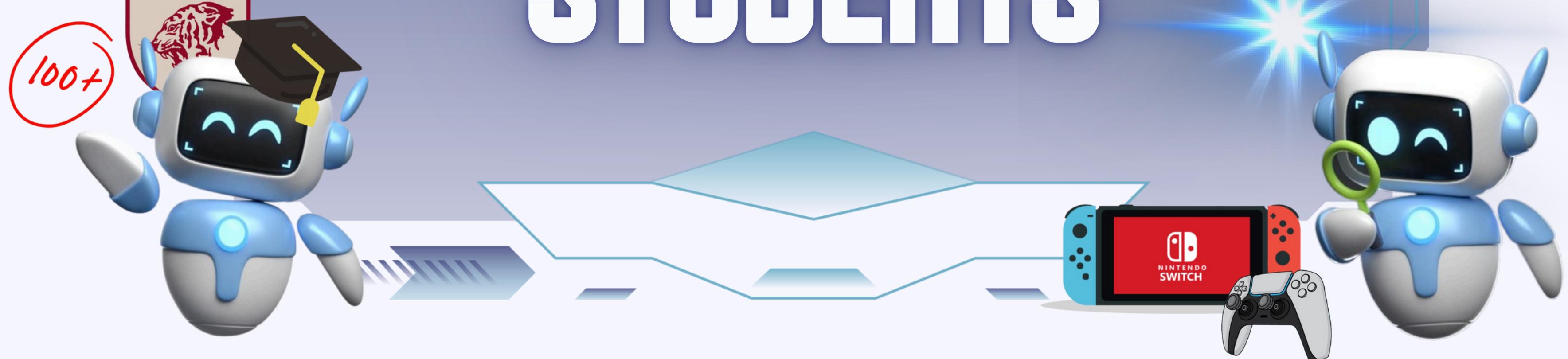


GAMES AND STUDENTS



Team Members

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Outline

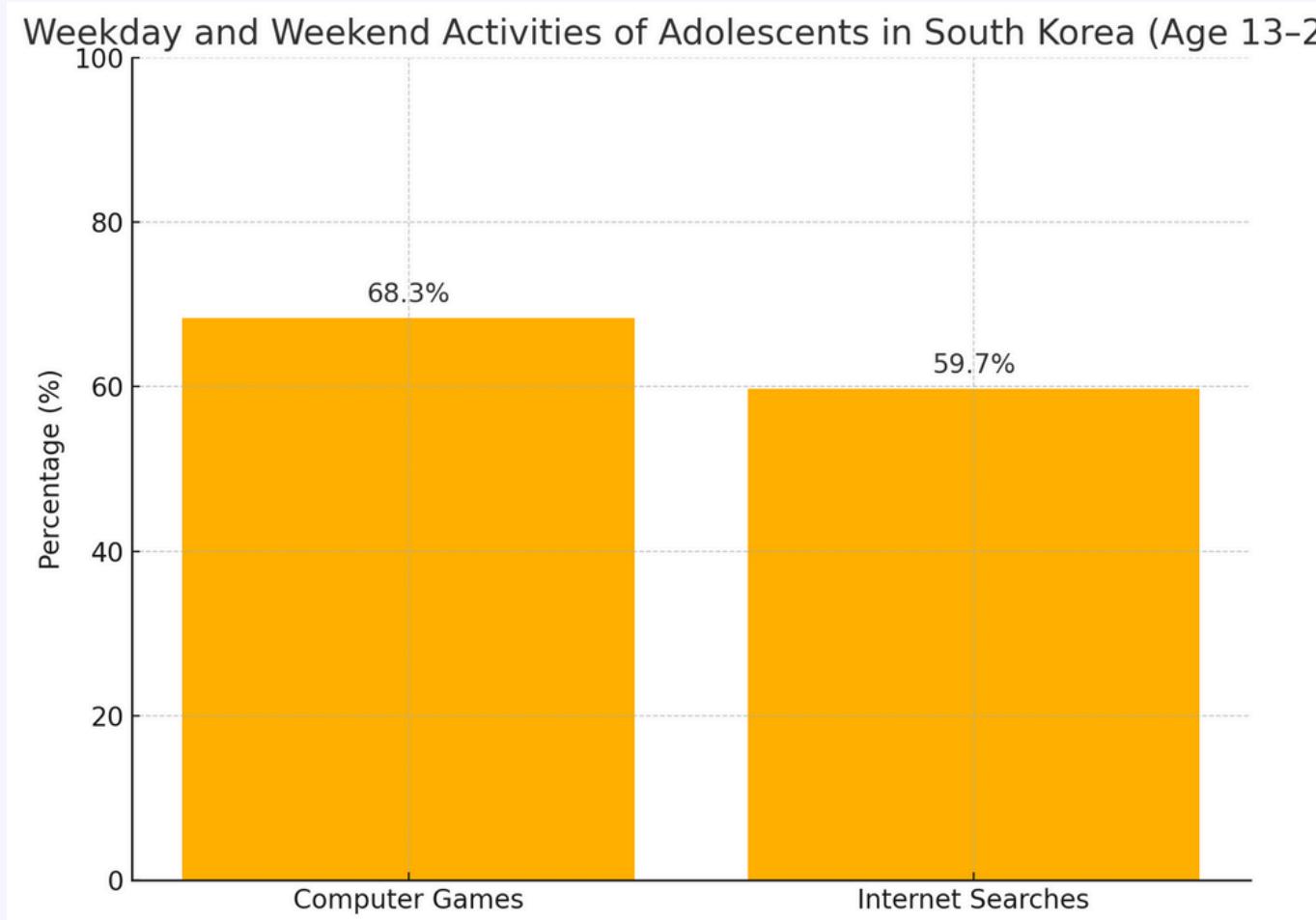
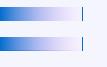
Problem Statement/ Motivation

Goal

Our dataset

Methods

Problem Statement & Motivation



Source: <https://doi.org/10.1016/j.childyouth.2018.09.009>

Problem Statement

According to a study conducted in 2018, **68.3% of adolescents** (13-24 years old) spend their weekend **playing games**.

Gaming has become a popular trend among students.

