A Diagnostic Tool that Scales Student Voice through Semi-Automated Text Analysis and Qualitative Clustering

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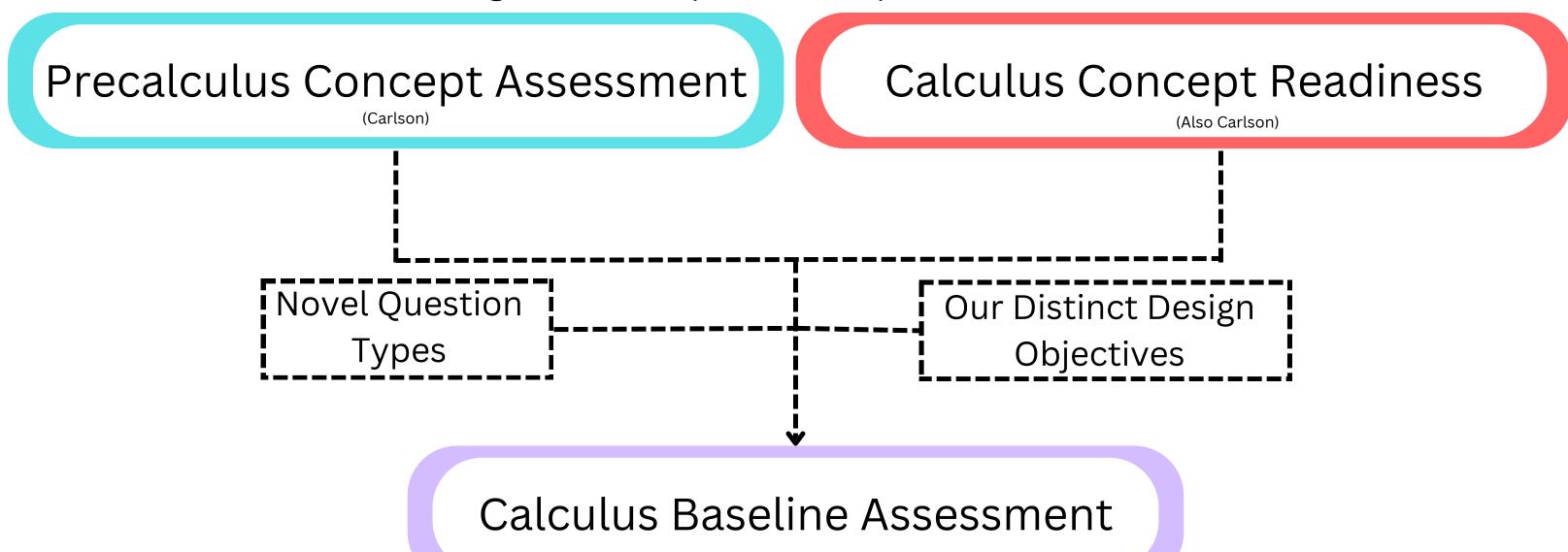


CBA Motivation

- Math is a cumulative subject:
 - Student readiness can be gauged based on their mastery of past subjects.
- Expediency is paramount for a diagnostic assessment that gauges said masteries:
 - This is achieved using short multiple choice questions.

