Noncognitive Skills & Traits Data in Student-level Predictive Analytics

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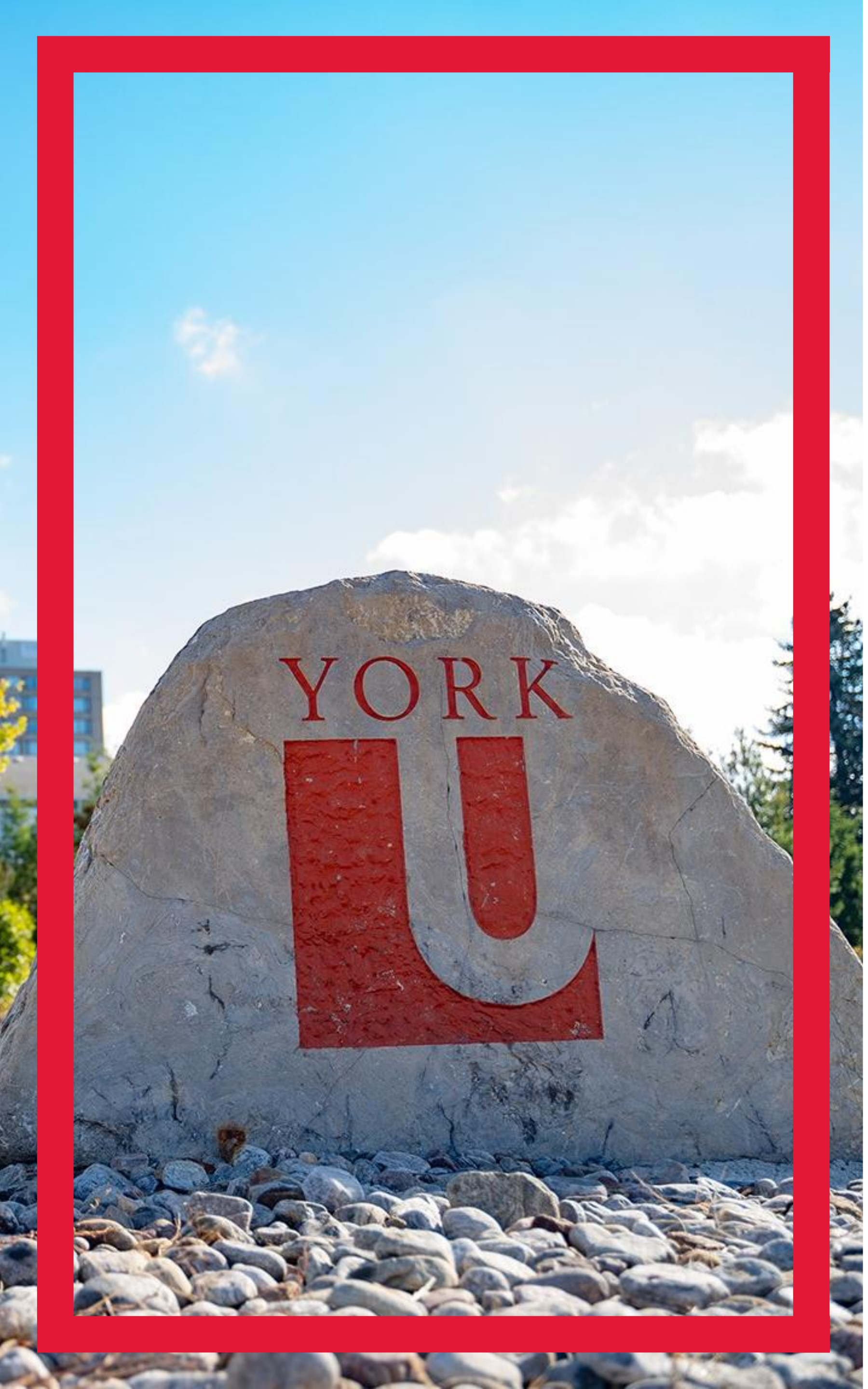

Outline

- What are noncognitive skills/traits/behaviors and why do they matter?
- Data about noncognitive skills/traits/behaviors
  - Student Self-Assessment
  - SAVY (York's Virtual Assistant)
- What changes when we leverage noncognitive datasets in predictive modelling?
  - Accuracy
  - Robustness to changing external factors
  - Interpretability

What Do We Mean by Noncognitive Skills & Traits and Why Do They Matter?

What do we mean by noncognitive skills and traits?

- Patterns of thought, feelings and behaviours
- Behaviors, attitudes, beliefs, and social & emotional skills

- Many noncognitive skills and traits associated with academic performance…
  - Mindsets: sense of belonging, belief in one's abilities, belief in the value of academic work
  - Perseverance and Coping: grit, self-discipline, self-help, help-seeking
  - Social Skills: empathy, cooperation
  - Learning Strategies: study skills, self-regulated learning
  - Academic Behaviors: going to class, participating in class, doing homework, organizing materials and time

(not even close to an exhaustive list)

- Noncognitive skills and traits develop over time
- Like habits, they are learned and can change

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Why do noncognitive skills and traits matter?

- As already mentioned, noncognitive skills and traits impact academic performance

- Paying attention to these skills and traits lets us...
  - Better understand individual students and the ways they approach and position themselves in relation to the academic experiences, how they make sense of and co-create those experiences
  - Notice behaviours that individual students are exhibiting and that typically lead to particular academic outcomes
  - Better understand exactly how to support an individual student
  - Help individual students understand their own academic experience and performance

- Paying attention to noncognitive skills and traits reinforces the idea that student-level analysis and outreach is a valuable approach
  - Net-new information
  - Weakly associated with cohort-based variables