Does gaming habits, such as playing time and frequency, have a measurable effect on students' academic performance?

Motivation

Problem Statement & Motivation



Problem Statement

Motivation

As students increasingly engage in gaming, it becomes essential for educators, parents, and students themselves to understand the behavioral patterns that may support or hinder academic success.

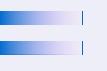
Discover the relationships in the dataset that can relate student behavior and their academic performance.

Goal

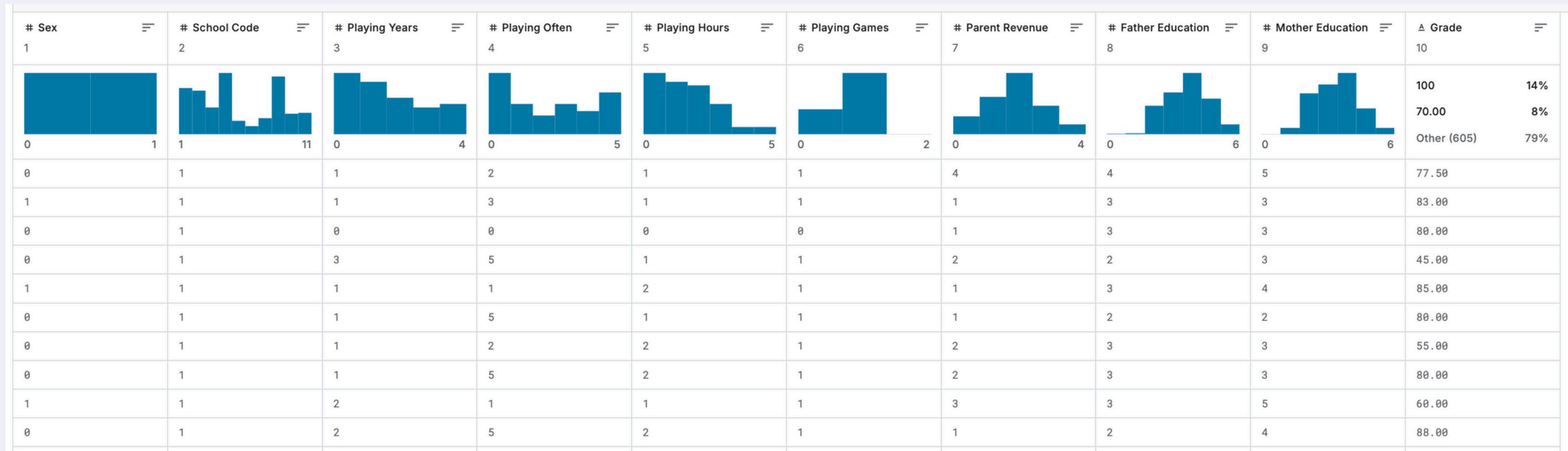


- **Group students into meaningful clusters** based on their gaming habits and academic performance.
- **Train a classification model to predict a student's performance level** based on gaming and background features.
- **Identify which features** (e.g., playing hours, parent education) are most influential in predicting grades.
- Discover frequent behavior patterns using **pattern mining** (e.g., “High playing hours + low parent education → low grades”).
- **Provide interpretable visualizations and insights** to support academic decision-making and self-awareness among students.

Looking into our Dataset

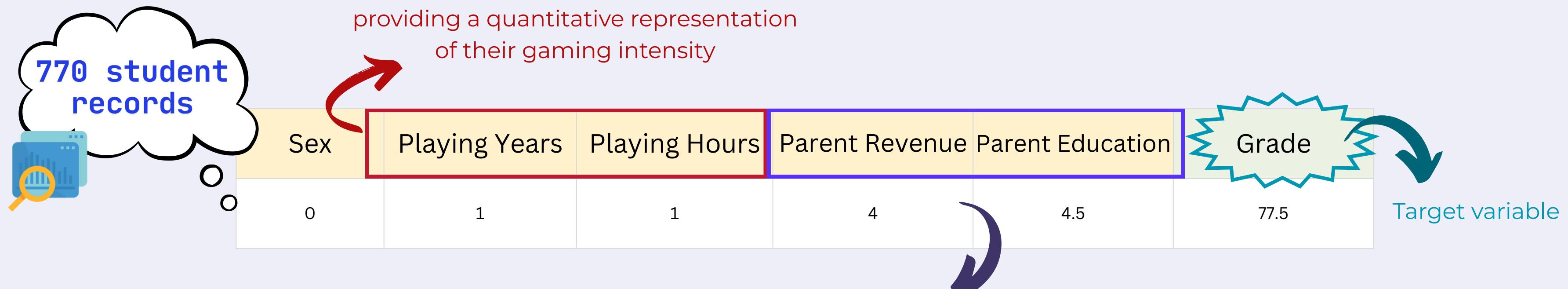


kaggle gameandgrade new.csv



What data types are we dealing with? How do we process/interpret them?

Our Dataset



These variables show how parents' education and family finances could affect their children's gaming habits and grades.

Data Preprocessing (How do we deal with abnormal data?)



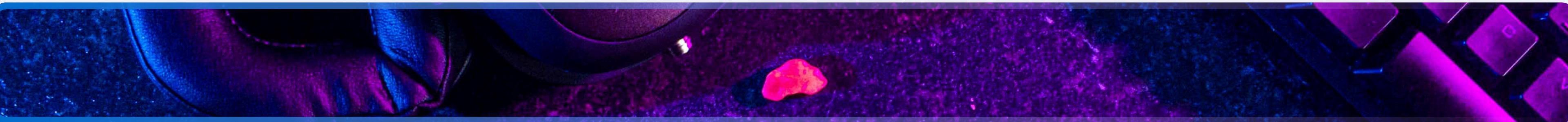
Example in dataset:

Sex	Playing Years	Playing Hours	Parent Revenue	Father Education	Mother Education	Grade
0	0	0	0	0	0	100

- The entire row is removed to ensure data quality and avoid noise.

Sex	Playing Years	Playing Hours	Parent Revenue	Father Education	Mother Education	Grade
0	0	0	2	4	4	92..00

- Field value is manually corrected to ensure consistent formatting.