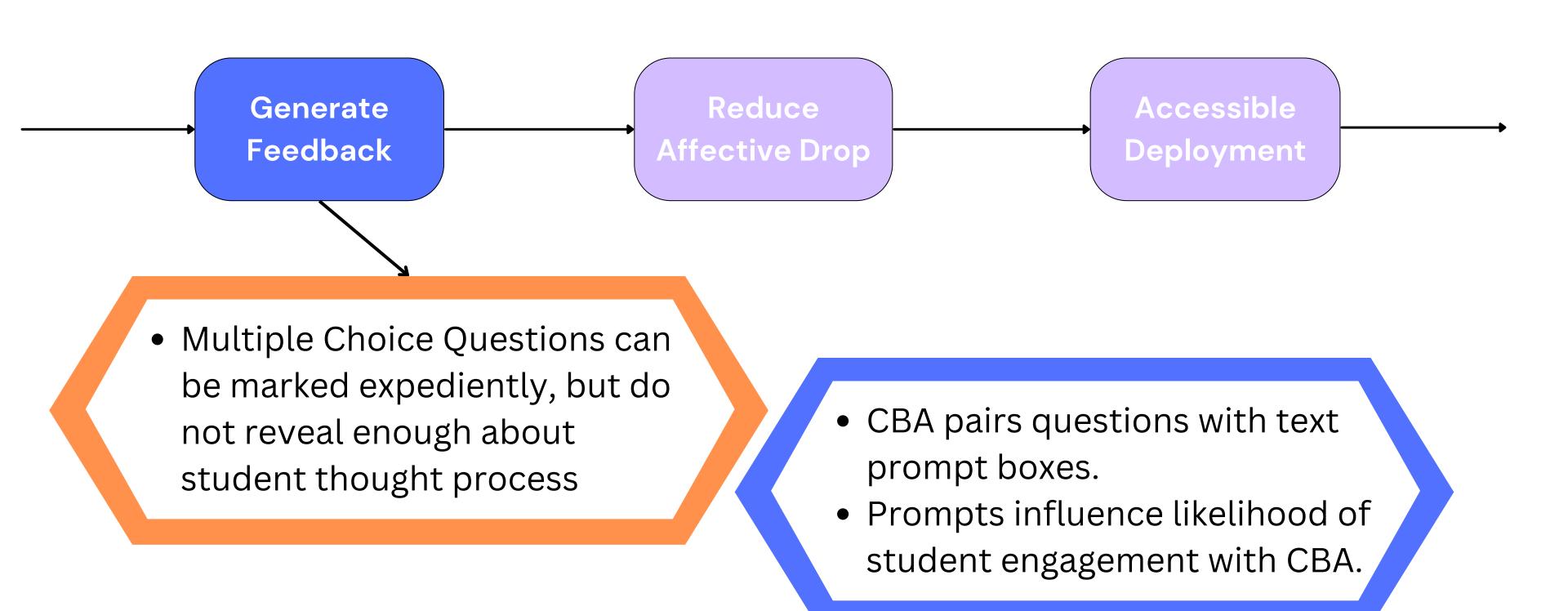
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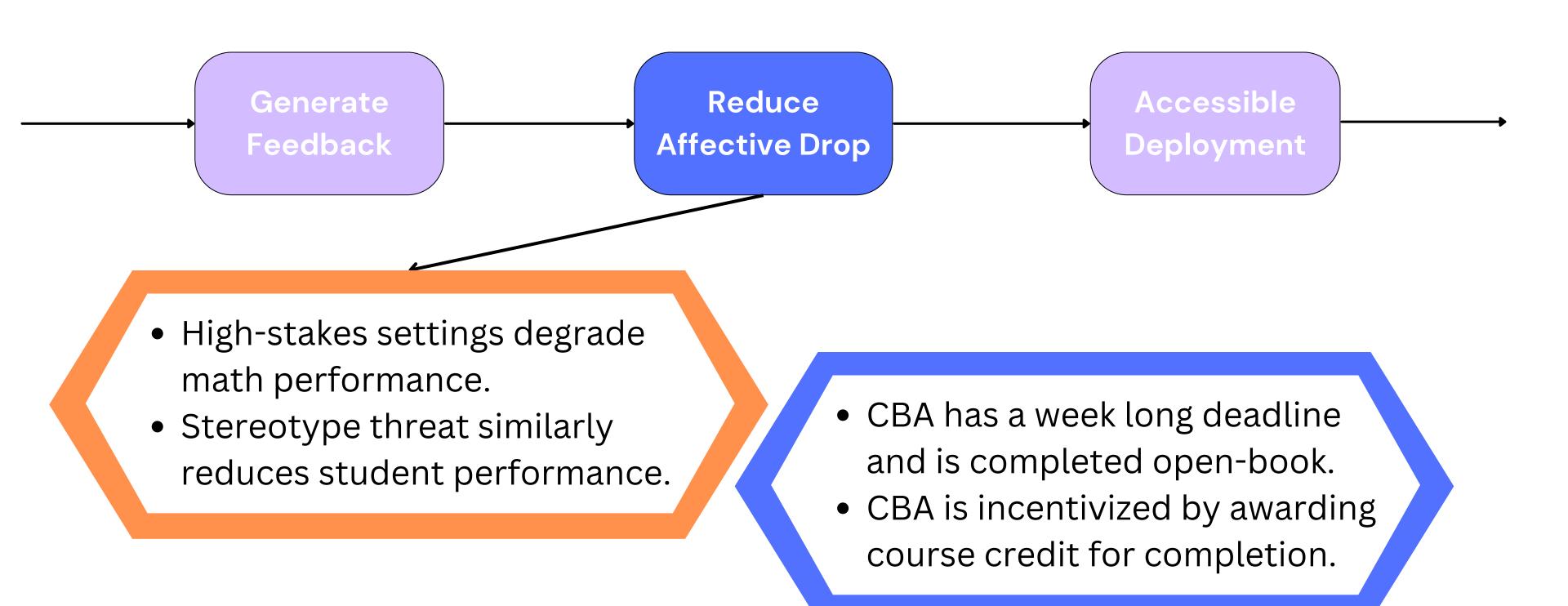
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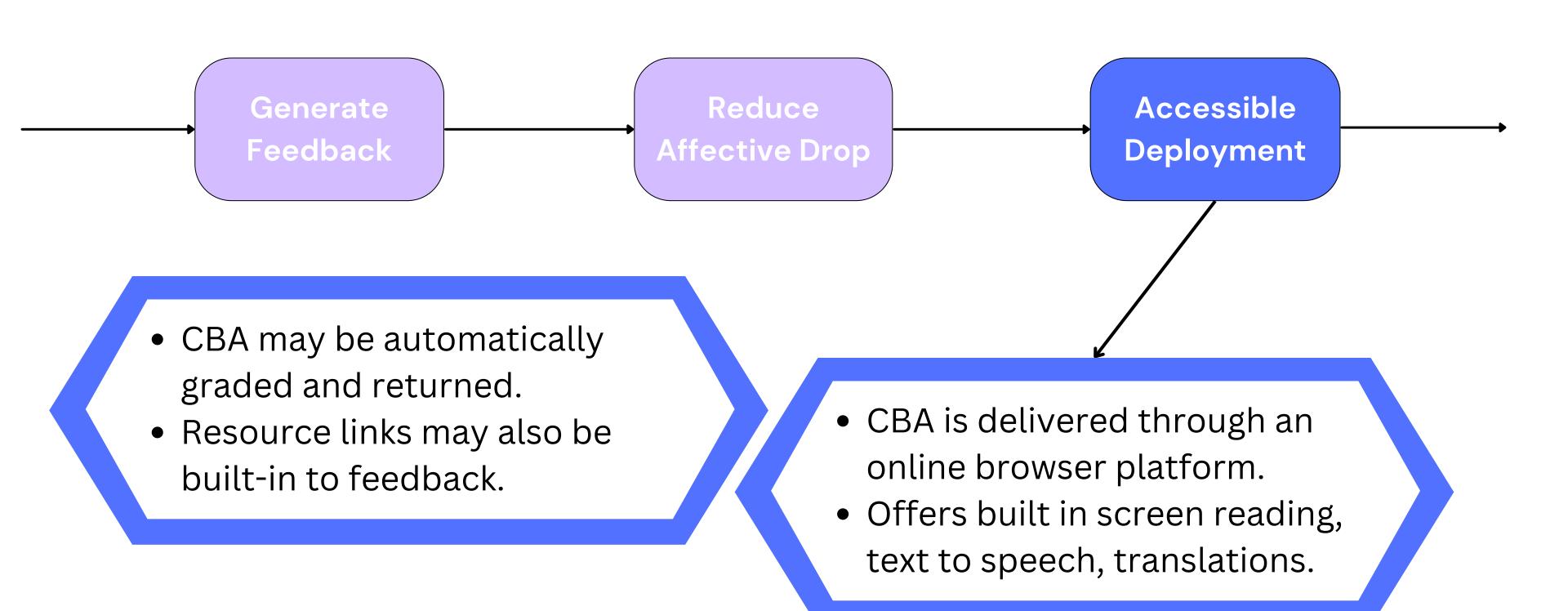


Our design objectives distinguish the CBA as its own distinct assessment.





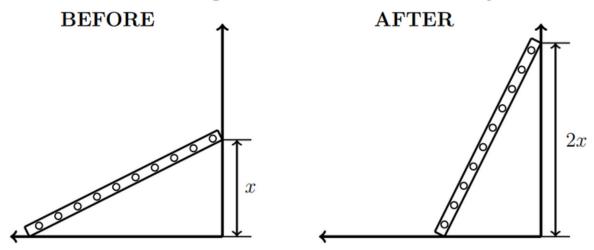




CBA Sample Question

Q13a (1 point)

A ladder - of fixed length - is leaning against a wall. The ladder is adjusted so that the distance of the top of the ladder from the floor is twice as high as it was before it was adjusted.

