

# Infinite Campus Early Warning

Understanding the GRAD Score

# Presenter Bio

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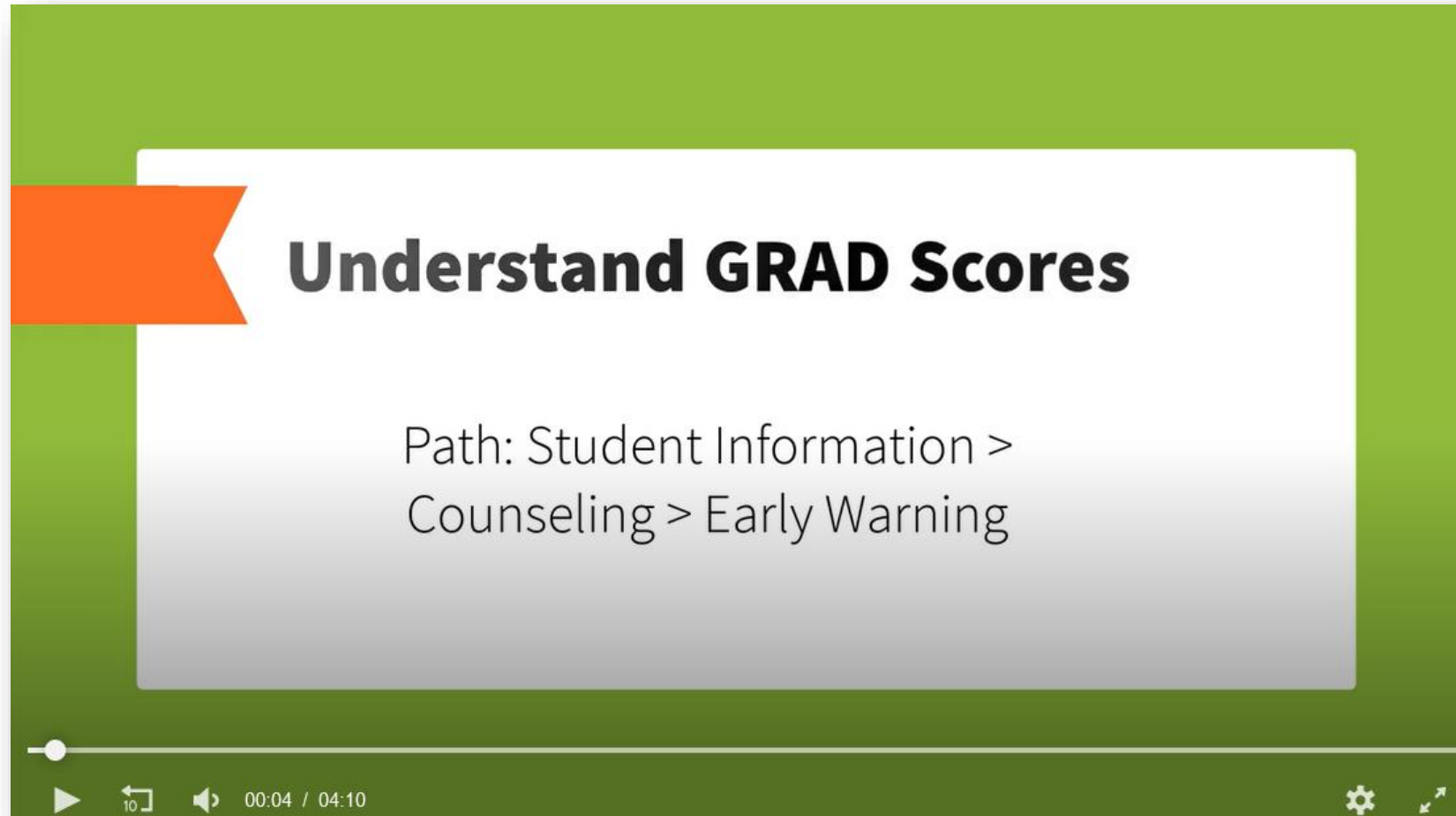
Product Owner | Data Science Team



# Agenda

- ▶ What is (and isn't) a GRAD Score
  - ▶ Overview Video (4:00)
  - ▶ Common Myths and Misconceptions
  - ▶ How the Model Works
  - ▶ What can Districts see
  - ▶ How is the Model Validated
  - ▶ Specific Factors affecting the Model
- ▶ Questions and Answers

# Understanding the GRAD Score Video



Attribute	Score	Weight	Adjusted Value
Days Absent	3	1	3
Assignments	95	0.8	76
GPA Score	2.4	1	2.4
Race/Ethnicity	6	0.7	4.2
Gender	2	0.5	1
Transcript	30	1	30
Grade Level	8	0.8	6.4
<b>GRAD Score</b>			<b>123</b>