Clustering

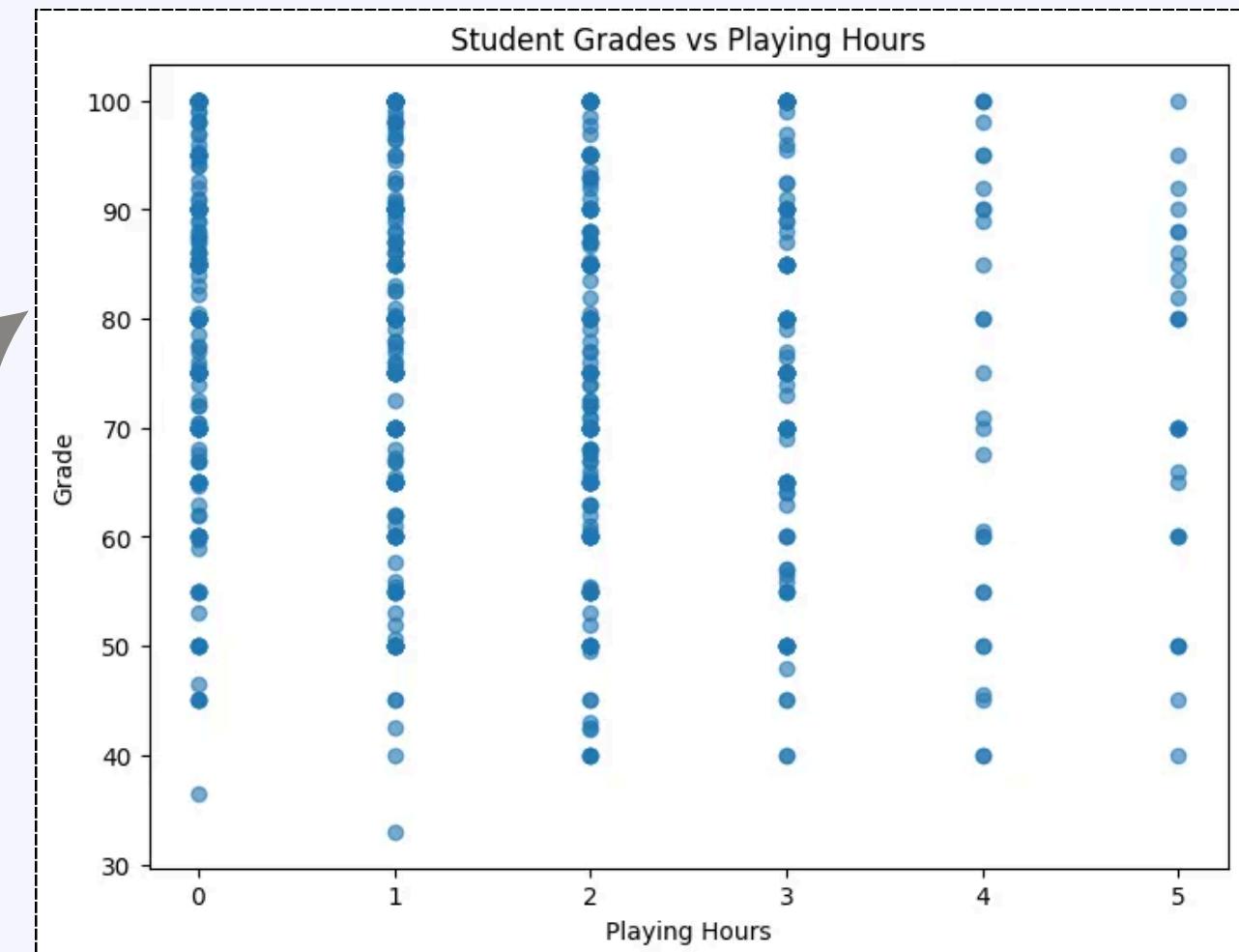
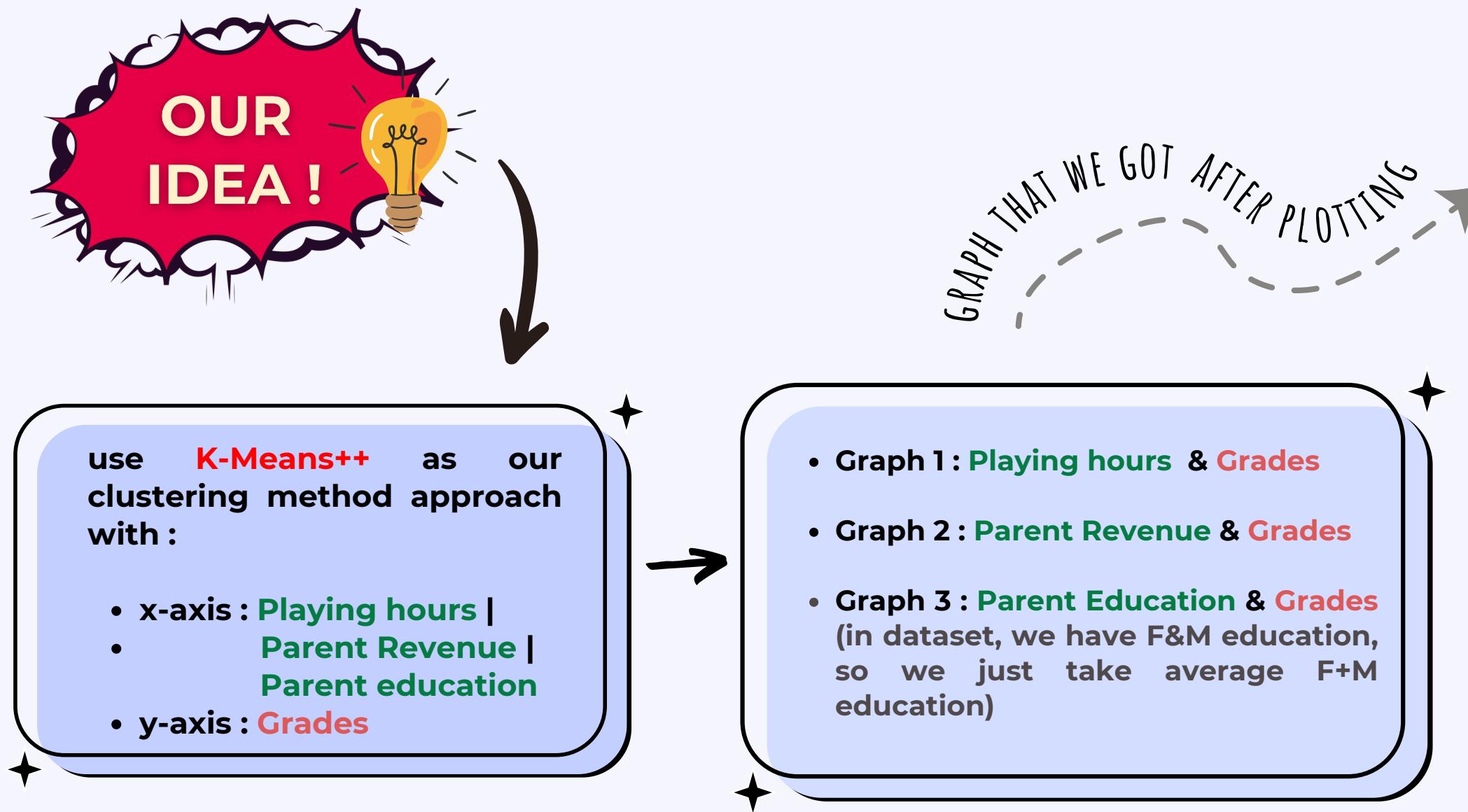
Classification