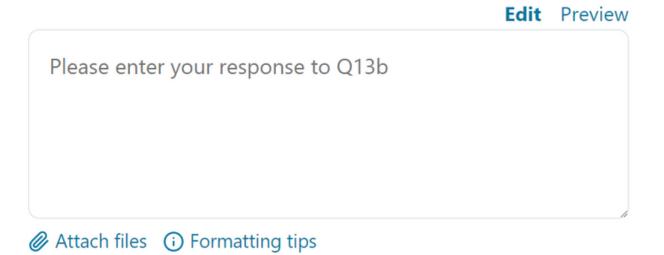


The slope of the ladder is:

- Less than twice what it was before
- Exactly twice what it was before
- More than twice what it was before
- The same as what it was before
- There is not enough information to determine if any of a through d is correct.

Q13b (0 points)

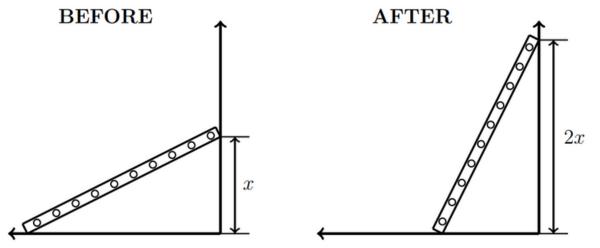
Explain the reasoning for your answer to Q13a in the box below.



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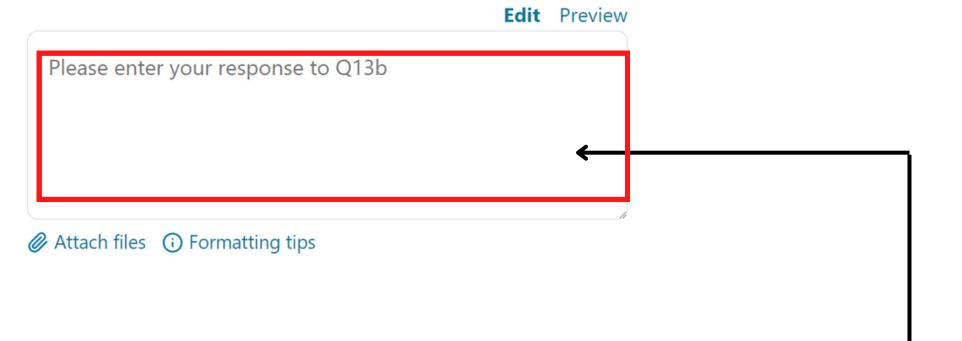


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Algebra Skills

Math Relationship Skills

Solution Framework

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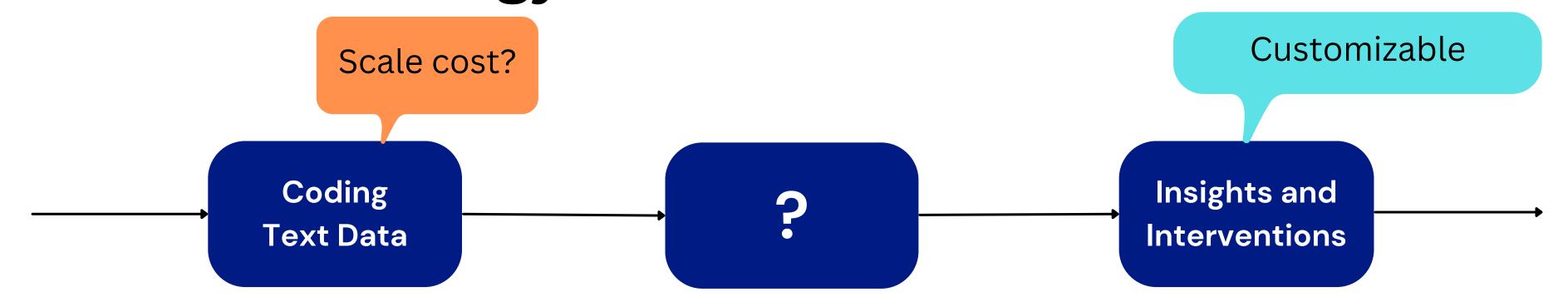
Knowledge Gaps