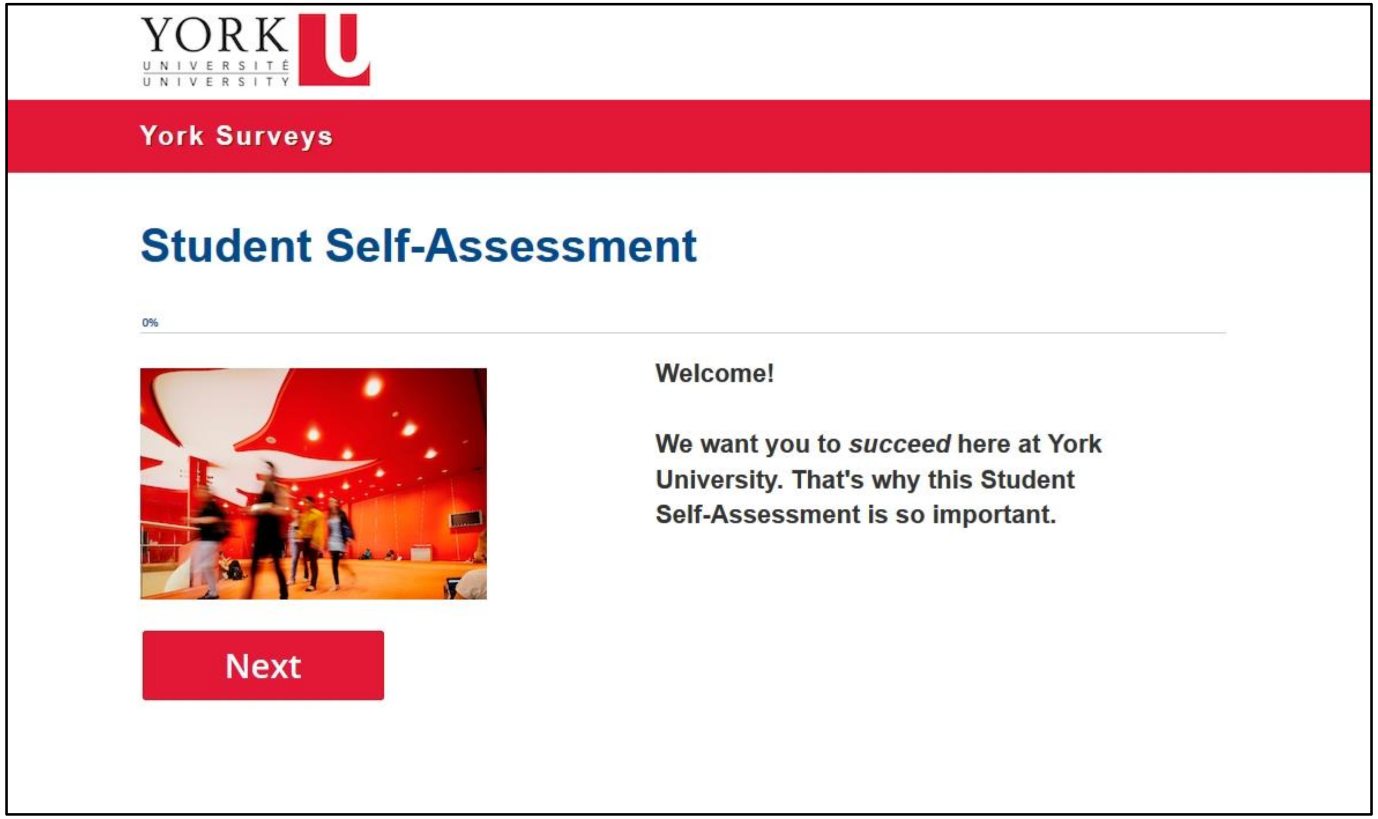
- The idea is to augment the 'cohort-level' data (e.g. domestic/international; gender; 101s/105s) and get down to the level of individual students: their aspirations, goals, skills, behaviors.

Data
About Noncognitive Skills and Traits

Self-Report: Student Self-Assessment

An online survey instrument ‘sent out’ to all new, first-year undergraduate students.

We use it to gather insights about our students’ non-cognitive skills and traits.



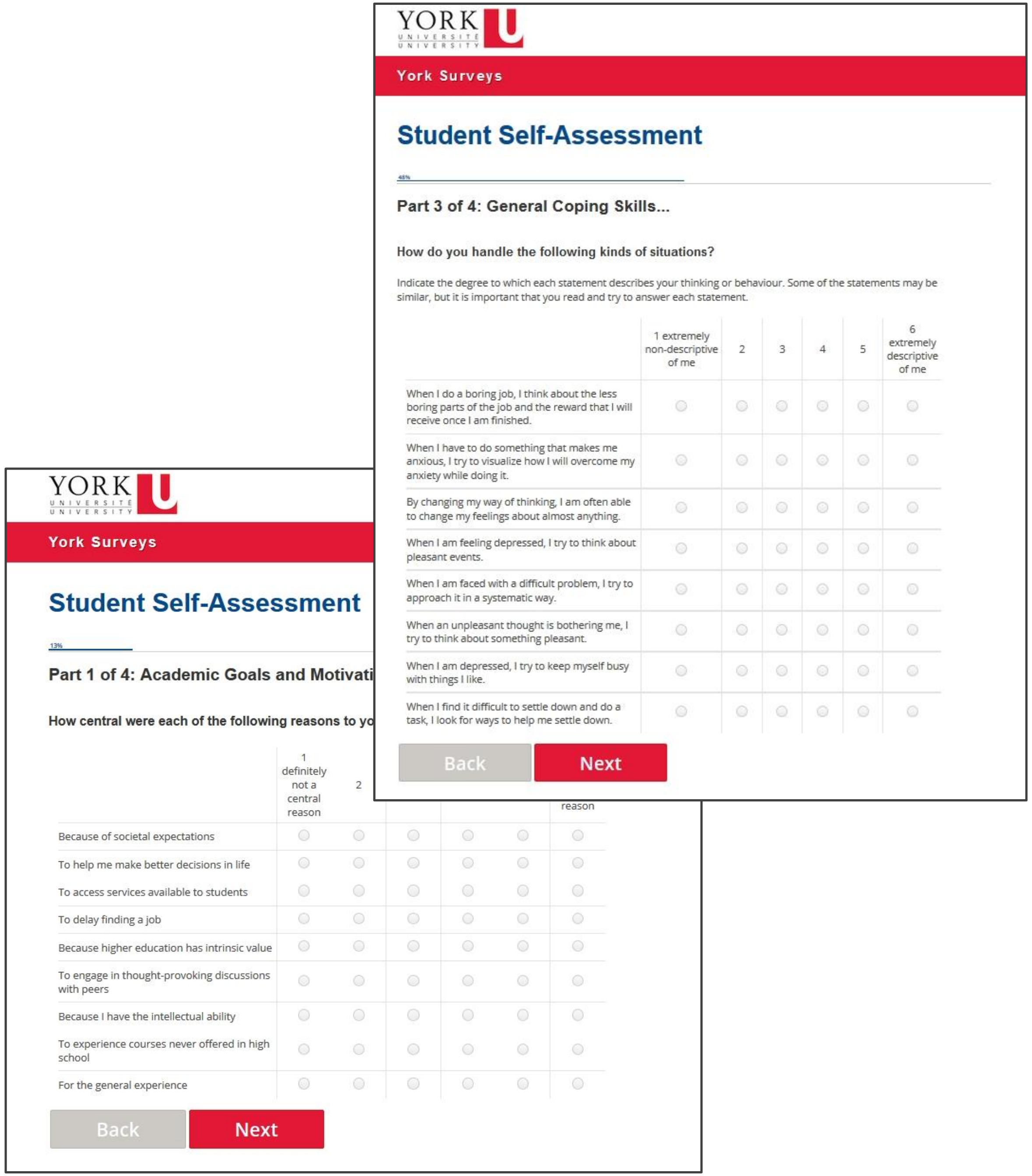
Self-Report: Student Self-Assessment

Insight is gained about our students'…

- internal & external motivations for attending university
- academic & career goal clarity
- academic self-efficacy
- coping skills
  - Personal resourcefulness (self-help)
  - Social resourcefulness (help-seeking)
  - Grit (persistence & passion for long-term goals)

- Uses existing measurement scales
- validated (except for the goal clarity scales)

- Also asks a small number of socio-demographic questions



Actual Behaviours: Using SAVY

SAVY

Hi, how can I help you?

