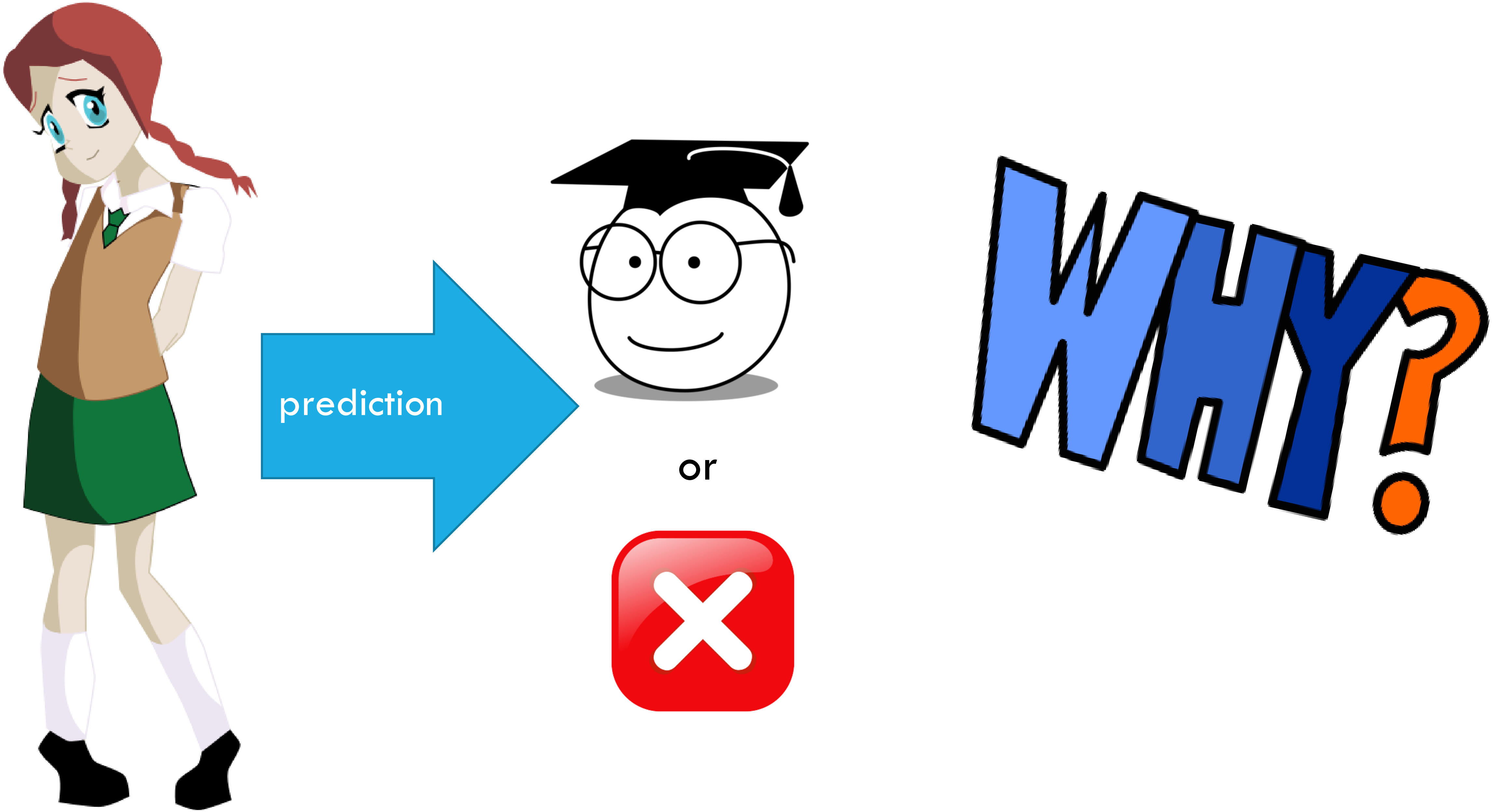

prediction
or


prediction
or
WHY?