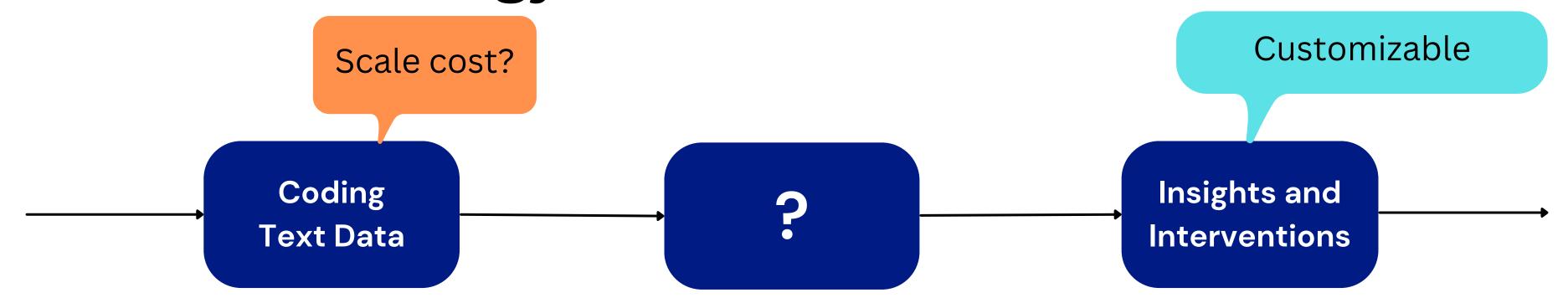
Visualization

Mathematical Language

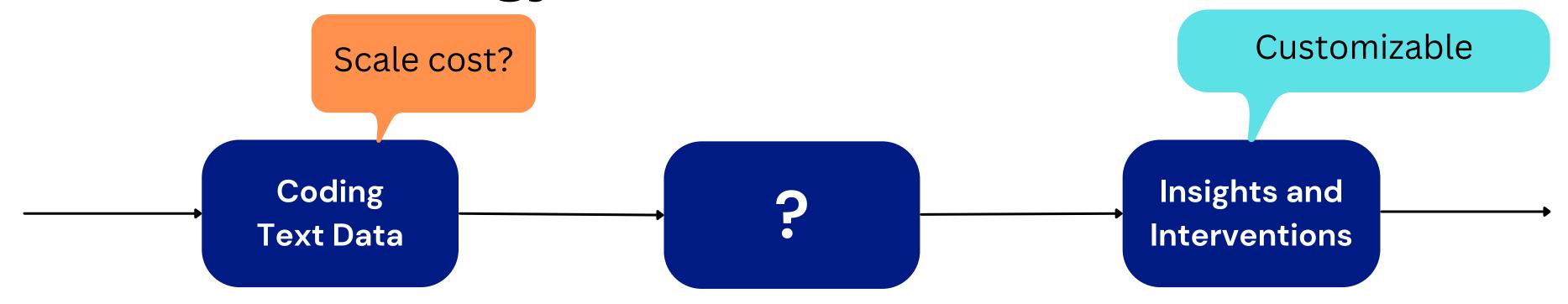
Contextual Reasoning

Heuristic View



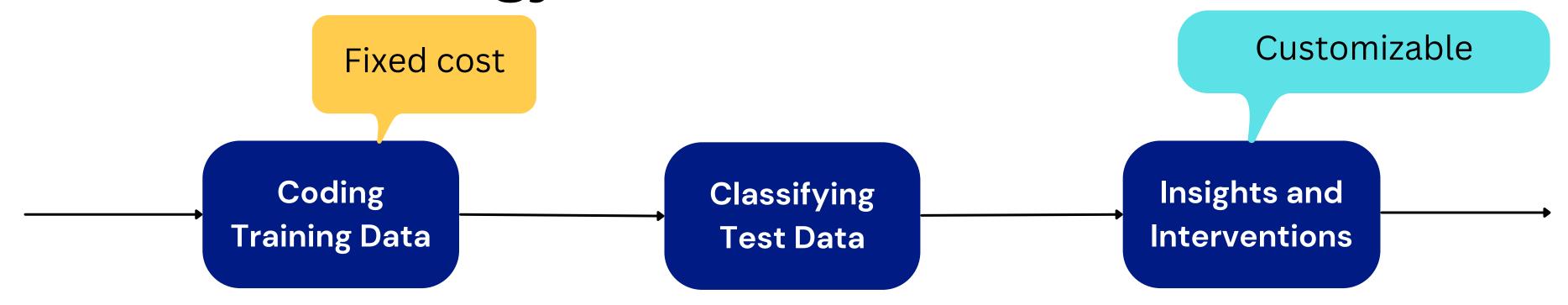


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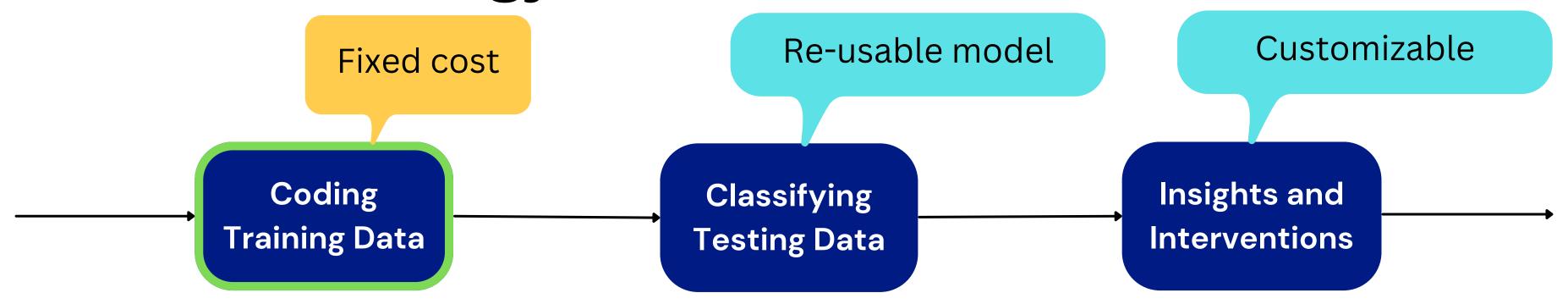
This is a massive time investment!



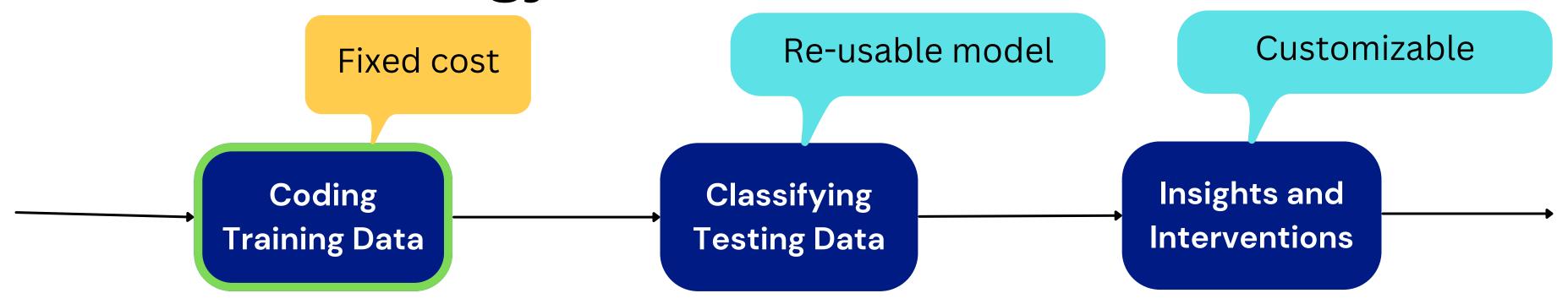
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This is a massive time investment!

Thankfully machine learning can automate this process!



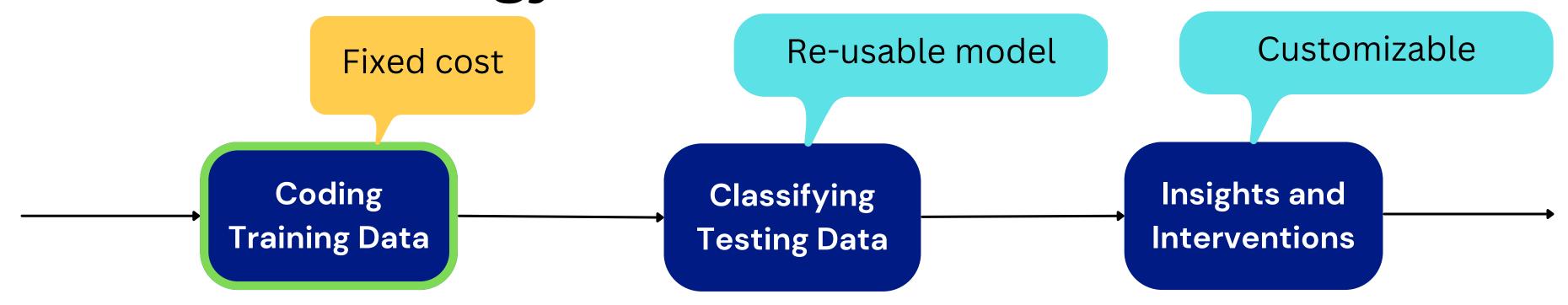
- For the sake of automation, each response is transformed using NLP.
 - The raw text is turned into a list of lemmatized tokens that have had their 'stop' words removed by a filter.