Pattern Mining

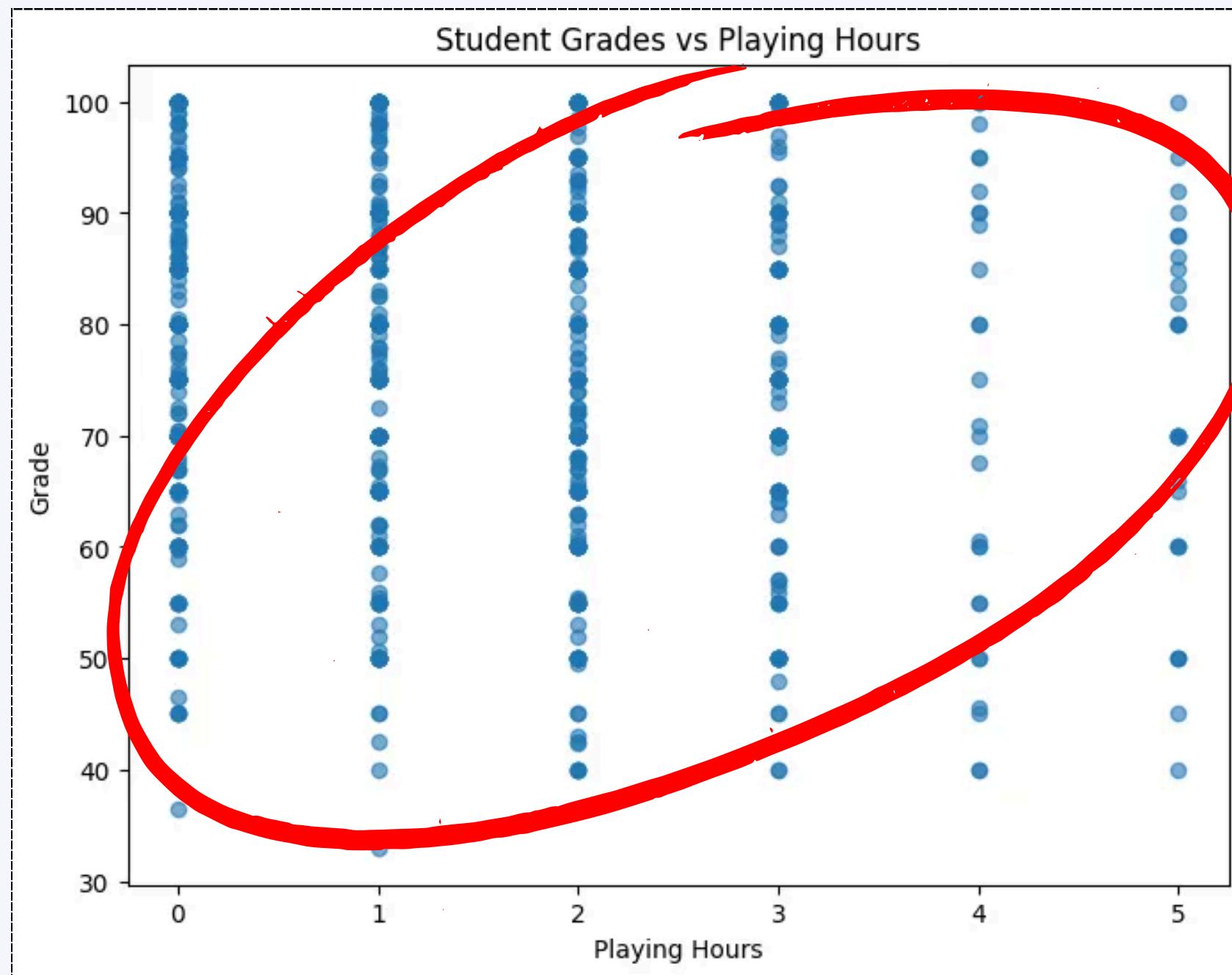
Clustering



Objective : To identify the clusters of students with varying gaming habits (e.g. playing hours) and traits (grades).



Clustering



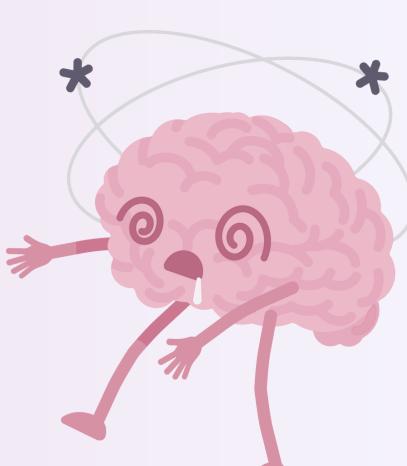
Problem

our **X- axis** (Playing hours, Parent Revenue, Parent Education) are **all ordinal and discrete data**.