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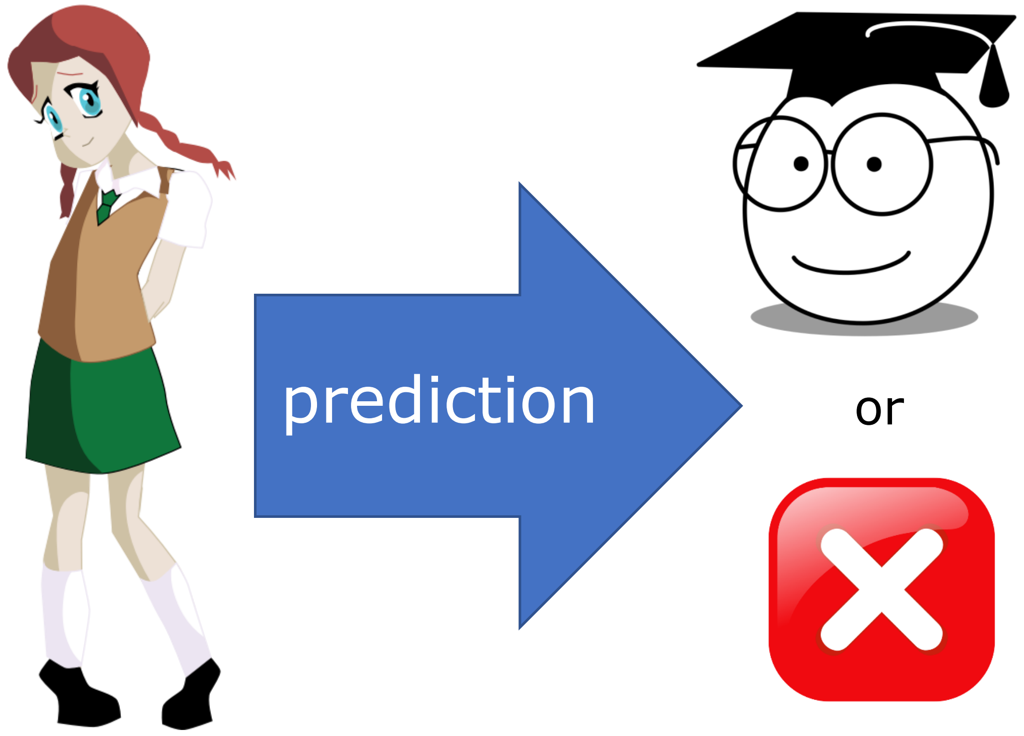
STELA

prediction

or

population-wide insights

individual predictions


prediction
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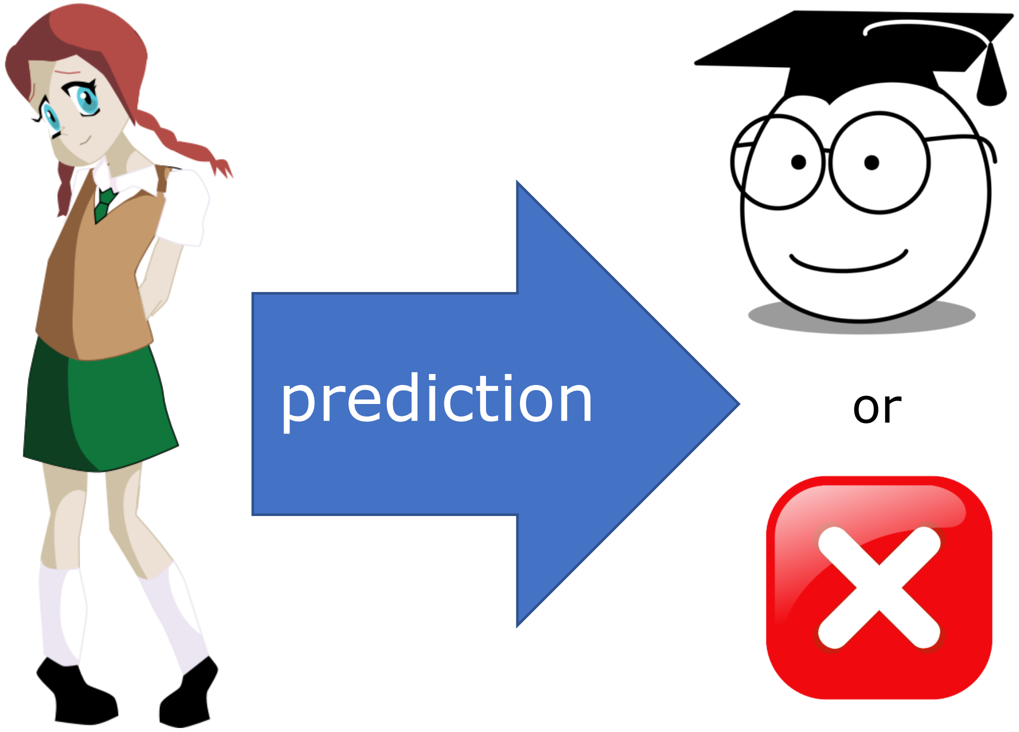
prior academic achievement (secondary education)

- grades math, physics, chemistry
- number of hours math
- effort level

learning and studying skills

- motivation
- time management
- concentration
- performance anxiety
- use of test strategies

preference for time pressure



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academic achievement (AA)
GPA of first semester (wavg)

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academic achievement (AA)
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explanatory modelling
- multiple linear regression

predictive modelling
- logistic regression
- boosted trees

Research questions

Do statistical modelling (multiple linear & logistic regression) and boosted trees identify the same factors for first-year engineering student success?

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Can Local Interpretable Model-agnostic Explanations (LIME) generate interpretable insights in the factors important for predicting first-year student success?