## Myth #1

An Early Warning GRAD Score is a cumulative sum of weighted inputs

# Reality

- ▶ Algorithm that utilizes machine learning to measure and estimate students' "persistence towards graduation"
- ▶ Evaluates the student based on patterns that have shown to be predictive to develop a risk score

Attribute	Score	Weight	Adjusted Value
Days Absent		1	3
Assignments	95	0.8	76
GPA Score	2.4		2.4
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Transcript		1	30
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GRAD Score			123





## Why did we build it?

- ▶ Early Warning from Infinite Campus was built to address a problem with conventional Graduation Monitoring systems

# Conventional Systems

- ▶ Conventional systems utilize a “cut score” to identify at risk students
  - ▶ Typical examples of this would be:
    - ▶ Students with more than 6 absences
    - ▶ Students with a GPA below 2.0
    - ▶ Students with a specific FRL Status



# Conventional Systems

- ▶ While this can be effective - it ignores the context of each variable and can over-identify students leading to a waste of District resources

“It is true that many students who qualify for FRL face additional challenges that may impact their ability to graduate, it is NOT true that ALL students who qualify for FRL will struggle to graduate”



# Early Warning

- ▶ Uses Machine Learning and decades of student data to identify patterns of predictability around dozens of different factors
- ▶ This enables the Early Warning system to view the factors for a student in context within the full picture of the student's data

## Early Warning

Missing 5 days of school in a row may be identified as an attendance risk factor for a student who also has a low GPA and a pattern of certain behaviors, but NOT a risk factor for a student with a High GPA and a different pattern of behavior