About SAVY

Who is SAVY?

- An AI virtual student assistant built using IBM Watson's Natural Language Processing.

- Trained with content to help students perform tasks related to their academic journey at York.

Vast Knowledge Base

- SAVY covers over 500+ topics
- 1500+ conversational dialog flows
- Serves international and domestic undergraduate students across 10 schools at York, in both English and French

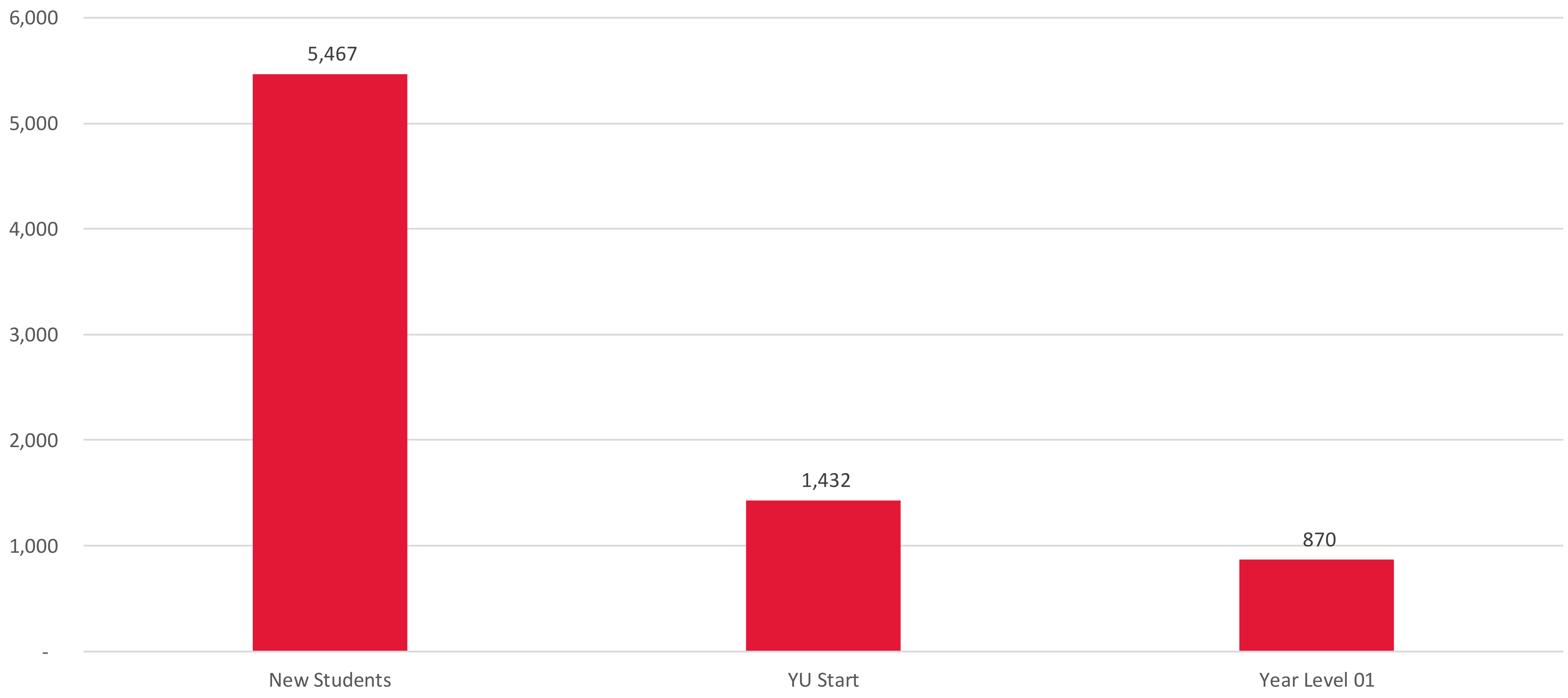
What makes SAVY different?

- SAVY knows enough about individual students to provide them with more personalized content including reminders about upcoming deadlines and tasks relating specifically to them.

SAVY

Hi, how can I help you?

SAVY Numbers – Incoming + Year Level 1



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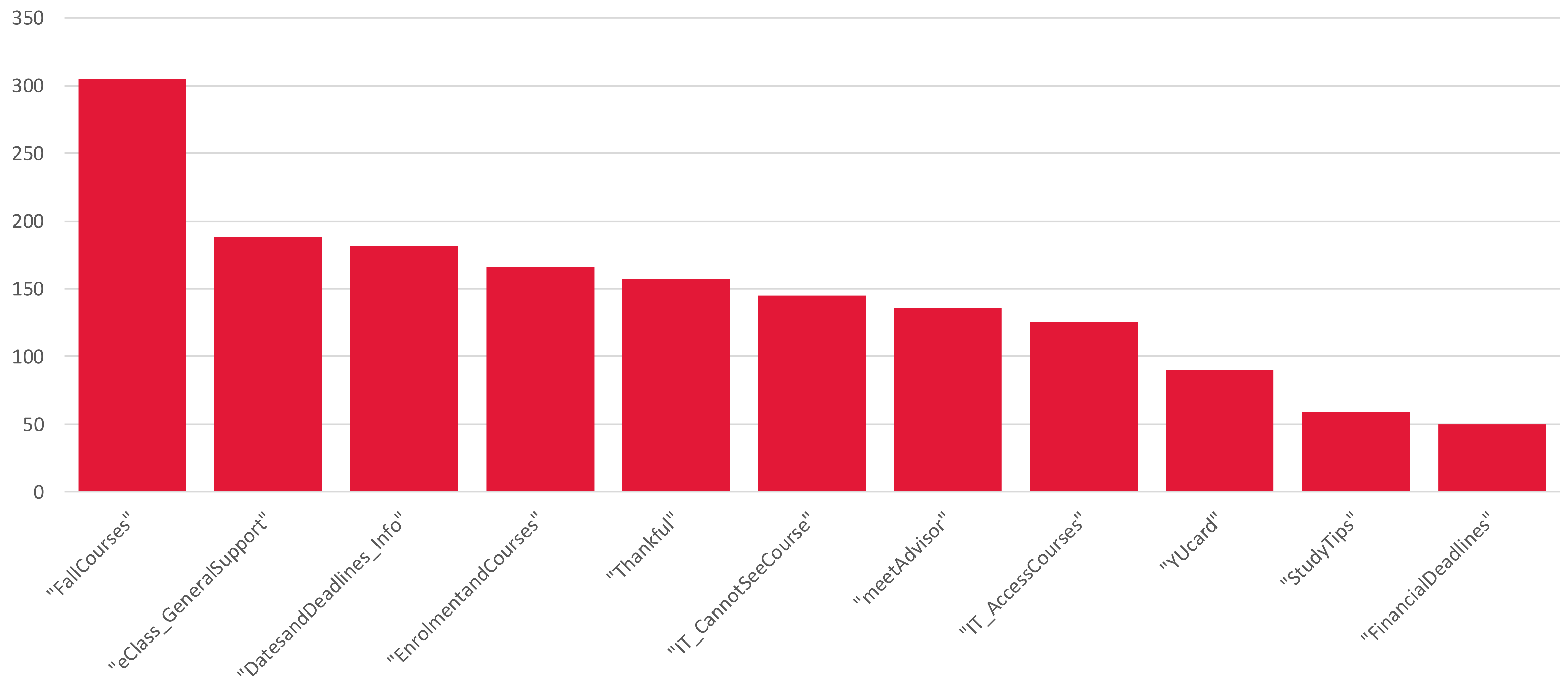
SAVY Top Answers – Incoming (YU Start)