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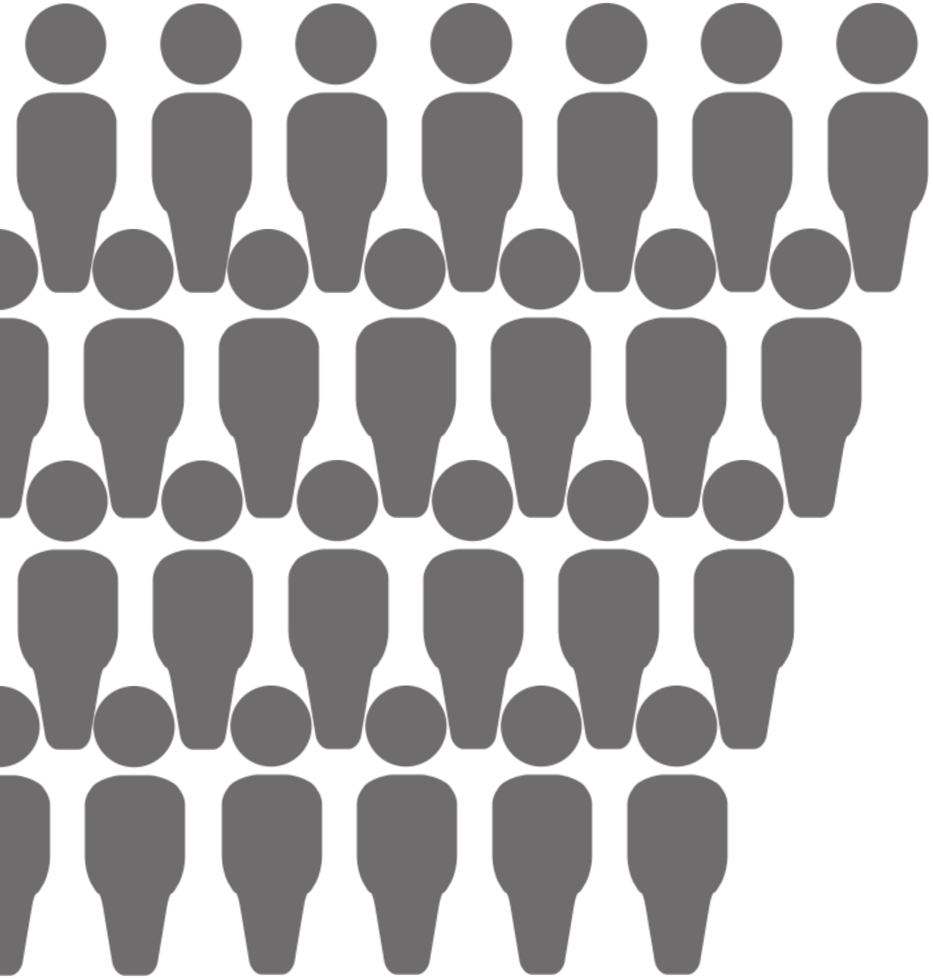

first-year Bachelor of Engineering Science students
two academic years: 2015-2016 and 2016-2017
N=811

EXPLANATORY MODELLING
→ MULTIPLE LINEAR REGRESSION

Dependent Variable
Population Y intercept
Population Slope Coefficient
Independent Variable
Random Error term

$$Y_i = \underbrace{\beta_0 + \beta_1 X_i}_{\text{Linear component}} + \underbrace{\varepsilon_i}_{\text{Random Error component}}$$

Hypotheses

- Prior academic experience positively AA.
- Affective and goal strategies positively affect AA.
- Preference for time pressure does not affect AA.

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	model	regression type	R^2
1	wavg ~ math+phy+chem+hrs	standard	0.37
2	wavg ~aff + goal + press	standard	0.06
3	wavg ~ math+phy+chem+hrs + aff + goal + press + eff	sequential	

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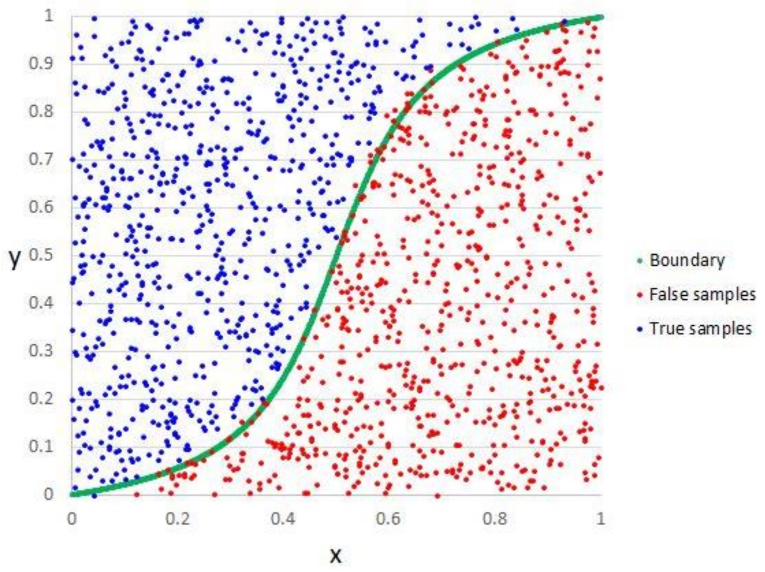
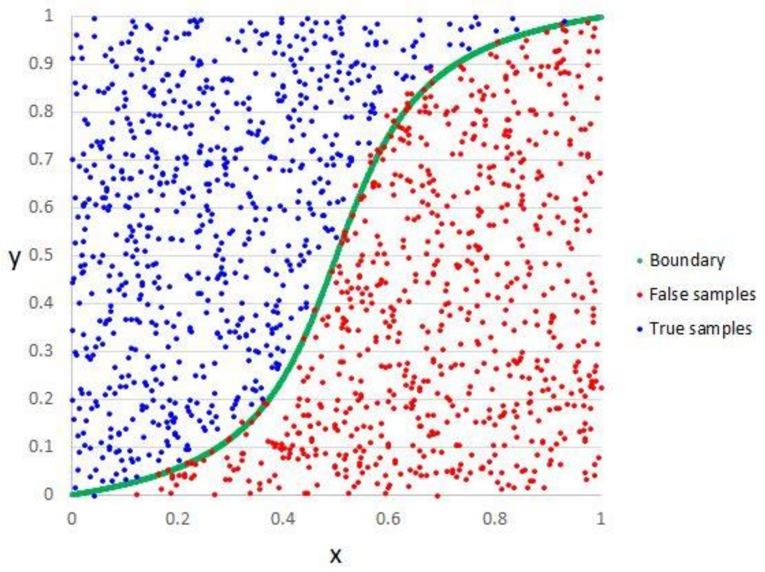
EXPLANATORY MODELLING WITH PREDICTIVE VALIDITY → LOGISTIC REGRESSION