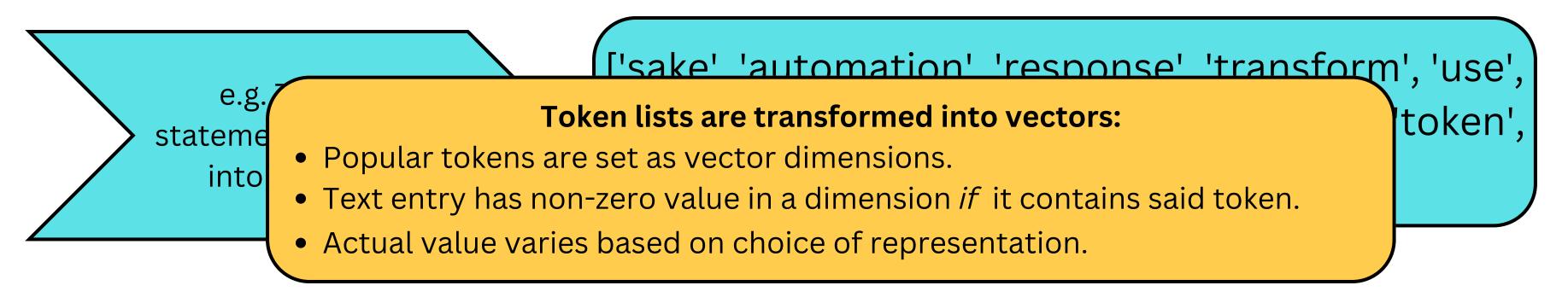
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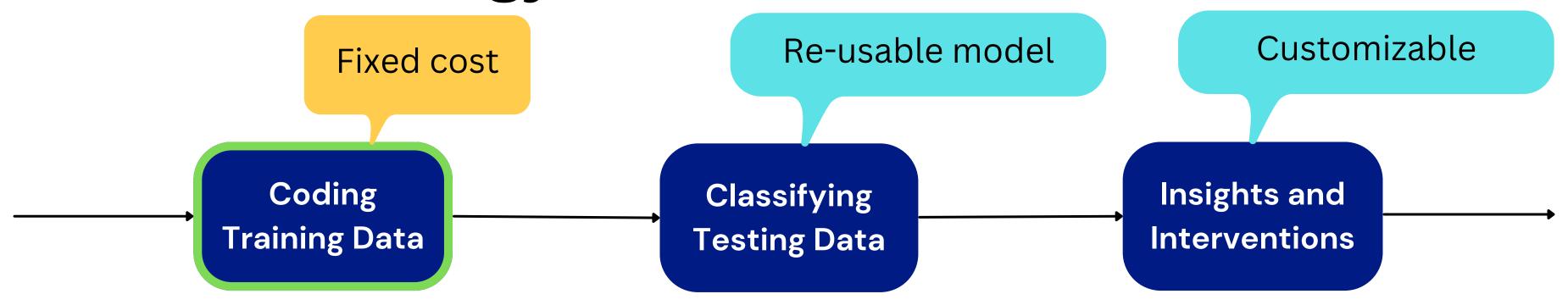
e.g. The previous statements are converted into this token list:

['sake', 'automation', 'response', 'transform', 'use', 'nlp', 'raw', 'text', 'turn', 'list', 'lemmatized', 'token', 'stop', 'word', 'remove', 'filter']