# Early Warning

Produces a numeric value from 50-150 defined as the student's **GRAD Score**

the **lower** the score, the **greater** the risk to graduation





A+

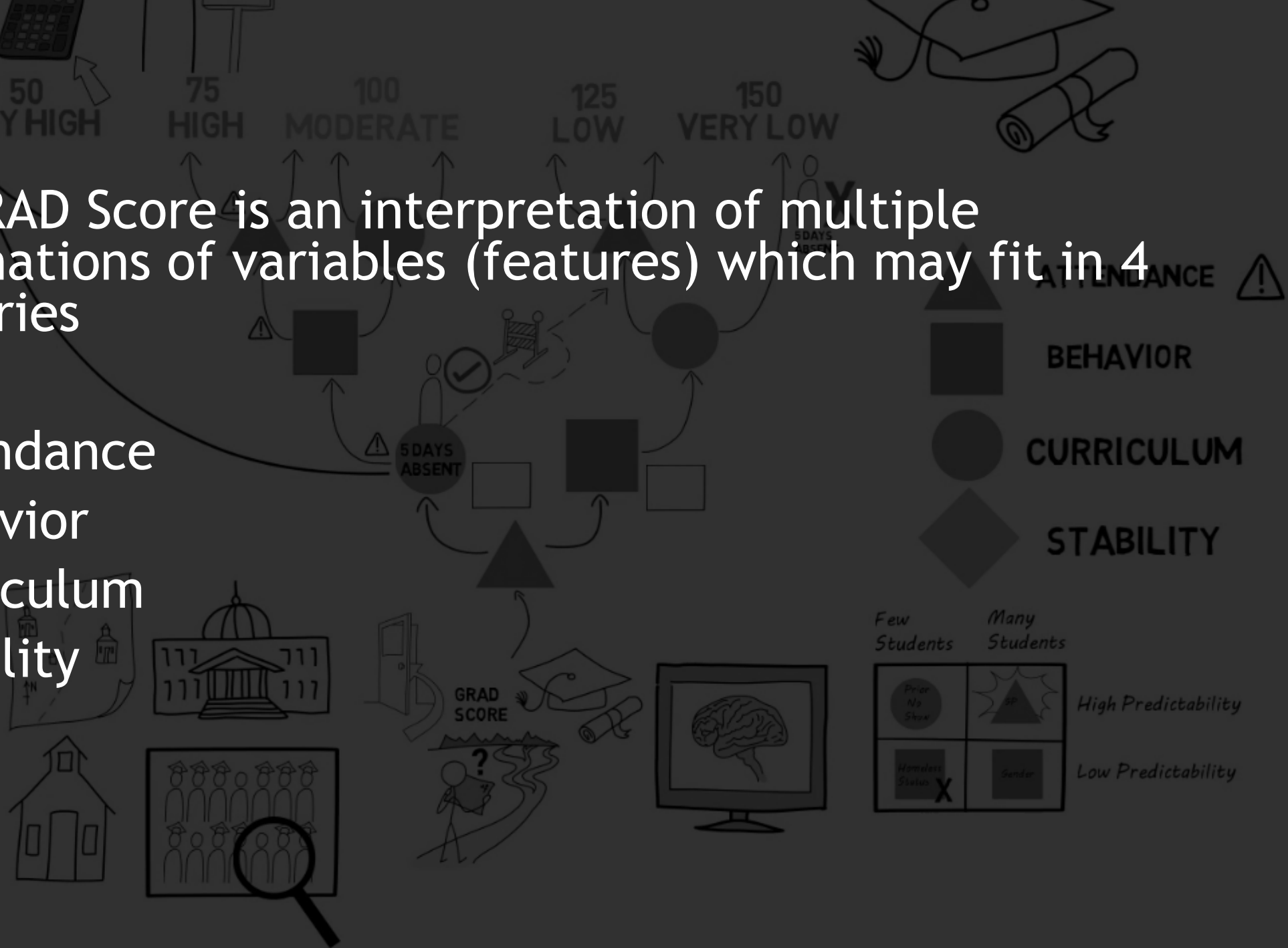
## Myth #2

A GRAD Score only  
considers Academic  
Factors

# Reality

The GRAD Score is an interpretation of multiple combinations of variables (features) which may fit in 4 categories

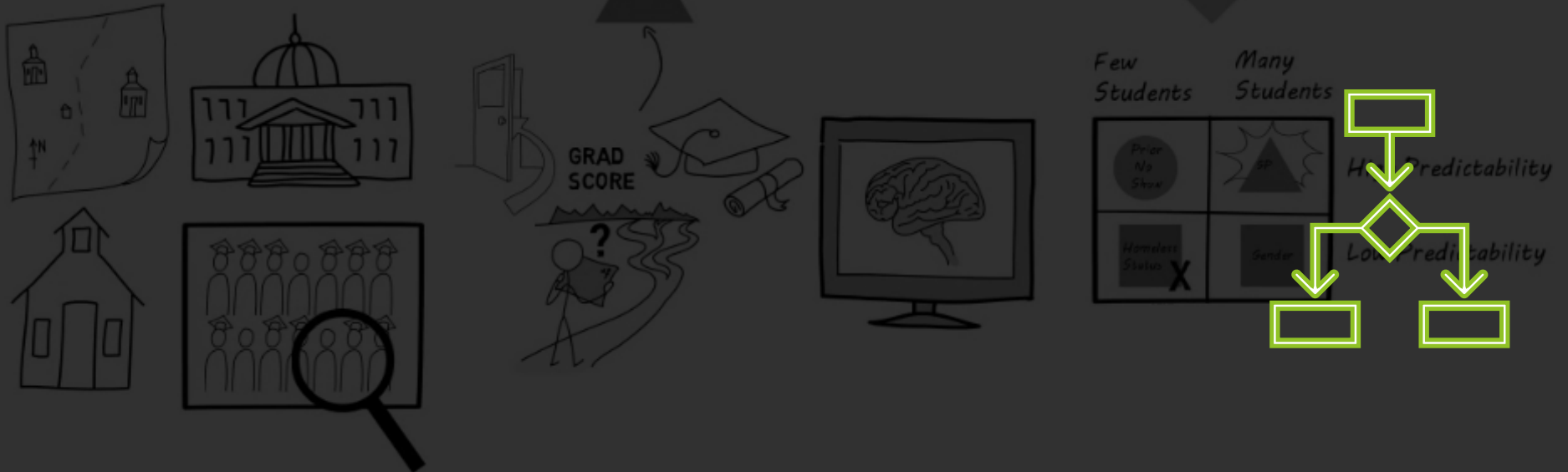
- ▶ Attendance
- ▶ Behavior
- ▶ Curriculum
- ▶ Stability





# GRAD Score

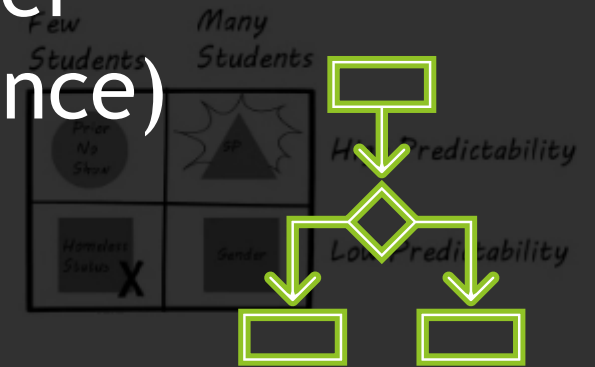
These features are viewed independently and in context to one another to identify whether the student follows any known patterns



# GRAD Score

Features may contain variables from multiple categories

- ▶ Ex. The number of times a student's guardian logged into Portal (stability) minus the number of unexcused periods absent (attendance)