prediction logistic regression

- no-risk (wavg > 11.5)
- moderate-risk
- at risk (wavg ≤ 8.5)

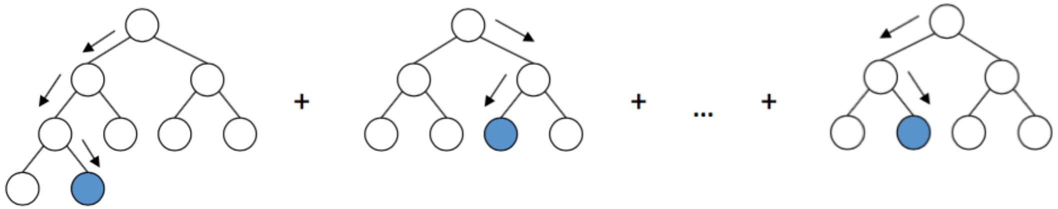
EXPLANATORY MODELLING WITH PREDICTIVE VALIDITY → LOGISTIC REGRESSION

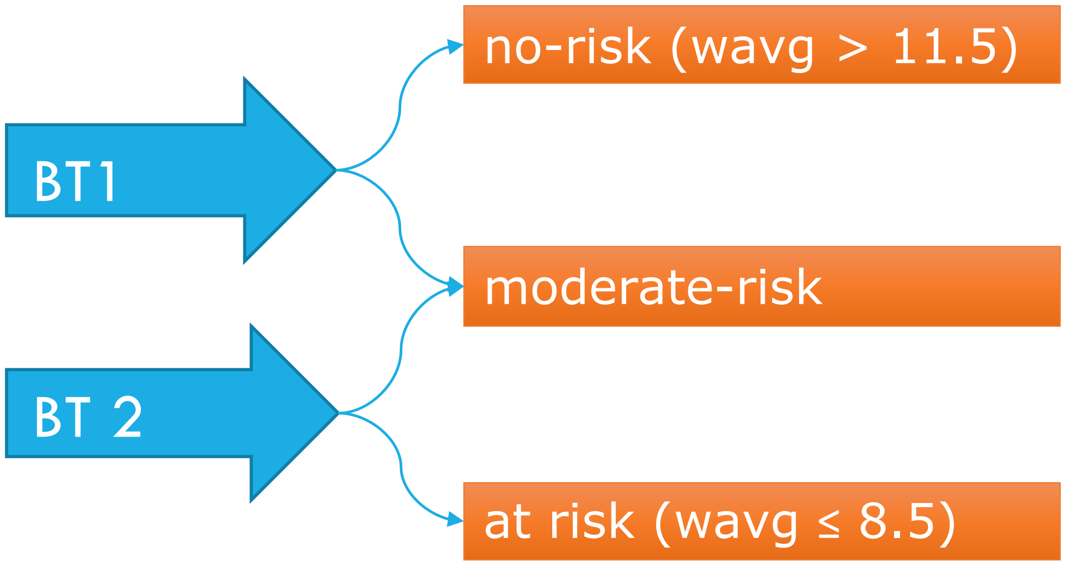


prediction logistic regression

	precision	recall	F1-score
no-risk (wavg > 11.5)	0.41	0.45	0.43
moderate-risk	0.63	0.59	0.61
at risk (wavg ≤ 8.5)	0.63	0.60	0.62