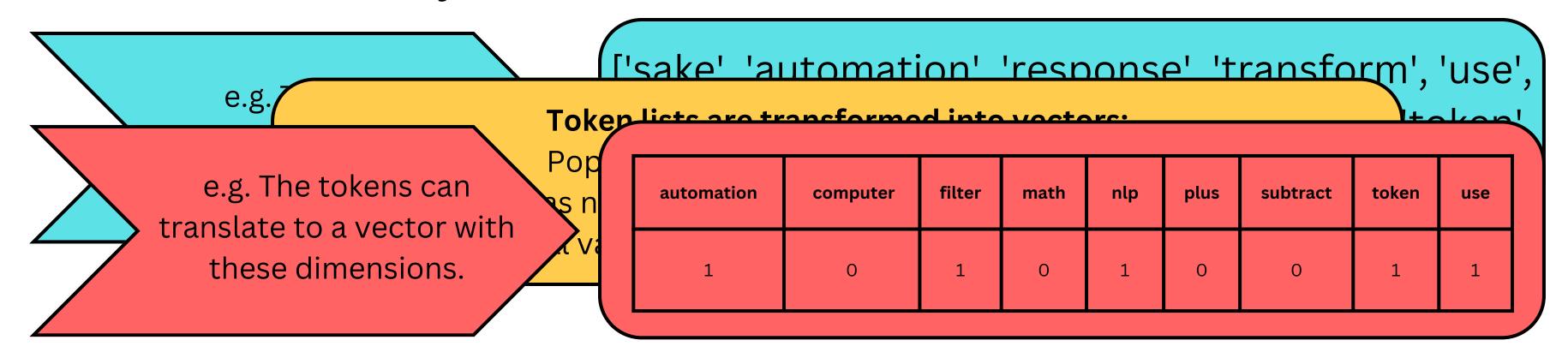


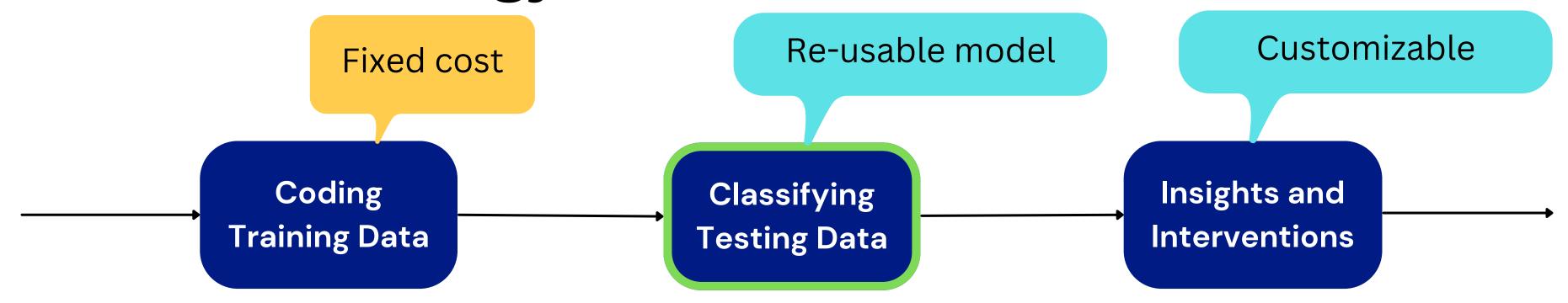
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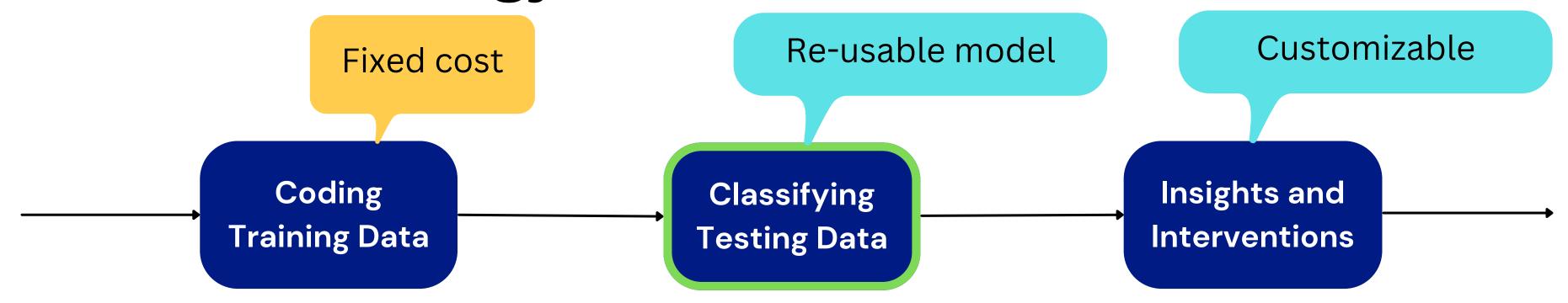


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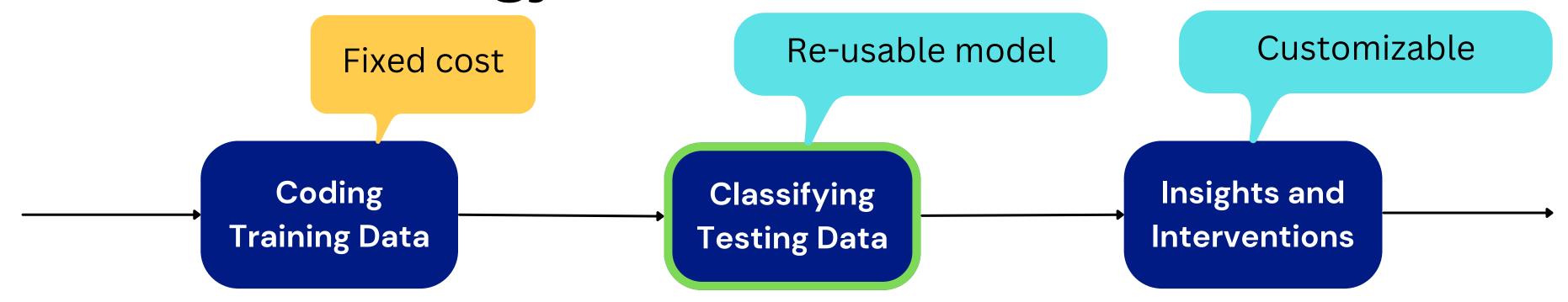




- Transformed vectors serve as input for our ML model (x)
- A separate vector serves as output (y)
 - Vector entries signal presence of a qualitative code.
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 - We use gradient boosting machines to do this.
 - GBMs iteratively design sequence of decision trees which classify vectors.

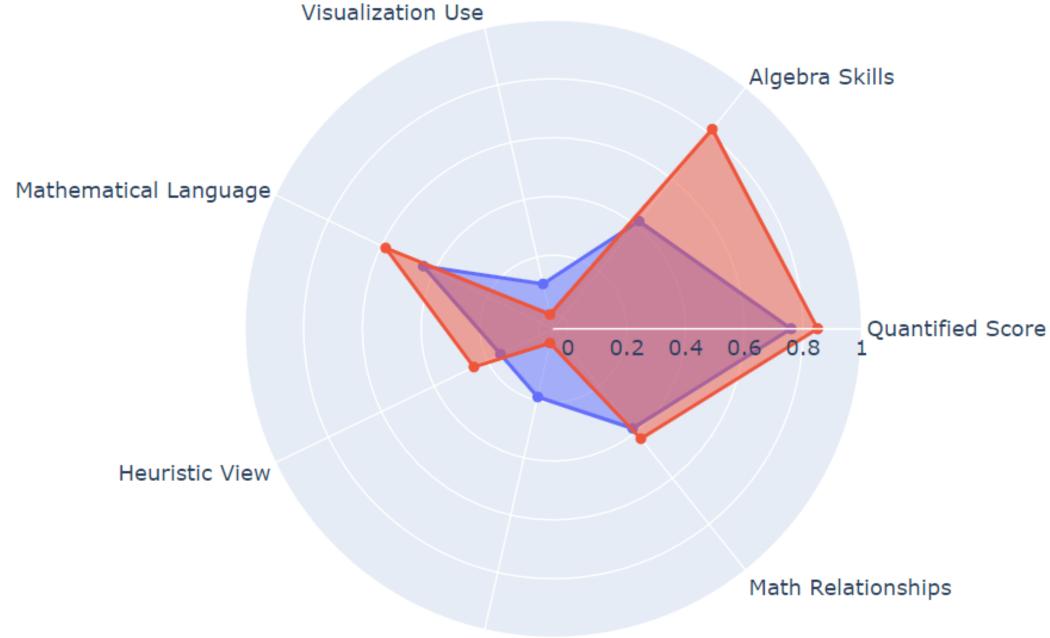


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 - We must discern where to apply models based on code frequency.