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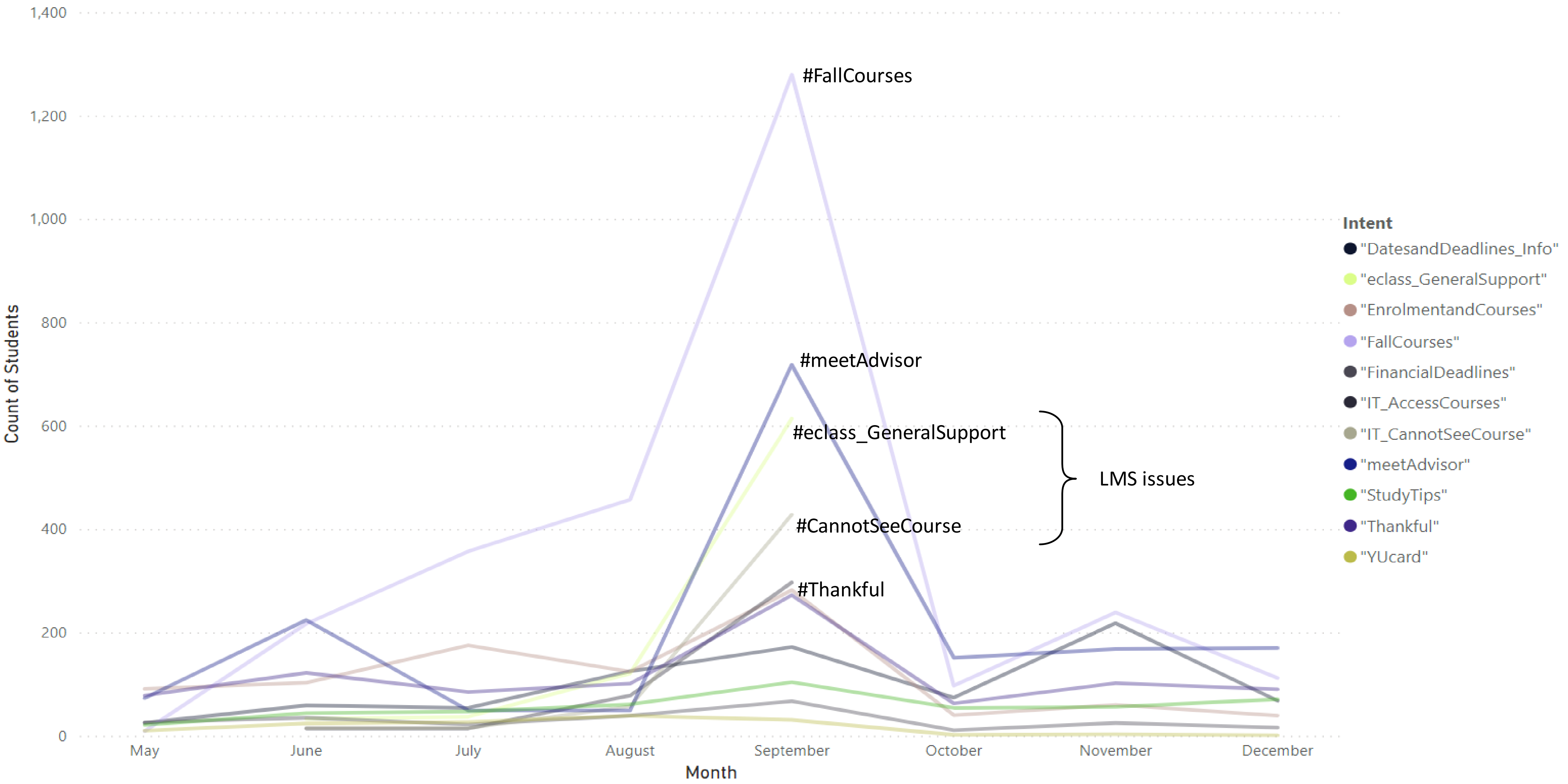
SAVY – Temporal Dynamics