PREDICTIVE MODELLING
→ BOOSTED TREES





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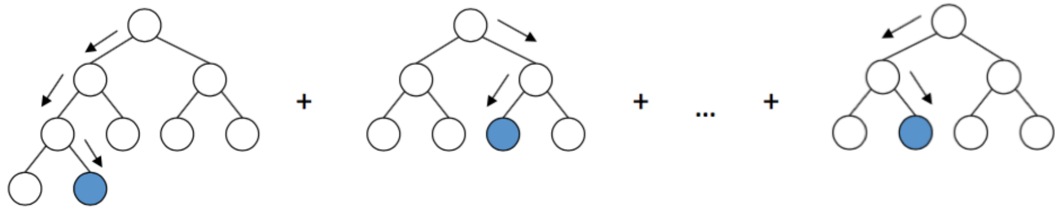
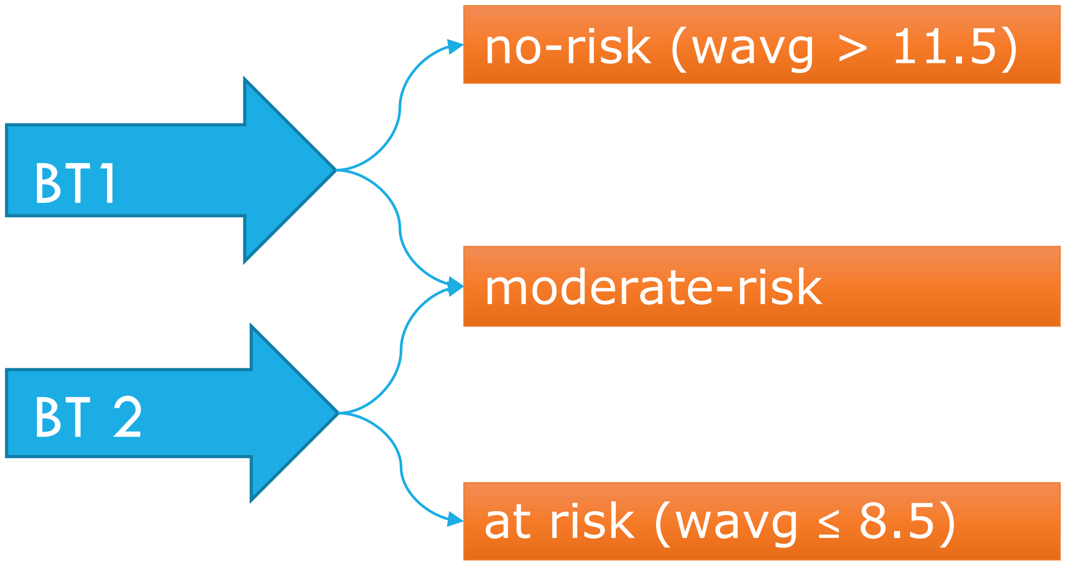
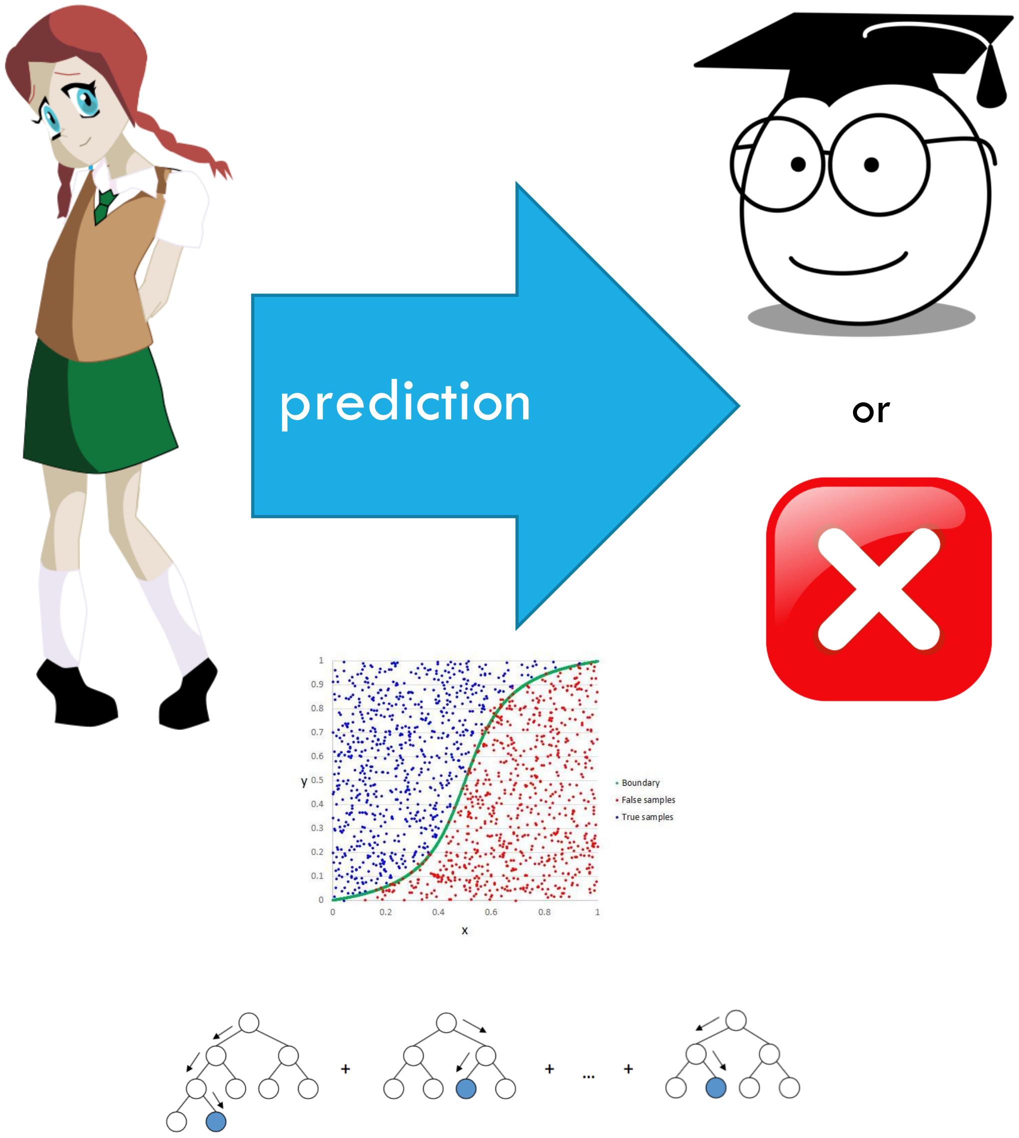
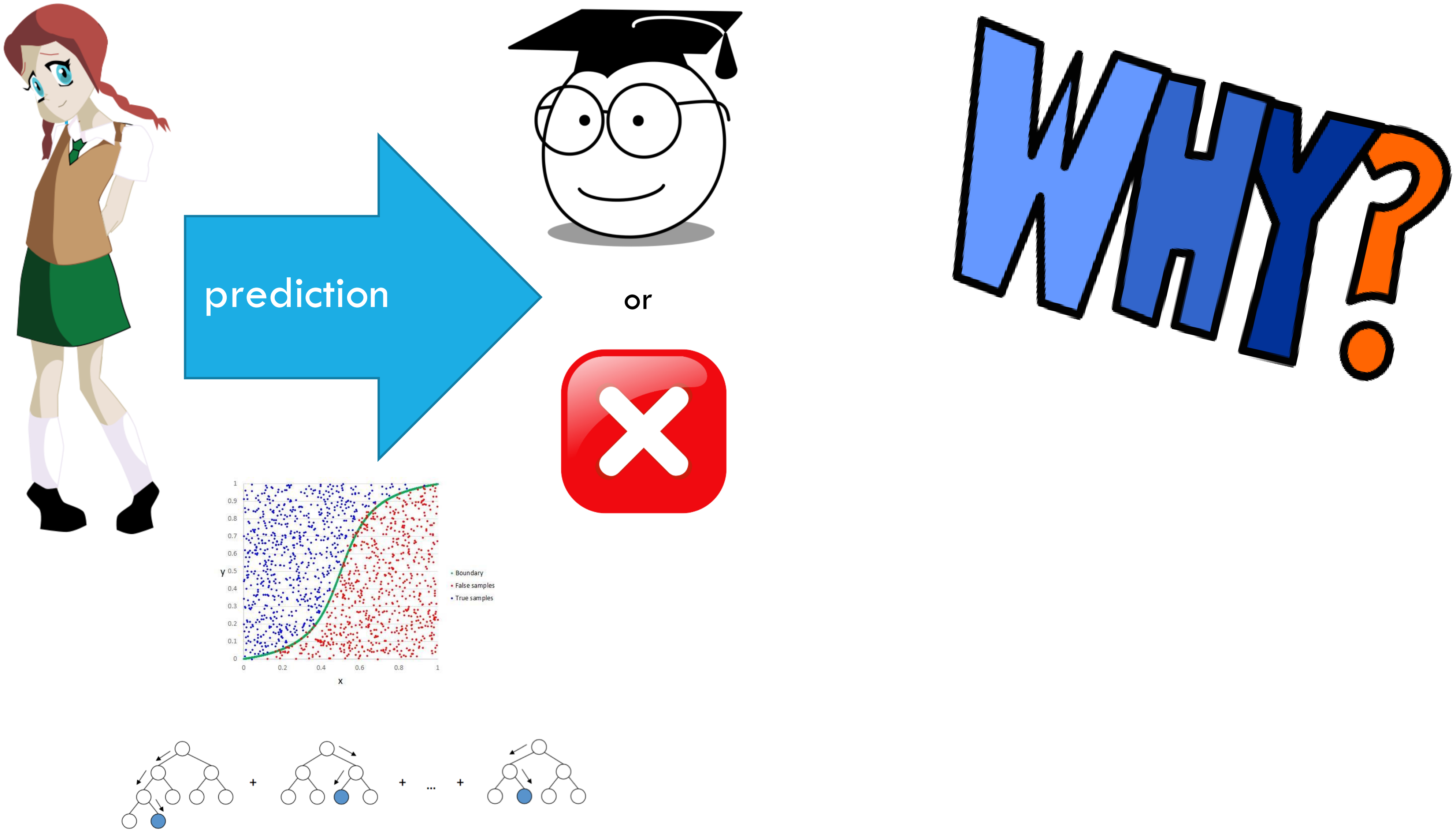