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|---|----|---|-------|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|
| Theme \ Question | 01 | 02 | 03 | 04 | 05 | 06 | 07 | 08 | 09 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 |
| Algebra Skills (11) | | | | | | | | | | | | | | | | | | | | |
| Math Relations (8) | • | | eme p | | | | | | | | | | | | | | | | | |
| Solution Frame (11) | | Green cells indicate > 10% frequency. Yellow cells indicate > 0 % frequency. | | | | | | | | | | | | | | | | | | |
| Algebra Traps (5) | | | | | | ı | | | | | | | | | | | | | | |
| Solution Misint. (13) | | | | | | | | | | | | | | | | | | | | |
| Knowledge Gap (1*) | | | | | | | | | | | | | | | | | | | | |
| Math Language (12) | | | | | | | | | | | | | | | | | | | | |
| Heuristic View (4) | | | | | | | | | | | | | | | | | | | | |
| Visualization Use (2) | | | | | | | | | | | | | | | | | | | | |
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Data Visualization with Spider Plots



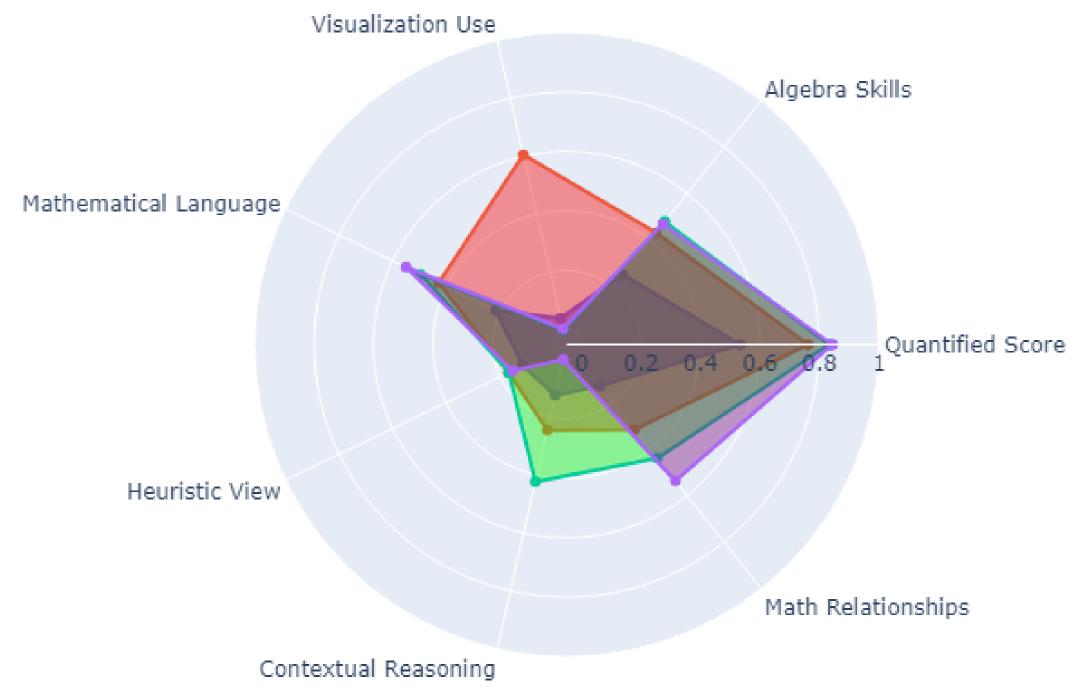
Contextual Reasoning

Six themes are joined with CBA score to create a profile of student readiness. The red plot shows the profile of a random student while the blue plot shows the averaged profile of every student in the cohort.

Collating Student Dimensions:

• We standardize the fraction of flagged theme instances as a single dimension.

Clustering Student Cohort



Four spider plots each depicting the same seven student attributes; each plot is the centroid of a student cluster where: cluster A (blue) contains 147 students, cluster B (red) contains 106 students, cluster C (green) contains 188 students, cluster D (purple) contains 222 students.