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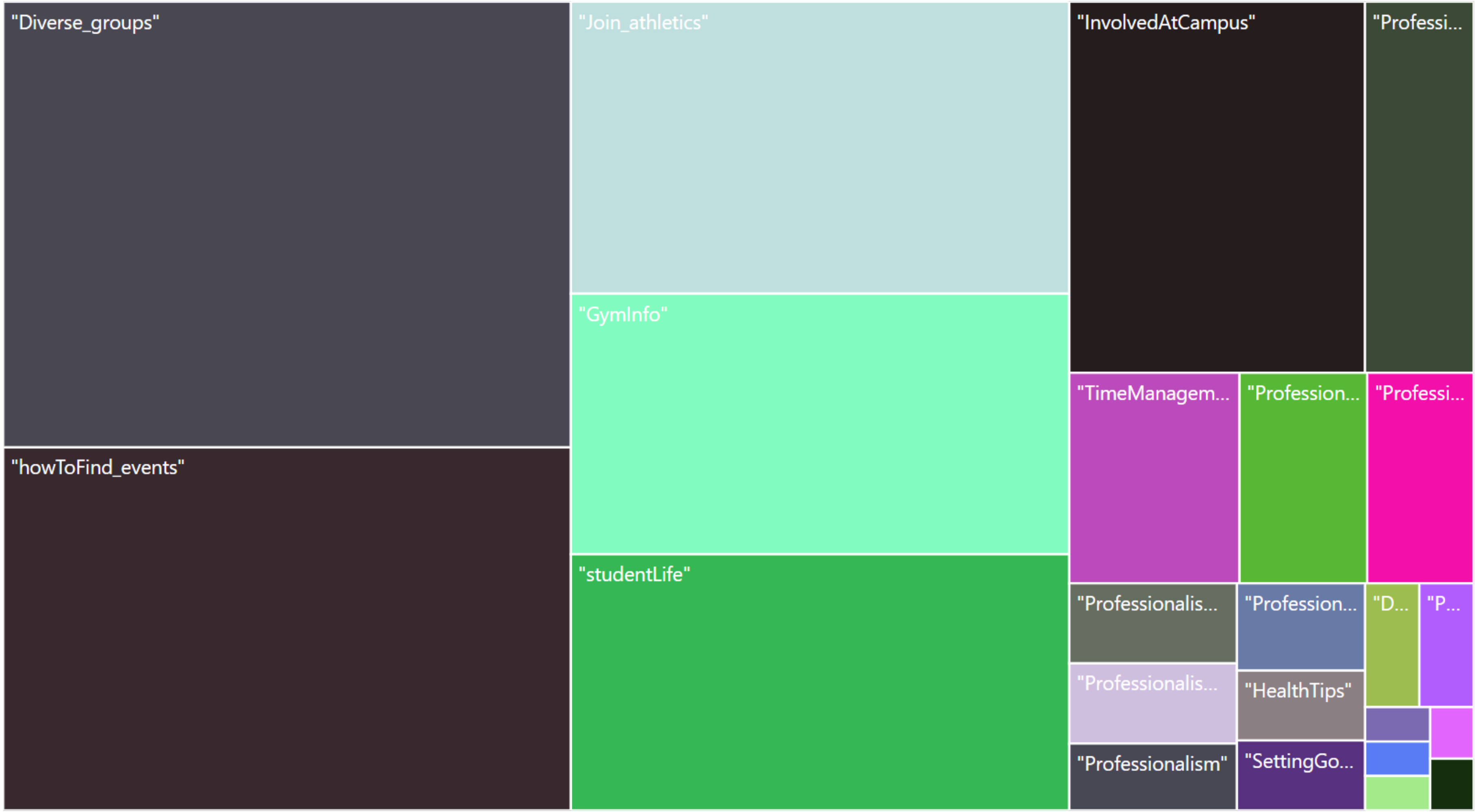
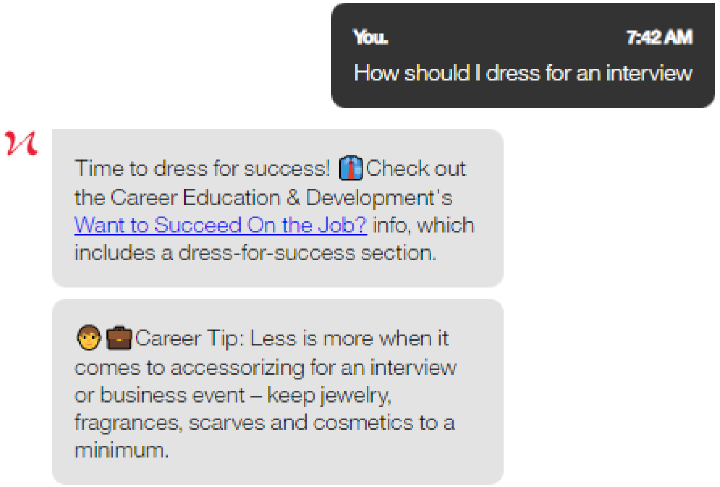
Other Noncognitive data captured in SAVY





Leveraging Noncognitive Data to Increase Predictive Accuracy at the Student Level

Making Predictions That Are Actionable

- Timeline must be ‘actionable’:
  - A given outcome has to be predicted with enough foresight that an intervention could be staged and has enough time to be successful.
- Model must be:
  - Accurate
  - Robust
  - Interpretable (for downstream decisions and accountability)

How can we support students on their academic journey?

We want to be able to provide relevant supports as early as possible in a student's unique academic journey.

Example Analysis: Identify Students At-Risk of Not Completing a Course

TASK

- Build a model:
  - Cohort: all incoming students to York
- Actionability:
  - Use early arriving data [prior to Oct 1st]
  - Predicts course drops at a student level [occurring after Oct 1st]
- Accuracy and robustness:
  - Train on one year and predict the next.
- Use a technique suitable for the data:
  - Handles missing and incomplete data
  - Good predictive power
  - In this case a boosted tree ensemble model (XGBoost)

DATA AVAILABLE

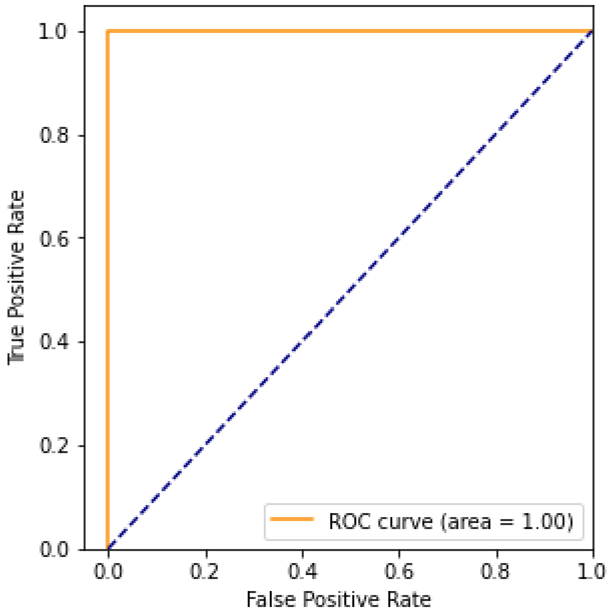
- Registrarial:
  - Admission grades (High School) when available
  - Demographic information (age, gender, citizenship)
  - Enrolment transactions (enrolment date, course switches/drops)
- Noncognitive skills, traits, behaviours:
  - Moodle: Student activity in LMS logs
  - Inspire: Student-Advisor interactions
  - ***Self-Assessment***: Scores on grit, goal clarity, motivation, and resourcefulness measurement scales
  - ***SAVY***: Student-SAVY conversations

Sidebar: Evaluating a Model with Unbalanced Data

UNBALANCED DROP RATES

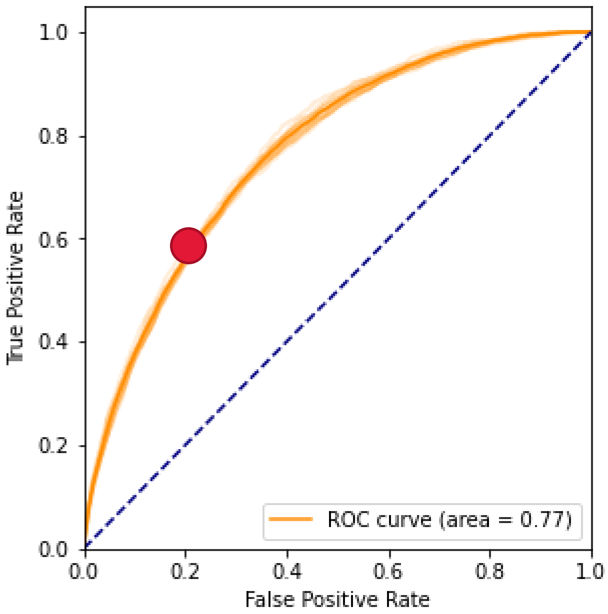
- Students are completing courses at a *much* higher rate than dropping them.
- A model that predicts no drops will do well (in terms of accuracy) on average.
- Receiver Operator Characteristic Curves shows the balance between the True Positive (TP) and False Positive (FP) rates.