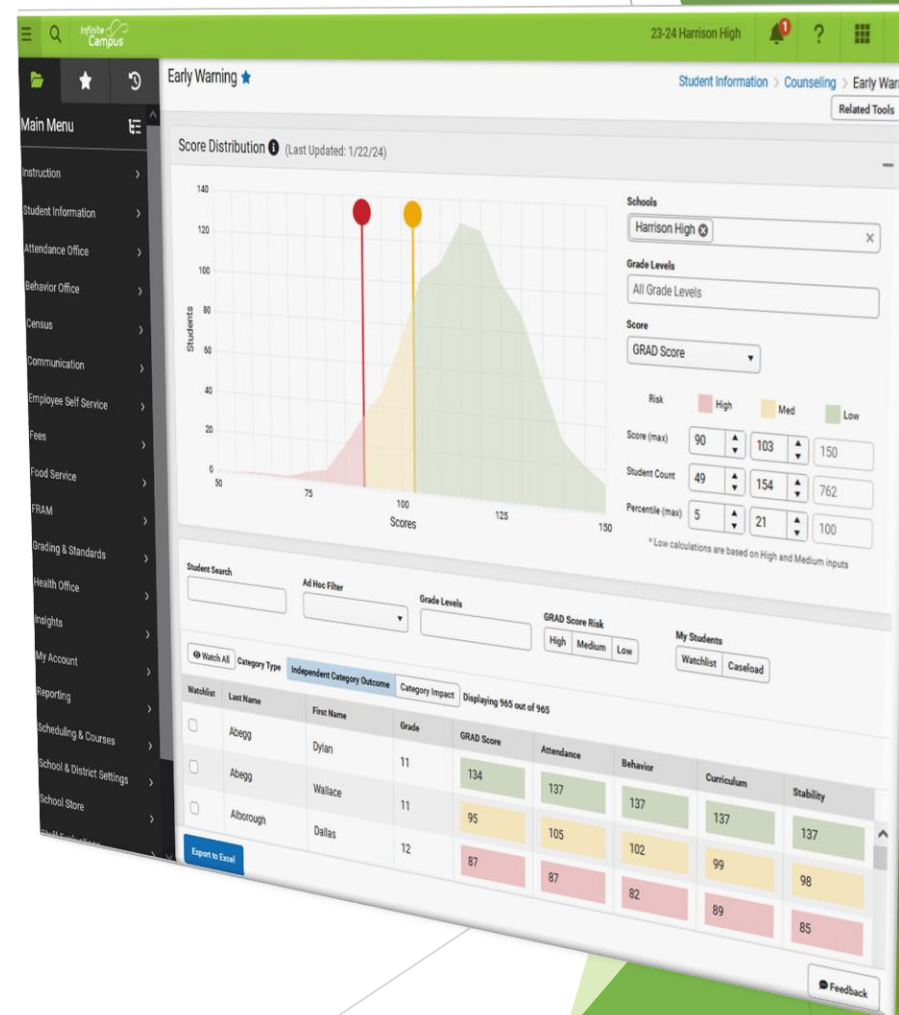


## Myth #3

District Staff has no visibility into the GRAD Score

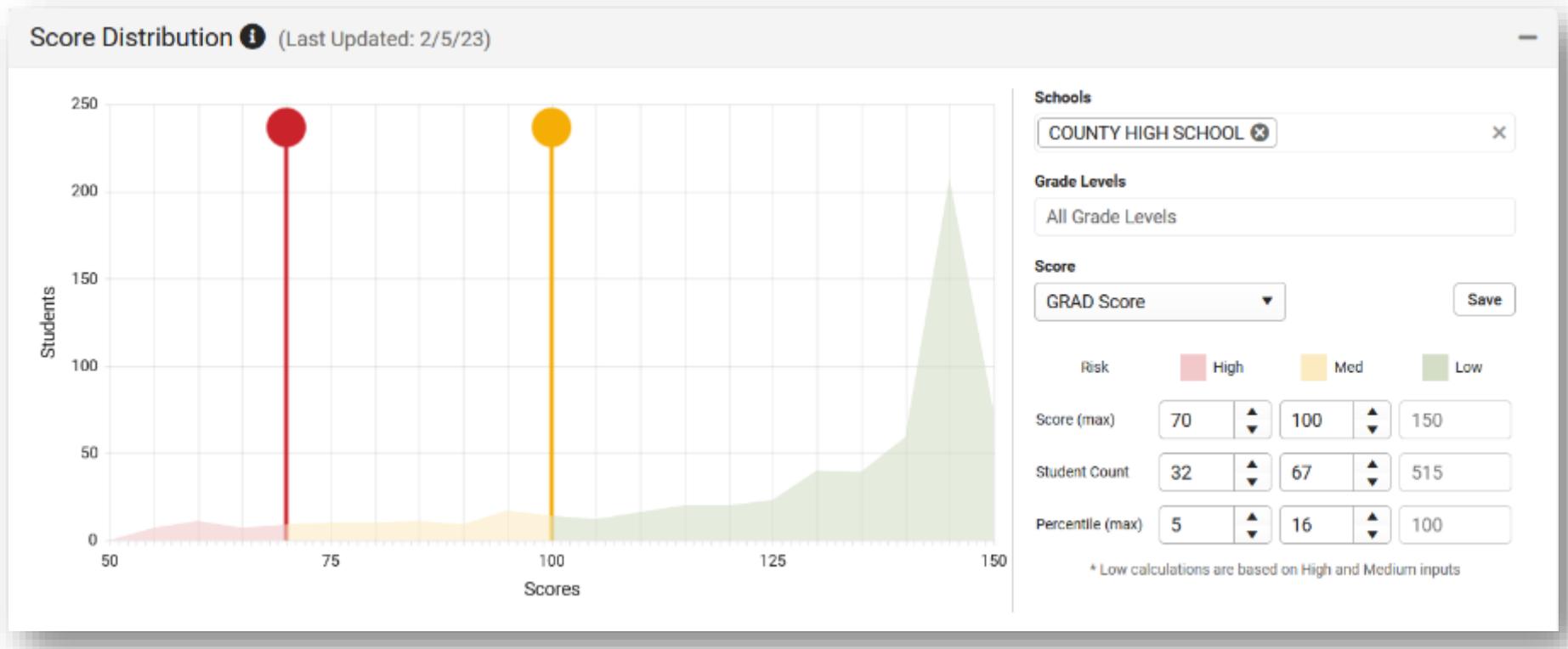
# Reality

- ▶ District Staff has real-time access to a student's GRAD Score, both current and historical, through various tools and Dashboards in Infinite Campus