precision	recall	F1-score
0.64	*0.80*	0.71
0.88	0.77	0.82
0.87	*0.85*	0.86
0.68	0.70	0.69


prediction
or
Boundary
False samples
True samples
x
y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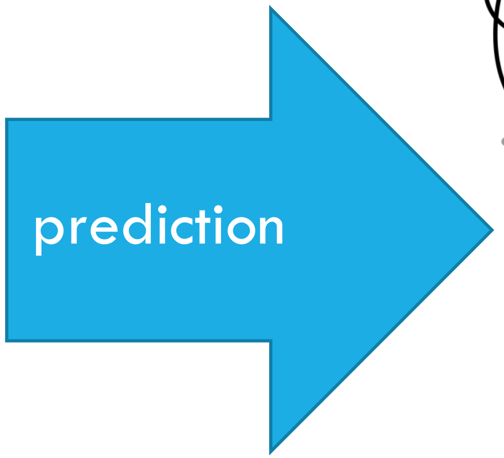
WHY?



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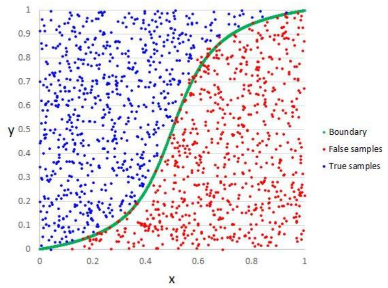
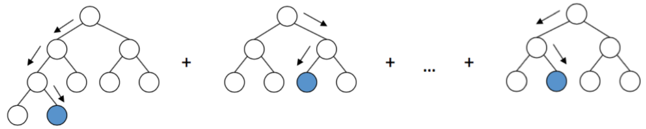


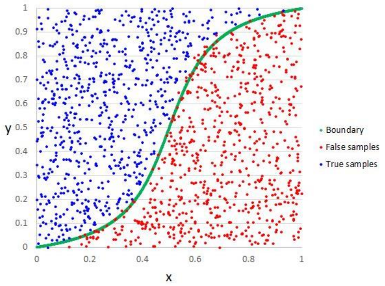


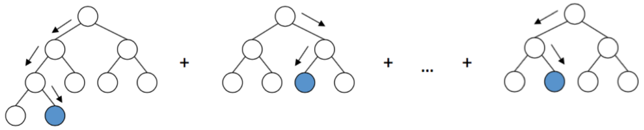
individual predictions

population-wide insights

prediction

or





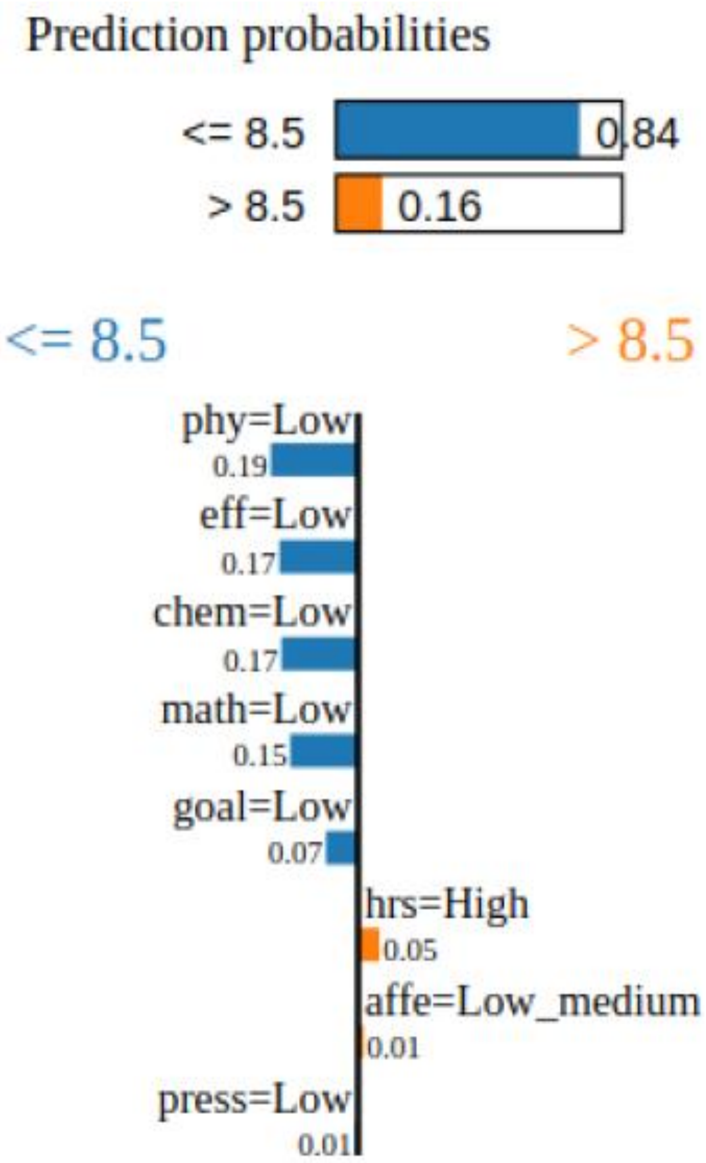
individual predictions

population-wide insights

Local Interpretable Model-agnostic Explanations (LIME)