PERFECT PREDICTOR



- At any threshold, the TP rate is 100%, and the FP is 0%
- Blue dash indicates random predictions

"GOOD" PREDICTOR

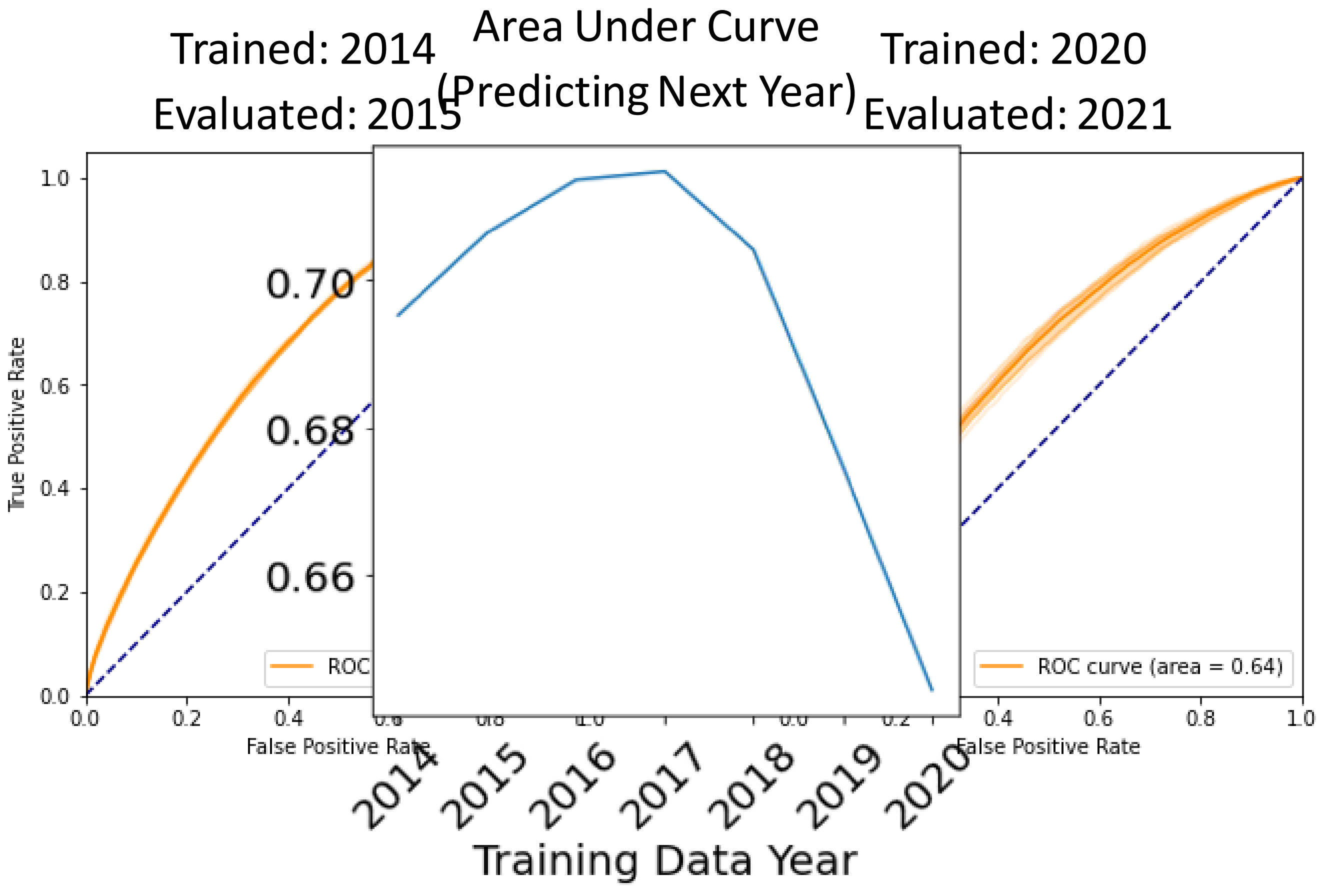


- By altering the threshold, one can change the TP and FP trade-off
- At the indicated point:
  - TP ≈ 60%
  - FP ≈ 20%

Using Only Registrarial Data (no Noncognitive Data)

- Given the highly unbalanced dataset, we used an under-sampling approach (for the training data).
  - Under-sampling discards data and therefore all results presented are the average of 10 runs.