# GRAD Score

## School/District Level



# GRAD Score

## Cohort/Watchlist Level

Student Search  Ad Hoc Filter  Grade Levels  GRAD Score Risk    My Students

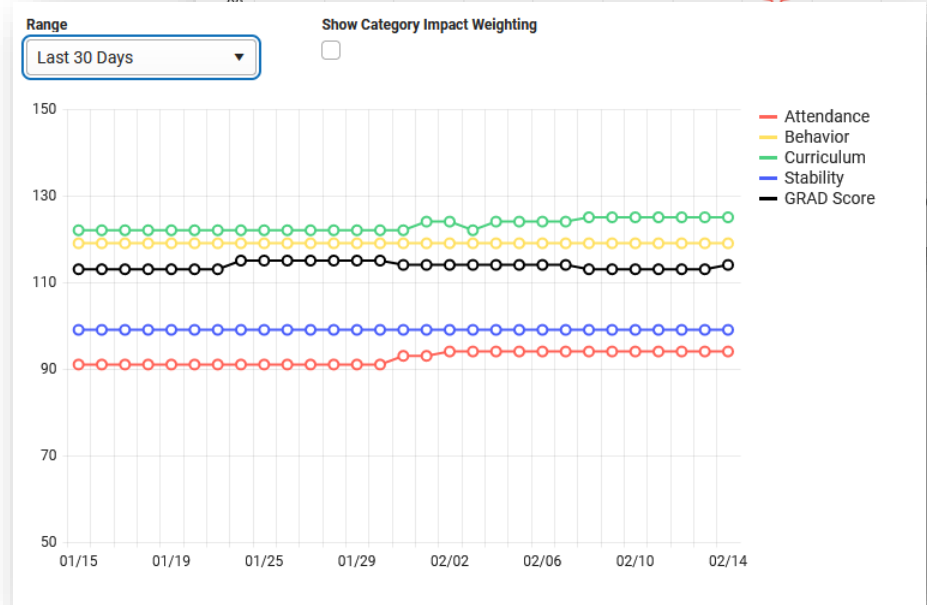
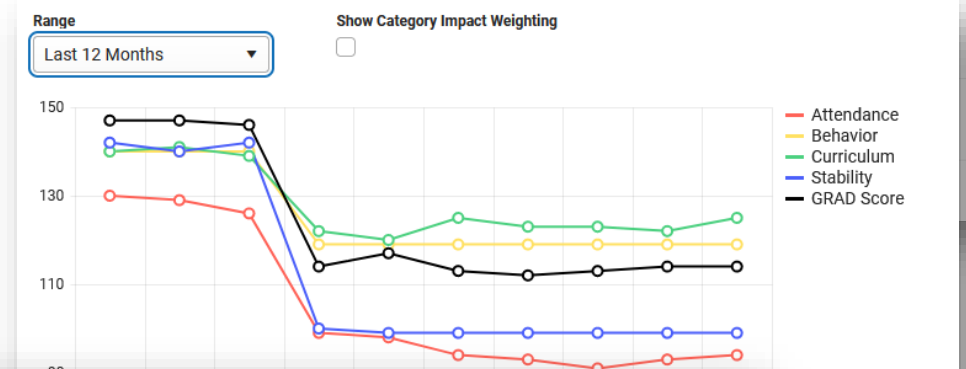
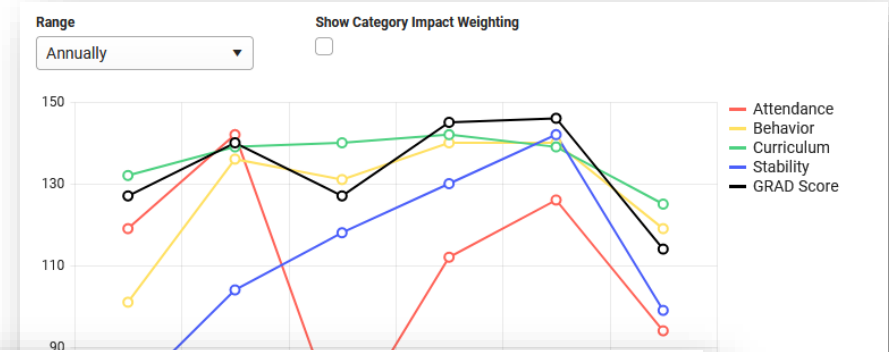
Category Type   Displaying 29 out of 408