EXPLANATORY MODELLING WITH PREDICTIVE VALIDITY → BOOSTED TREES + LIME

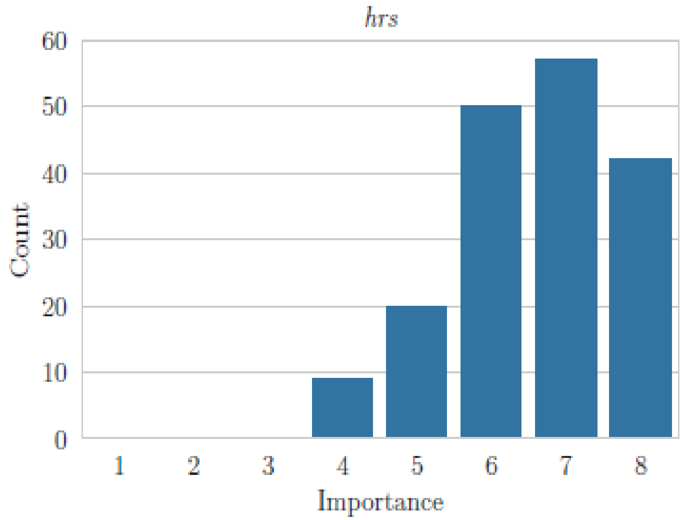
individual predictions

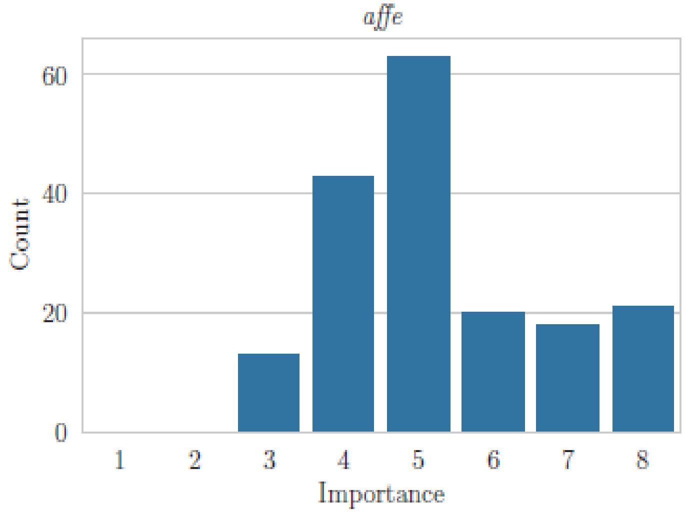


EXPLANATORY MODELLING WITH PREDICTIVE VALIDITY → BOOSTED TREES + LIME

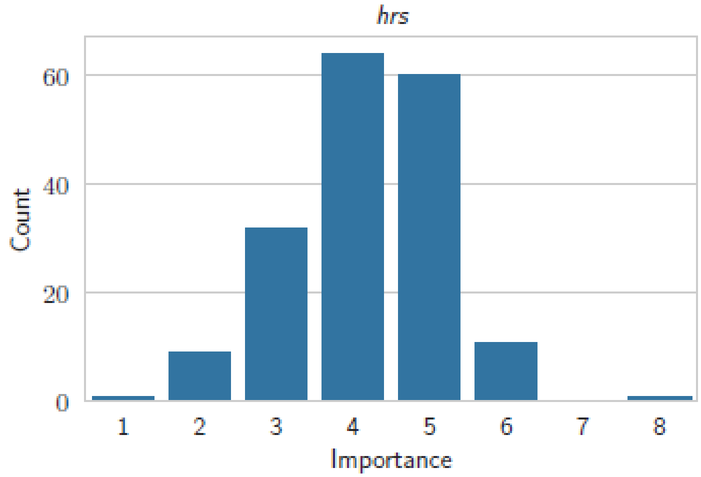
population-wide insights

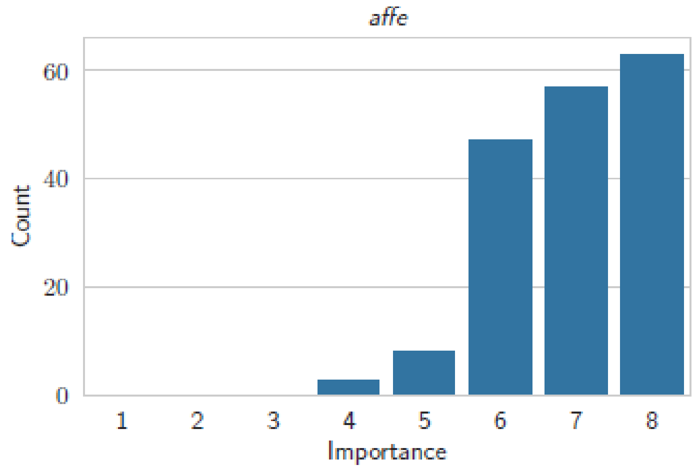
no-risk (wavg > 11.5)





at risk (wavg ≤ 8.5)





Conclusion

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precision & recall ↗ 20%

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Questions for discussion during the conference

How would your university profit from research on first-year student success?

What is still required to transfer the research to practice?

Successful Transition from secondary to higher Education using Learning Analytics

enhance a **successful transition from secondary to higher education** by means of **learning analytics**

- ✓ design and build **analytics dashboards,**
- ✓ dashboards that go beyond identifying at-risk students, allowing **actionable feedback** for all students on a **large scale.**

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