So, it turns out to be different than what we expected (not suitable for clustering).



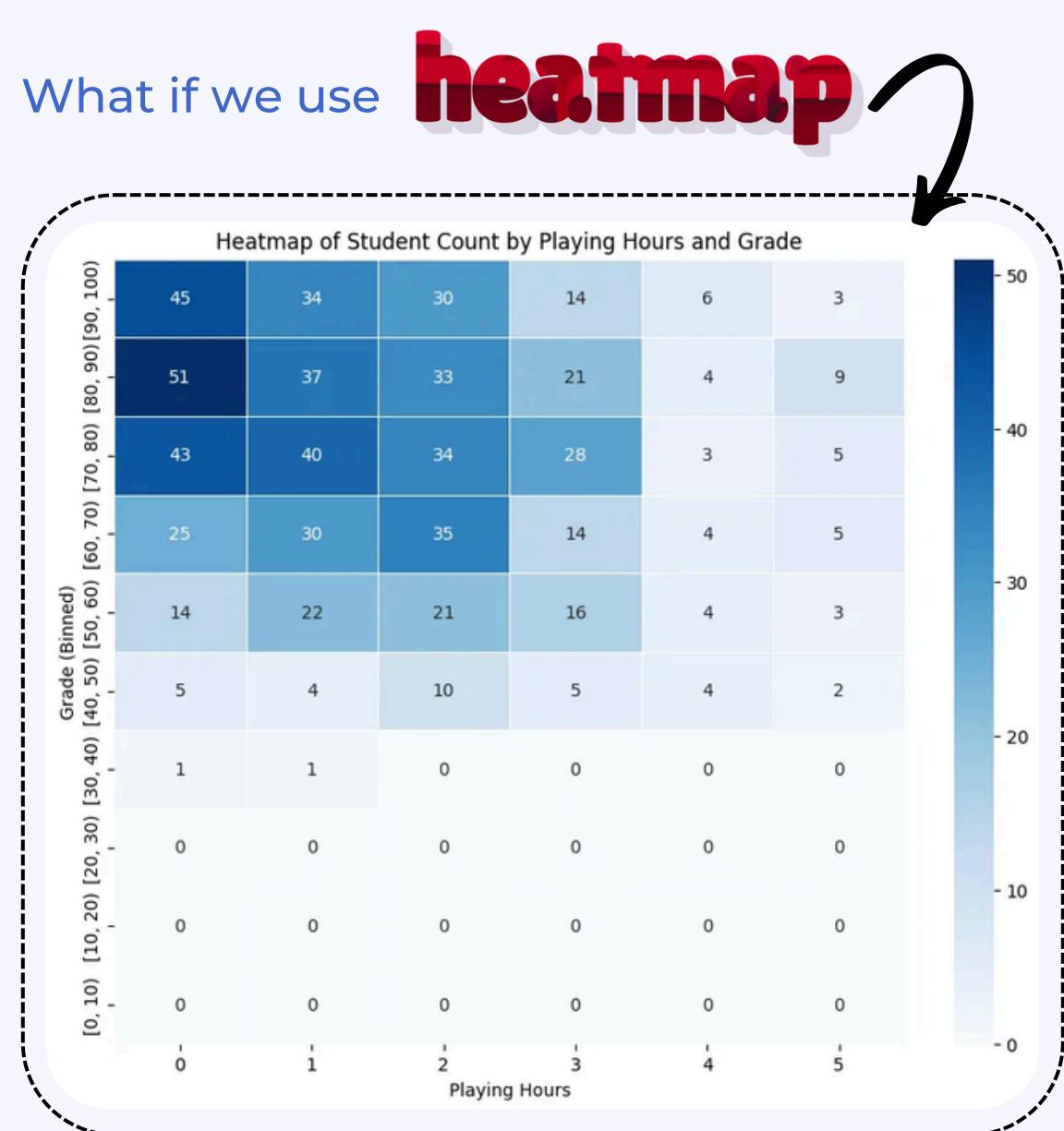
The data isn't scattered the way we want! How can we form clusters if each grade just appears as a horizontal line?



Clustering



Alternative way to visualize data :



But... This raises a concern

Is a heatmap a suitable way to visualize relationships in this discrete data instead of using k-means, or is there a better alternative we could try?