Watchlist	Last Name	First Name	Grade	GRAD Score	Attendance	Behavior	Curriculum	Stability
<input type="checkbox"/>	STUDENT	SAVANNAH	11	56	Low (-1)	Low (-0)	Low (-2)	Low (-3)
<input type="checkbox"/>	STUDENT	JACOB	11	56	Low (-0)	Low (-0)	Low (-0)	Med (-13)
<input type="checkbox"/>	STUDENT	CHARLES	11	58	Low (-0)	Low (-0)	Low (-2)	Low (-9)
<input type="checkbox"/>	STUDENT	KAITLYN	11	58	Low (-1)	Low (-0)	Low (-1)	Low (-7)
<input type="checkbox"/>	STUDENT	AUSTIN	11	56	Low (-0)	Low (-0)	Low (-0)	Low (-9)
<input type="checkbox"/>	STUDENT	SELINA	11	57	Med (-3)	Med (-1)	Low (-0)	Med (-12)



# GRAD Score

- ▶ Viewed per Student; Districts can look at how a score has changed by Year, Month or Day





# GRAD Score Update and Visibility

- ▶ The GRAD score is re-evaluated daily
- ▶ Scores are frozen monthly and yearly
- ▶ Historic Scores are available
  - ▶ 30 Daily Scores
  - ▶ 12 Monthly Scores
  - ▶ All Yearly Scores

# Category Impact (student level)

- ▶ In addition to the GRAD Score, the District User Interface identifies “Opportunities for Change” per student which define the categories of features that would have the greatest potential positive impact on the student’s overall score



# Campus Analytics

## Insights Dashboard





## Myth #4

The GRAD Score does not take into account my District/State's unique setup

# Reality

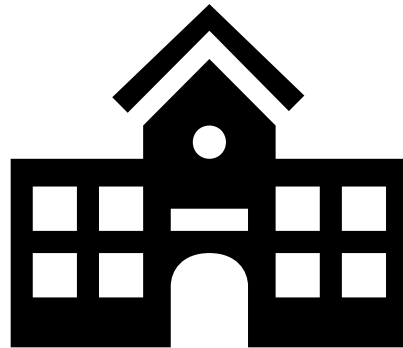
- ▶ The GRAD Score evaluates each Student as a member of multiple subpopulations to find patterns that apply to their context
- ▶ Subpopulation Aggregation Features
  - ▶ School
  - ▶ District
  - ▶ State
  - ▶ ZIP code





# Examples of Contextual Factors

- ▶ Difference between a student's Cumulative GPA and their State's Average
- ▶ Ratio of Behavior incidents resulting in a suspension for a student compared to the average number for students in that school



# Myth #5

The GRAD Score calculation only works for Secondary students, not Elementary students