- Initially promising power, but inconsistent across years

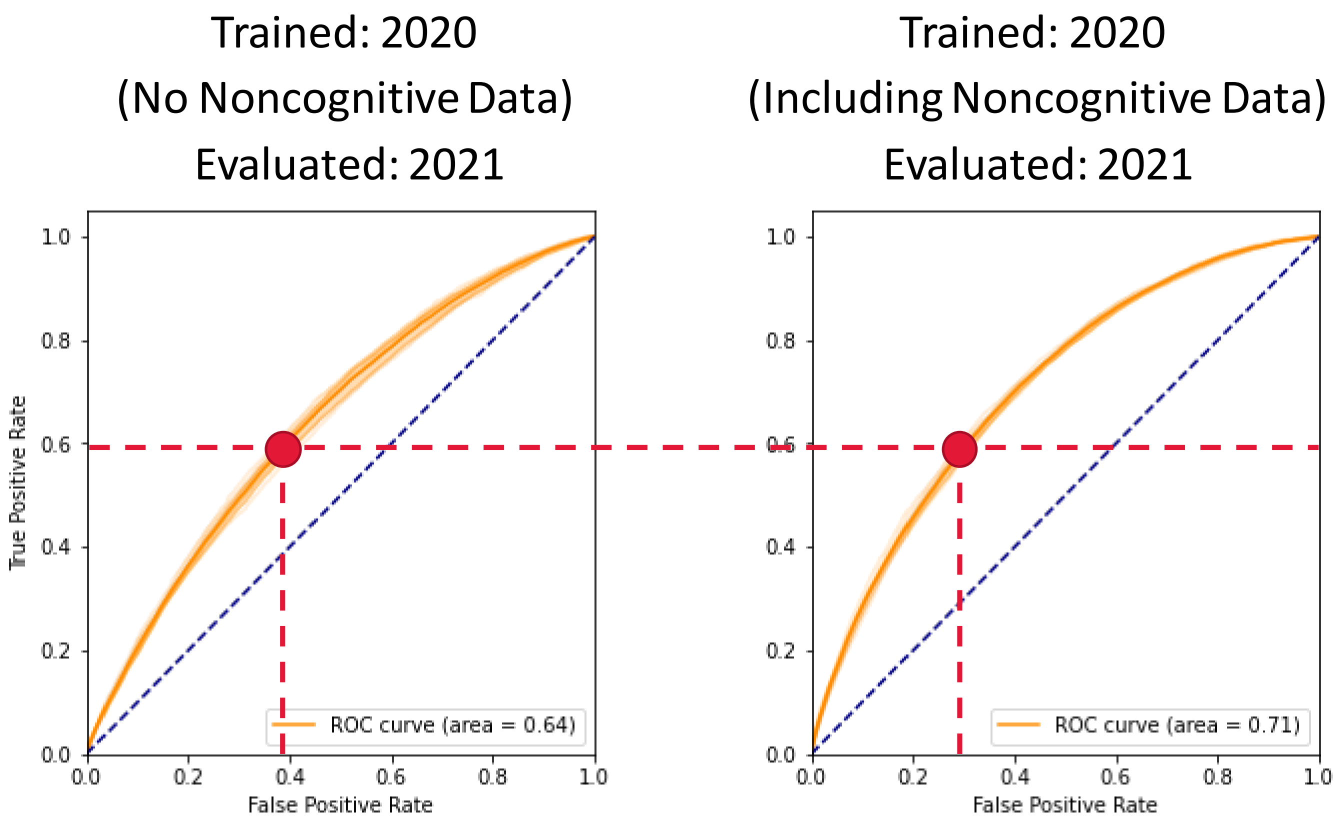


… We need a way to increase year over year robustness

Improving Predictive Performance with Noncognitive Data

- Goal is to increase overall accuracy and create a more robust model by adding other sources of data:
  - Non cognitive / Behavioral:
    - ***Self assessment***
    - ***SAVY interactions***
    - Advisor access
    - Moodle activity

- Also tested:
  - Training on previous years (with diminishing weights on previous years) – overall improvement
  - Normalizing by year – no consistent improvement



Adjusting the threshold for TP to 60%, FP decreases ≈ 10%

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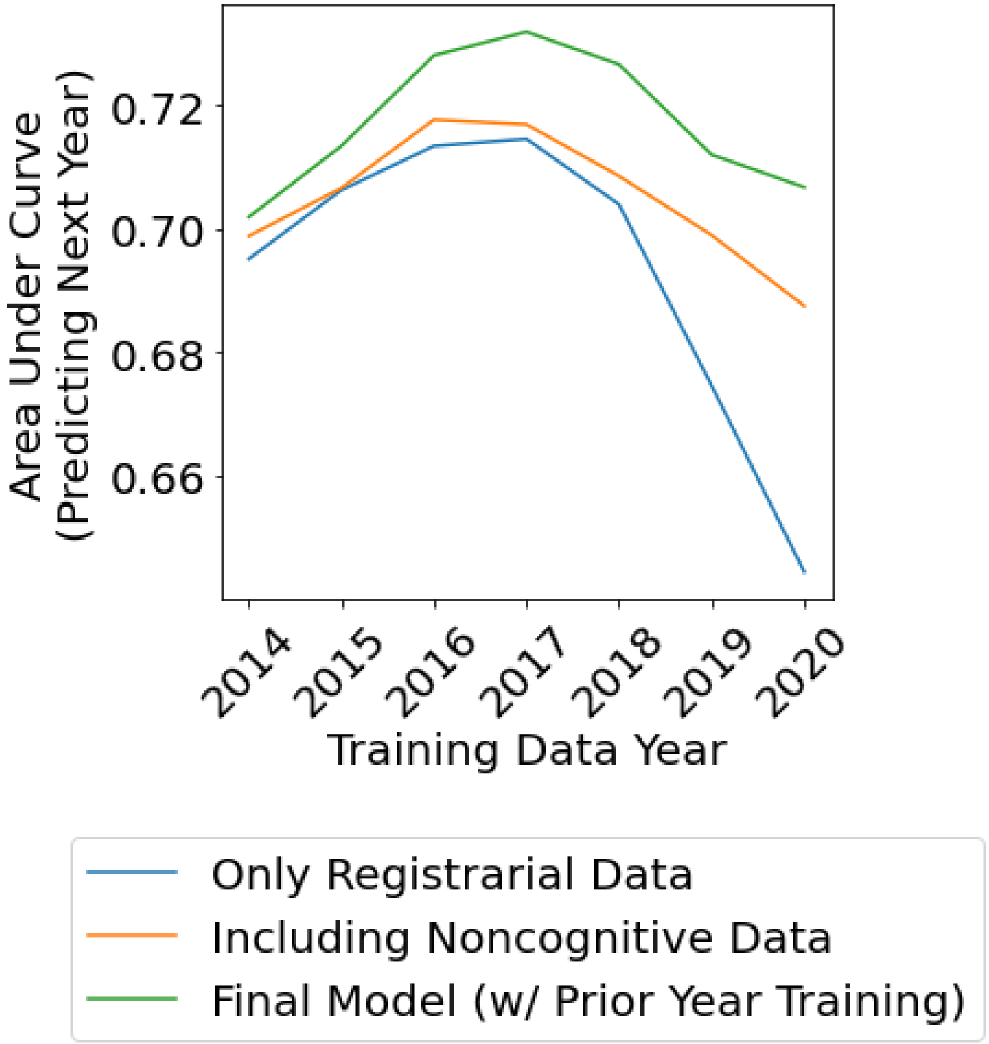
Improving Predictive Performance with Noncognitive Data

Increased predictive accuracy
and robustness to external variables

Model Benefits from multiple sources of data:

- Behavioral
- Noncognitive

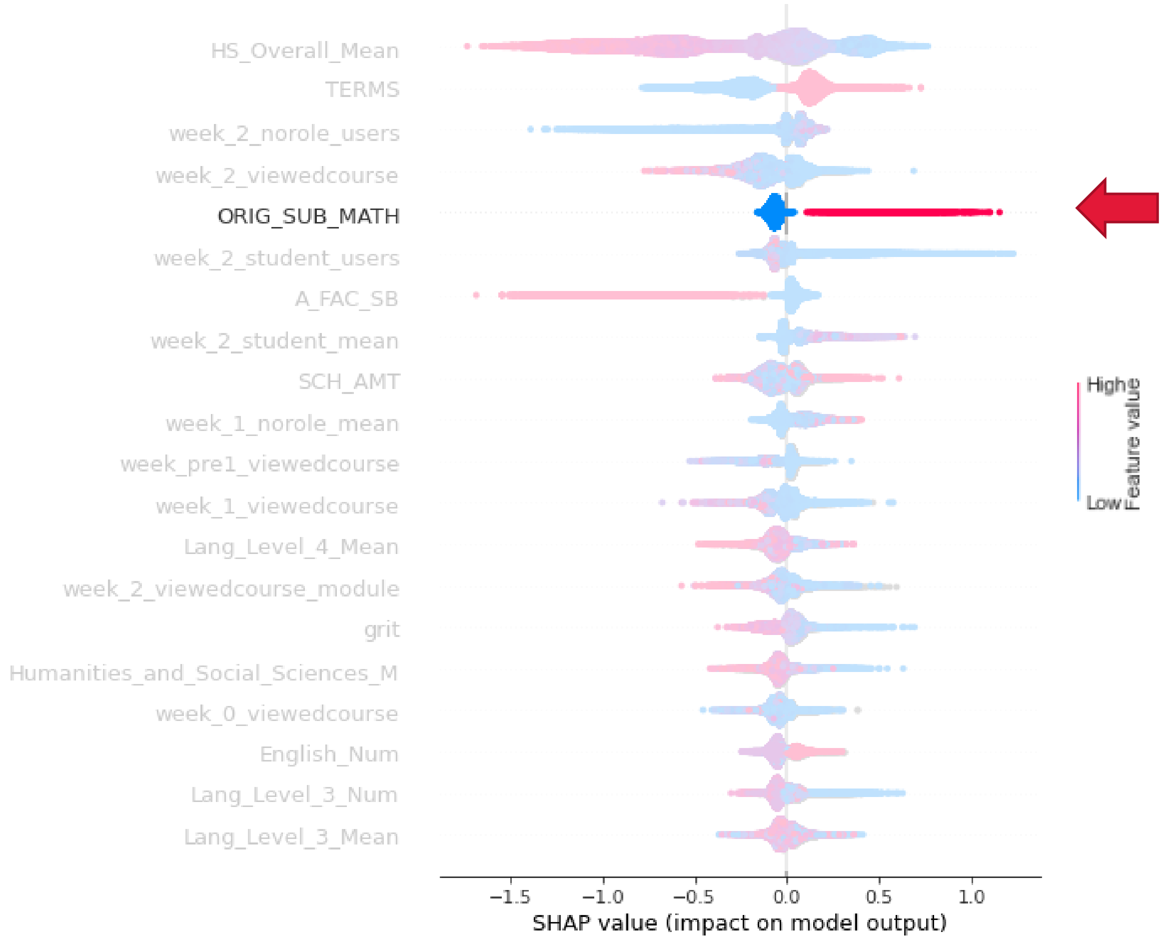


Sidebar: Interpretability

- There are ethical considerations when any model is 'deployed'
  - Ideally, we could understand the *exact* rules used (such as with Logistic Regression)
    - But… as the models get more complex, it becomes more and more difficult to parse (so called 'black boxes')

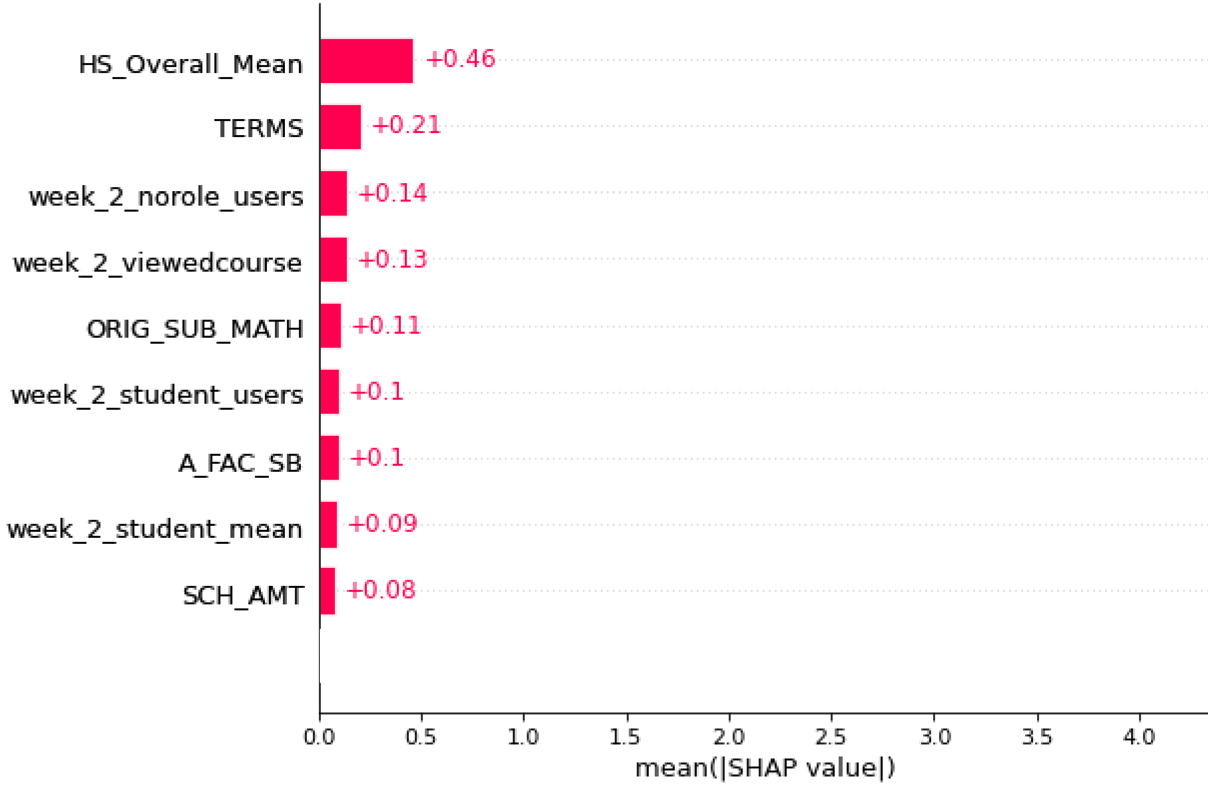
- Many advancements have been made, including:
  - **SHAP** (SHapley Additive exPlanations)

- While not perfect, they attempt to explain the model (not the data).



Making Inferences at the Cohort Level

- How important, *on average*, a feature is for predicting
- Is the model *fair*?
- Usually concerned with the 'Top-N' features…
  - But that misses a lot of importance when predicting at the student-level

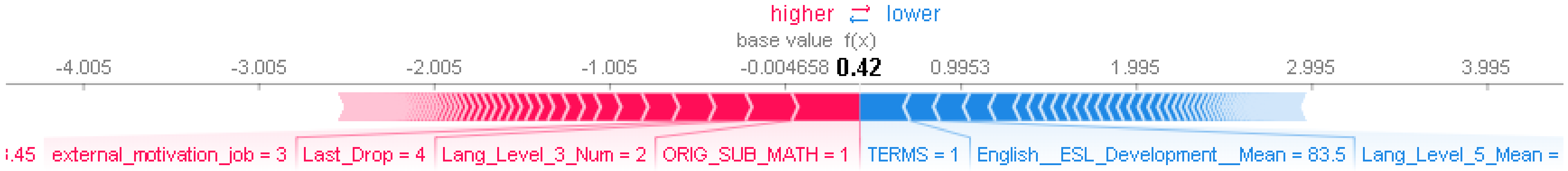


Making Inferences at the Student Level

Can lead to different inferences about what's important

Can we "trust" a student-level model?

- *Why* is the model predicting what it is?
- *Should* it be acted on?



Final Thoughts and Observations

- SAVY – Promising new data source
  - 2020 was the first year data are available
  - SAVY was still 'learning' at that point
- Increased predictive ability by incorporating noncognitive skills and traits
  - Increases accuracy
  - Increases robustness
- Cohort-level vs student-level predictions
  - Tools available to interpret models at both levels
  - Downstream intervention approaches can be based on either cohort-level or student-level inferences
  - Inferences, and thus interventions, can differ depending on level of analysis


Questions?