Classification



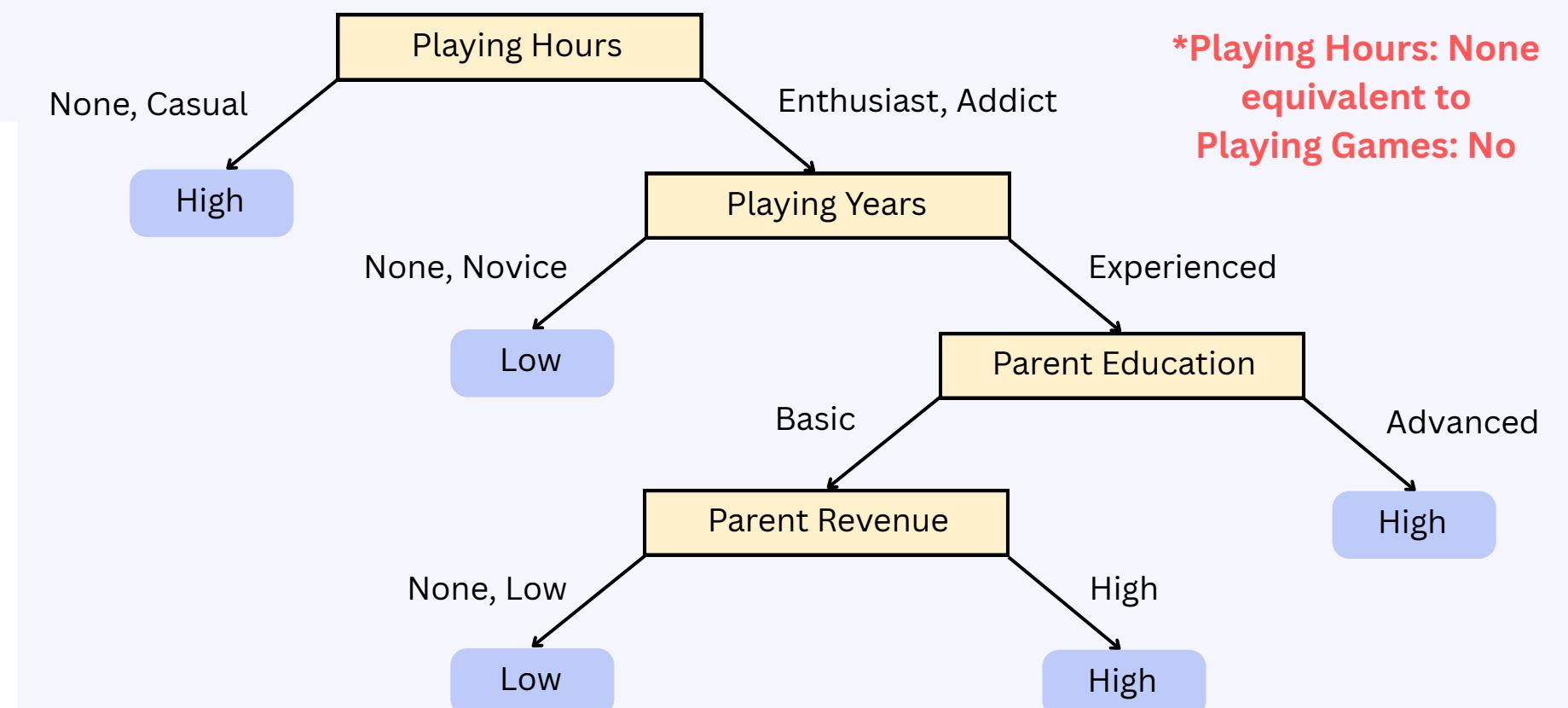
Objectives

- Construct decision tree & classify data into labels (Grade).
- Train simple DNN model to predict label of unseen data.

Does sex matter?

ID	Sex	Playing Years	Playing Hours	Playing Games	Parent Revenue	Parent Education	Grade
1	0	Novice	Casual	Yes	High	Advanced	High
2	1	Novice	Casual	Yes	Low	Basic	High
3	0	None	None	No	Low	Basic	High
4	0	Experienced	Casual	Yes	Low	Basic	Low
5	1	Experienced	Addict	Yes	Low	Advanced	High
6	0	Novice	Casual	Yes	Low	Basic	High
7	1	None	None	No	High	Advanced	???

Possible Decision Tree Deduction



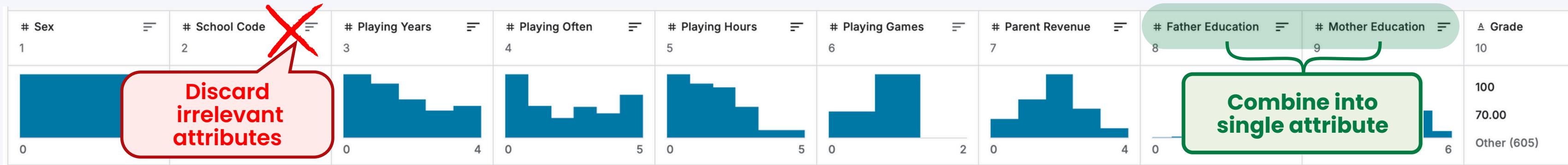
Finding out which attributes in our dataset matters

Interpreting the data values from dataset

Deciding on the best split & split criterion for decision tree

Classification

Attributes in the Game & Grade Dataset

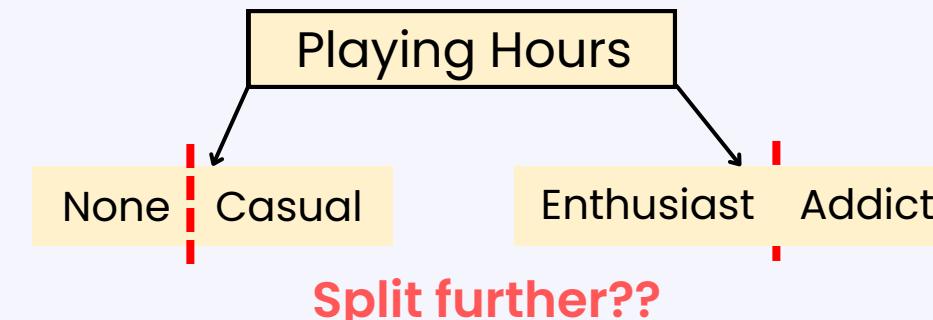


Interpretation of Attributes for Classification Purposes

	Sex	Playing Years	Playing Hours	Playing Games	Parent Revenue	Father Education	Mother Education	** Parent Education	Grade
	S. Binary	Numerical	Numerical	Binary	Ordinal*	Ordinal*	Ordinal*	Ordinal*	Numerical
Range from Raw Data	0 (F) 1 (M)	0~4	0~5	0/1	0~4	0~6	0~6	0~6	0~100
Range for Decision Tree	0 (F) 1 (M)	0 (None) 1~2 (Novice) 3~4 (Experienced)	0 (None) 1~2 (Casual) 3~4 (Enthusiast) 5 (Addict)	0 (Yes) 1 (No)	0 (None) 1-2 (Low) 3-4 (High)	Combined for Parent Education	Combined for Parent Education	(FE + ME) / 2 ** Equal weights 0.0~3.0 (Basic) 3.5~6.0 (Advanced)	< Median (Low), ≥ Median (High)

Parent Revenue: Which is more optimal?