# Reality

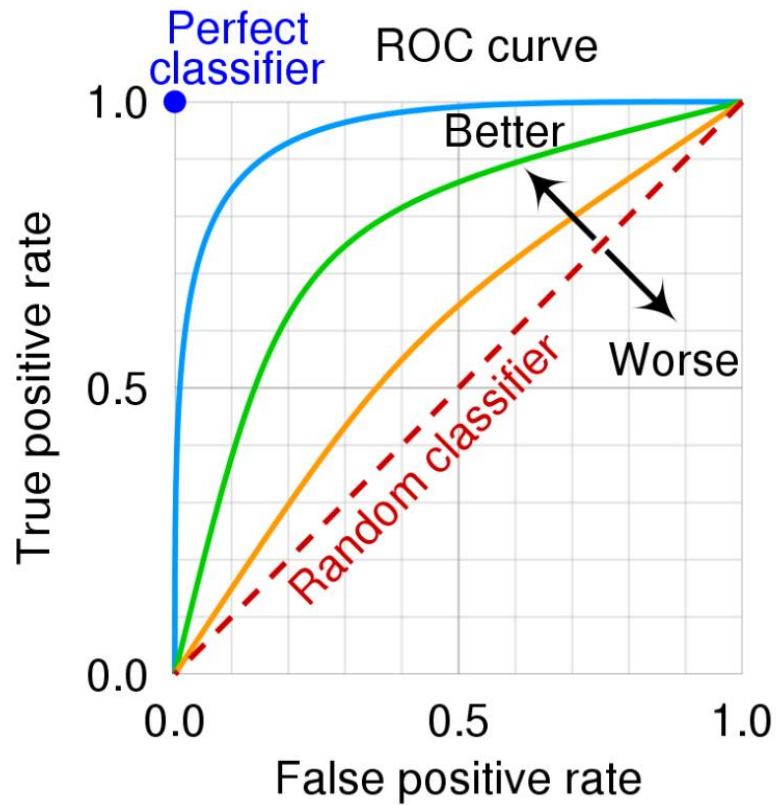
- ▶ This was a concern as of the writing of the Whitepaper in 2018/2019
- ▶ The Early Warning Model is retrained annually by the Data Science team
- ▶ The Data Science Team released an elementary-specific model tailored to students in grades K-5 in 2020





## Myth #6

There's no way to know how well the  
Early Warning GRAD Score predicts Risk

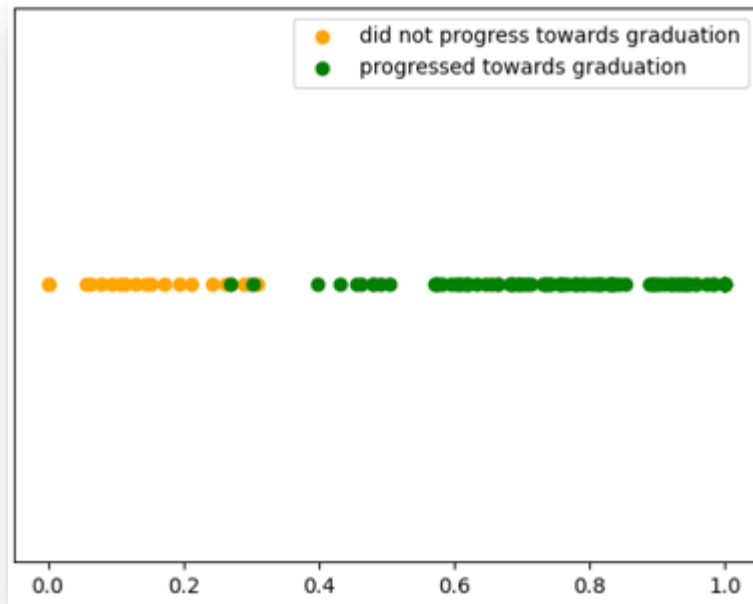


## Reality

- ▶ The Early Warning Model is regularly challenged and validated by the Data Science Team

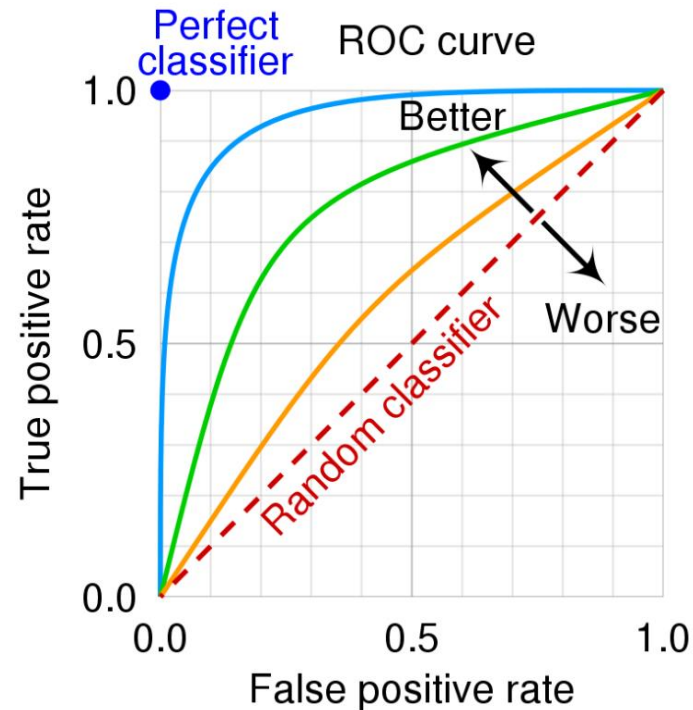
# AUC is the metric of the model's performance

- ▶ AUC measures performance based on the ordering of students from lowest to highest risk
  - Because of this, it is a balance of maximizing true positives and minimizing false positives





# Model Validation

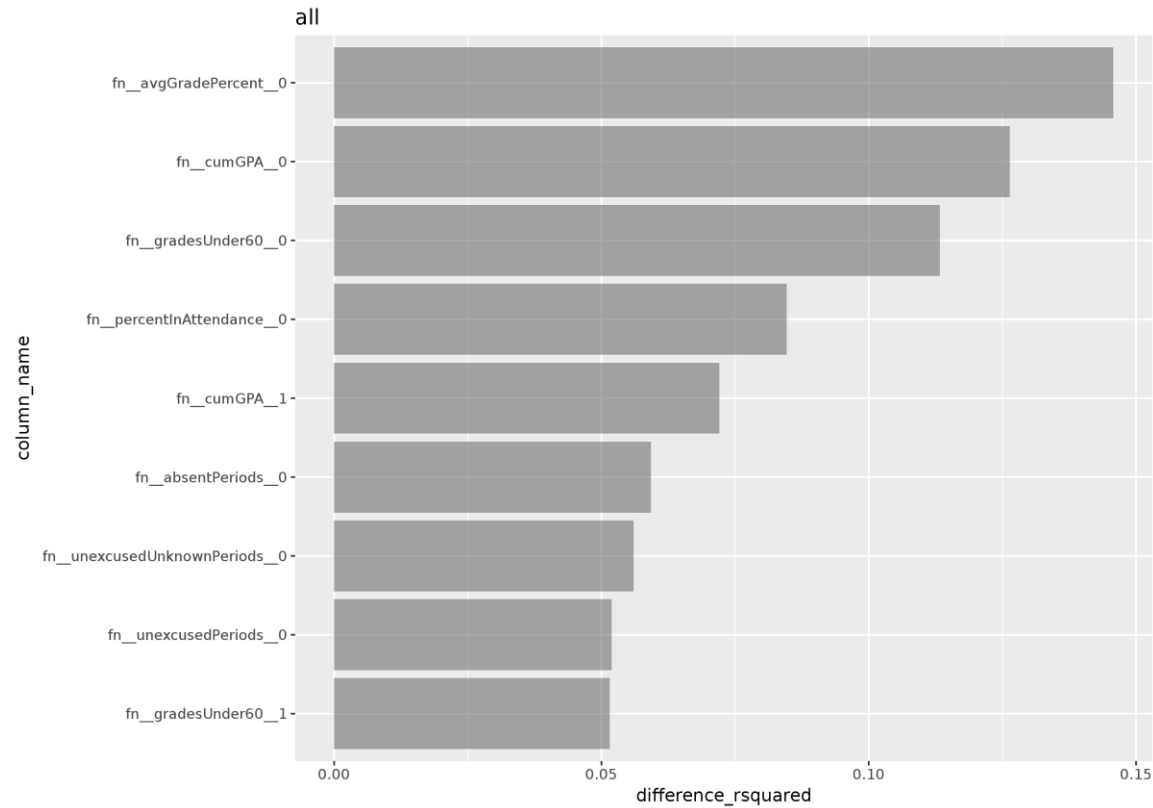


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4.0

## Area under receiver operating curve (AUC)

- ▶ The current model has 0.947 AUC
- ▶ The AUC is 0.942 for students not eligible for FRL

# Model Validation



Monitor data drift and predictability of features

# Specific features that impact the GRAD Score

# Features Are Grouped into 4 Categories

## Some Examples



### **Attendance**

Attendance Rate by Status  
Attendance Rate by Excuse



### **Behavior**

Count of Classifications  
of Negative Behavior  
Events

# Features Are Grouped into 4 Categories

## Some Examples



### **Curriculum**

Cumulative GPA  
Credit Progression



### **Stability**

Count of Districts in student's  
Enrollment History  
FRL Status

# Not All Features Are Weighted Equally

## Examples of Highly Predictive Features with Higher Weight

- ▶ Guardian Portal Logins / Unexcused Absences
- ▶ Number of times students changed schools in the same District
- ▶ FRL Status

# Not All Features Are Weighted Equally

## Examples of Very Low Predictive Features with Much Lower Weight

- ▶ Last Year's Enrollment Start Status
- ▶ Race / Ethnicity
- ▶ Gender
- ▶ Proportion of non-gifted and talented students in the same zip code

# References

- ▶ <https://www.infinitecampus.com/pdf/Machine-learned-School-Dropout-Early-Warning-at-Scale.pdf>
- ▶ <https://www.infinitecampus.com/products/campus-analytics-suite>
- ▶ <https://kb.infinitecampus.com/help/understand-grad-scores-video>



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