0	1	2	3	4
None	LOW		HIGH	



Use median as threshold for splitting the continuous valued label classes

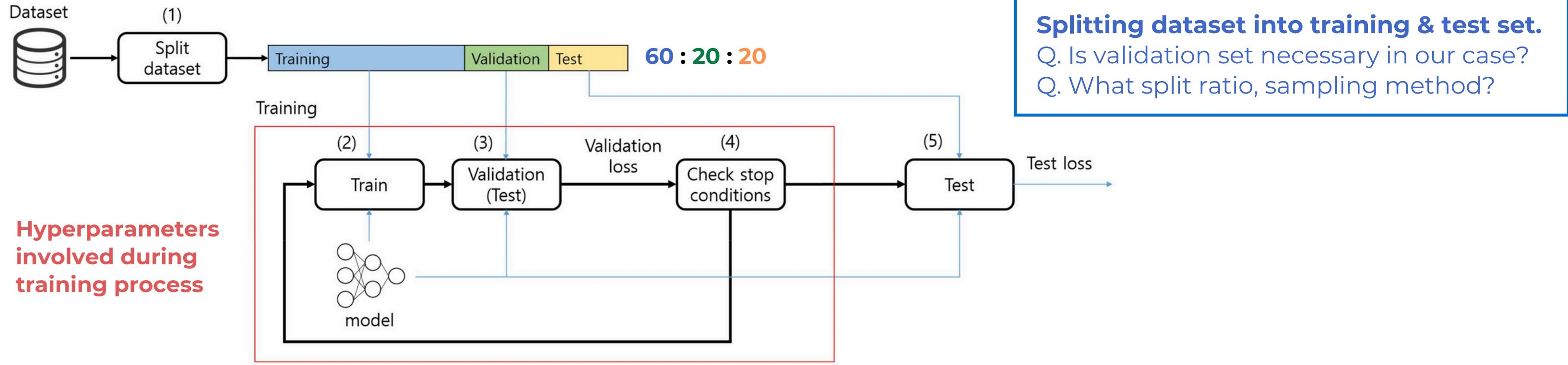
Total rows : 770

≥ Median (High)

Median : $(X_{385} + X_{386}) / 2 = 80.00$

< Median (Low)

Classification



Measuring split quality/criteria

GINI Index
Entropy

Stopping criteria

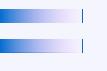
`min_samples_split`
`min_samples_leaf`
`max_depth/max_node_size`

What's on our mind?

Train model to successfully predict student Grade (High/Low) based on features from our dataset. (gaming behaviours & household factors)

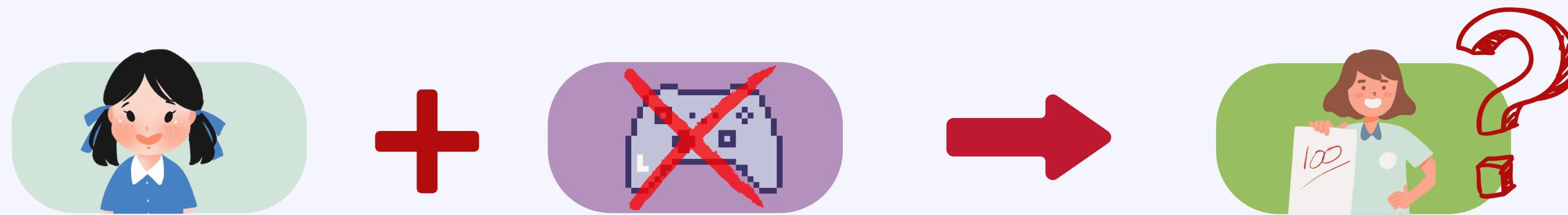


Pattern Mining



What Are We Trying to Find Out?

- Which student characteristics tend to appear together?
- Which behaviors are frequently associated with high or low grades?
e.g. **Does high gaming hour, low parental income → low grades?**



Pattern Mining



1. Data Preprocessing

- Continuous data (parent education, grade) and ordinal numerical (ex. playing hours, parent revenue) are binned into categorical data (e.g., High, Low)
- Convert data into transaction**

Sex	Playing Years	Playing Hours	Parent Revenue	Parent Education	Grade
0	1	1	4	4.5	77.5

{Sex=0, Playing Years=Novice, Playing Hours=Casual, Parent Revenue=High, Parent Education= Advanced, Grade=Low}



2. Apriori for pattern mining

- Easy to use and interpret
- Works well with our dataset (~770)



3. Support threshold selection

- Initial: $\text{min_support} = 0.1$
- Adjust the support based on observed result:
many general rules → increase to 0.15
too few rules → decrease to 0.07

to find pattern in at least 10% of the students

e.g. {PlayingHours=High, ParentEdu=Low} ⇒ {Grade=Low}

- 50 out of 770 students match the rule:
support = $50/770 = 6.5\%$
- 70 students have {PlayingHours=High, ParentEdu=Low}, and 50 of them have {Grade=Low}:
confidence = $50/70 \approx 71\%$

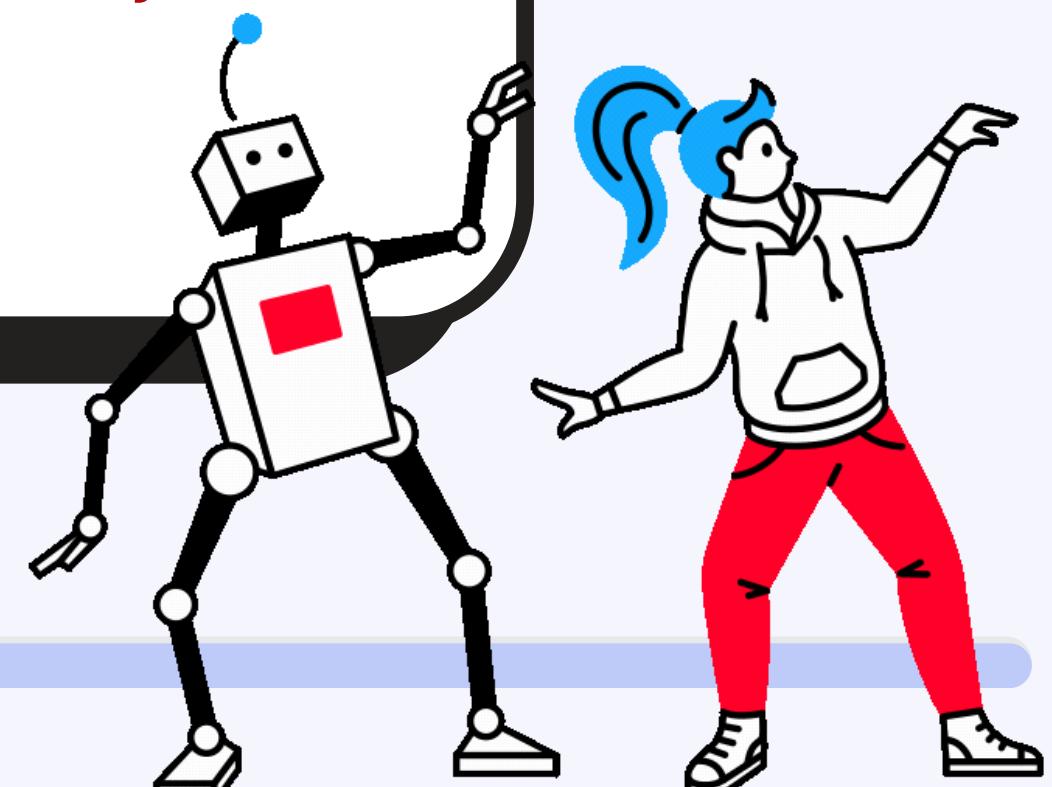
4. Interpreting result

- Is the pattern common? → **Support**
- Is the rule reliable? → **Confidence**



However...

1. Is our minimum support selection strategy sufficient?
2. Are frequent combinations truly related — or just coincidental?

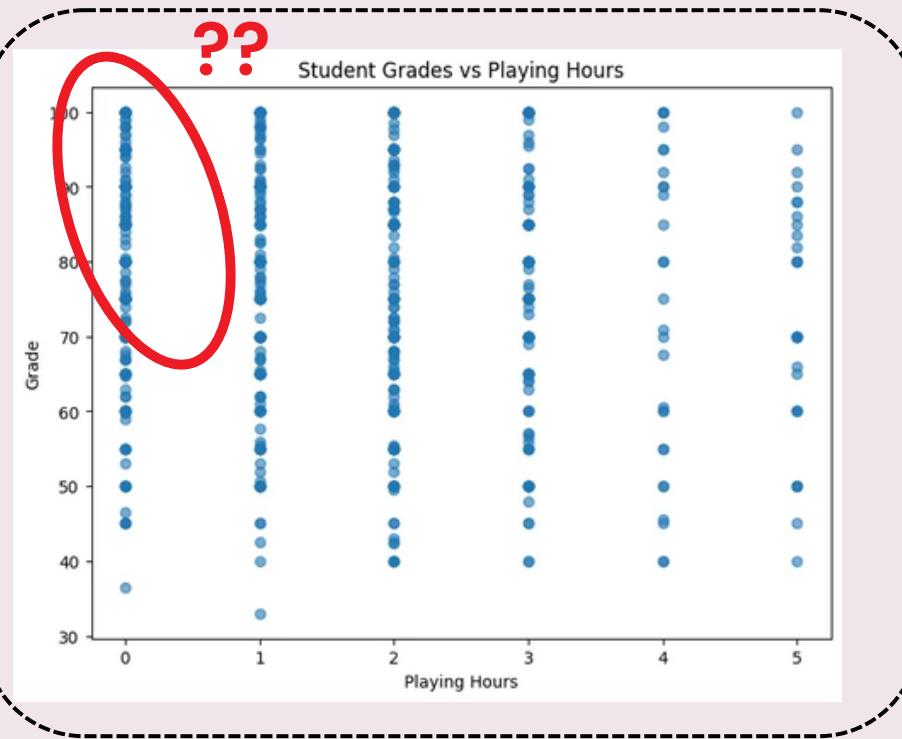


Discussion and Q&A

Clustering helps with revealing underlying structures or patterns that may not be immediately apparent. But in our case,

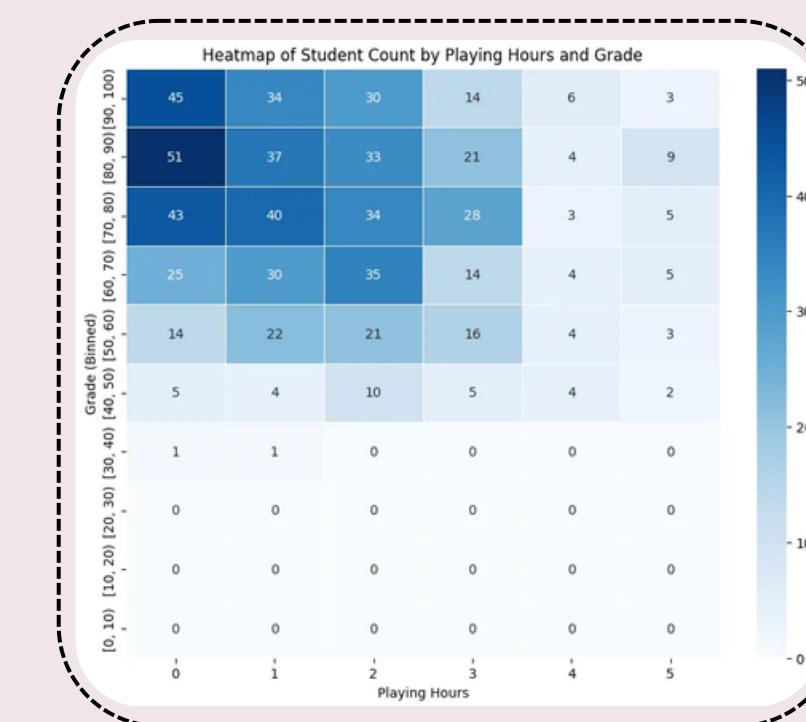
Is clustering with Discrete Values truly effective?

Clustering with K-Means++



OR

Heatmap



Difficult to visually identify clusters due to shape of graph

Shows clear pattern of data density distribution

Challenges with deciding on classification factors

Classification

Parent Revenue: Which is more optimal?

0	1	2	3	4
None	LOW	HIGH		



Use **median** as threshold for splitting the continuous valued label classes

Total rows : 770

\geq Median (High)

Median : $(X_{385} + X_{386}) / 2 = 80.00$

$<$ Median (Low)

Thank you!