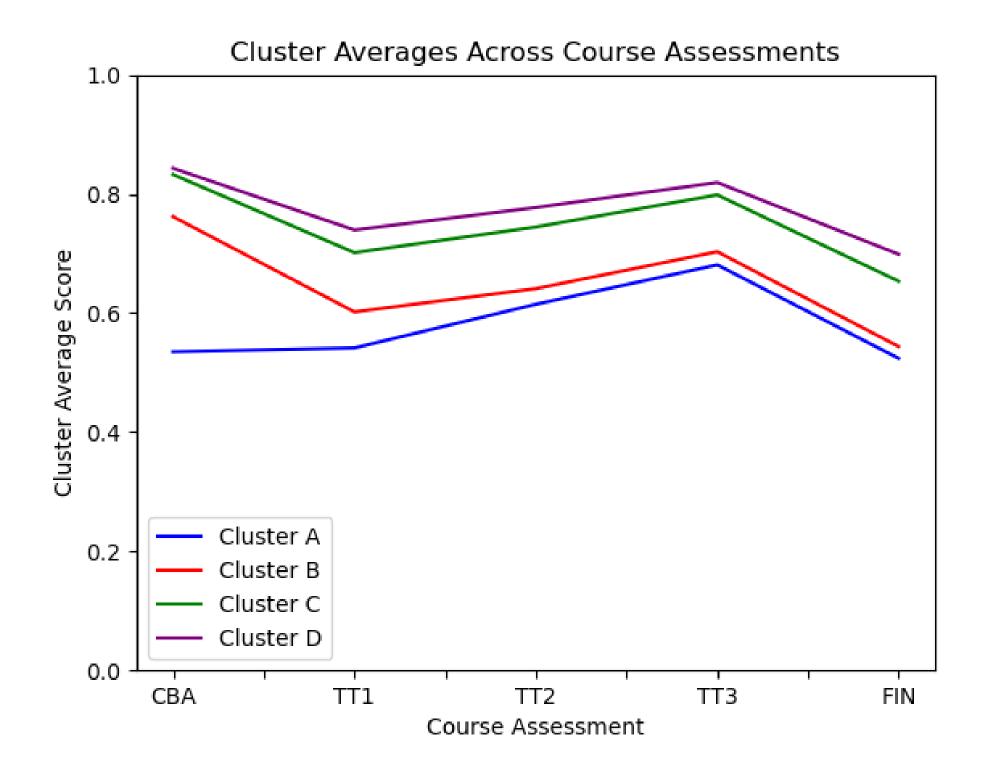
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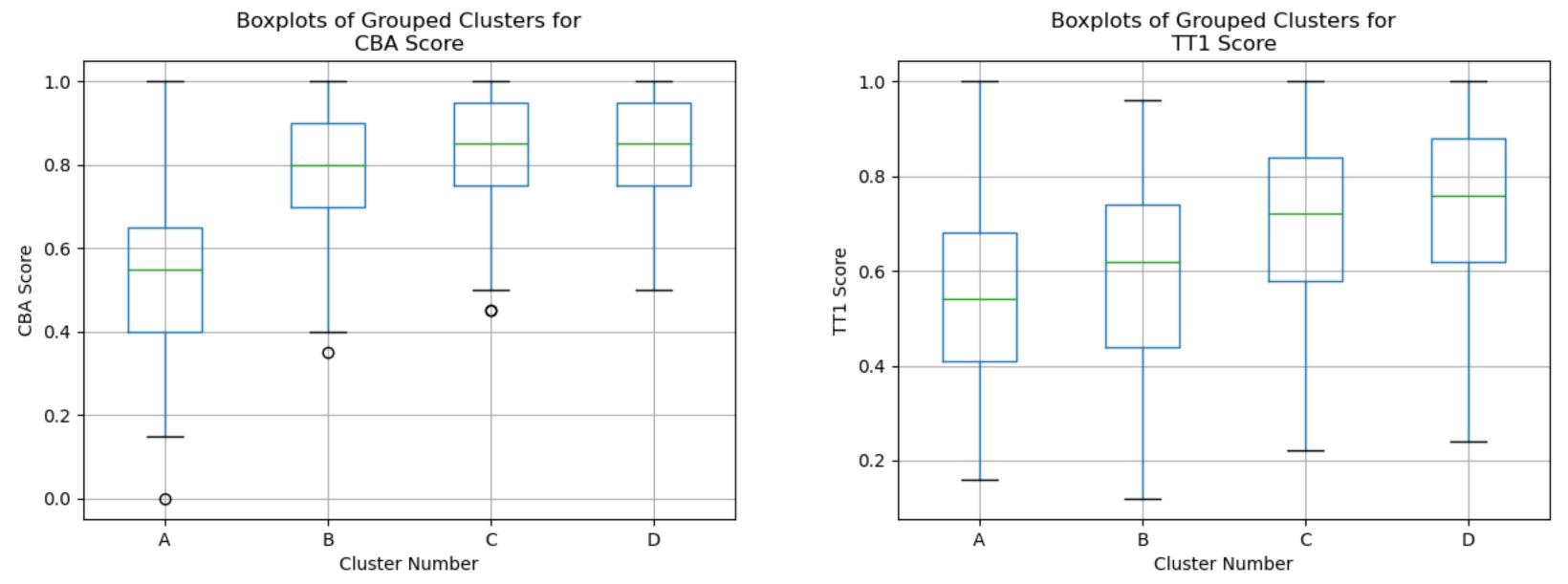
Using k-clustering:

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Tracking Cluster Performance:

 We track cluster performance across a semester for longitudinal observation.

Clustering Student Cohort



Boxplots depicting spread of student scores on math assessments when cohort is partitioned by student cluster.

Concluding Remarks

Using these clusters, targeted student interventions can be designed by instructors.

Future CBA implementations can allow for these interventions and supports to be automatically delivered upon completion.

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THANK YOU FOR YOUR TIME!

Please ask away with any questions you may have!

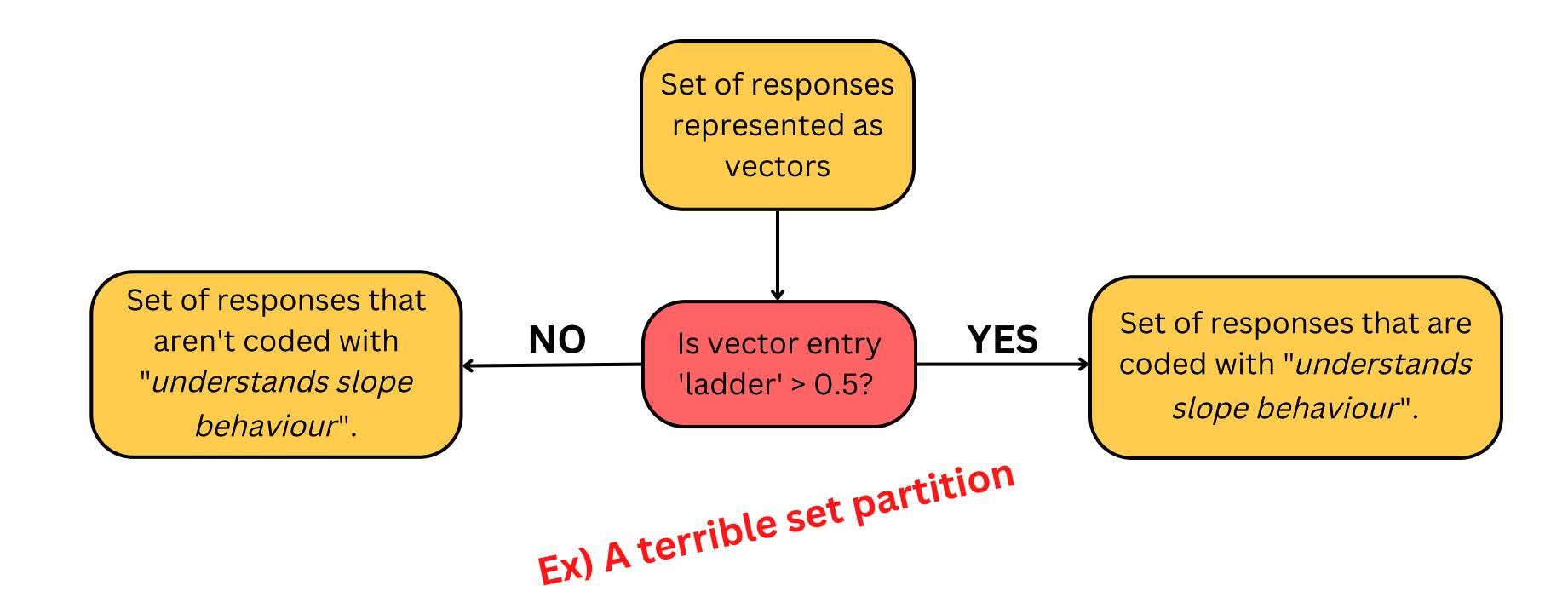
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Or visit our Github for a demo!



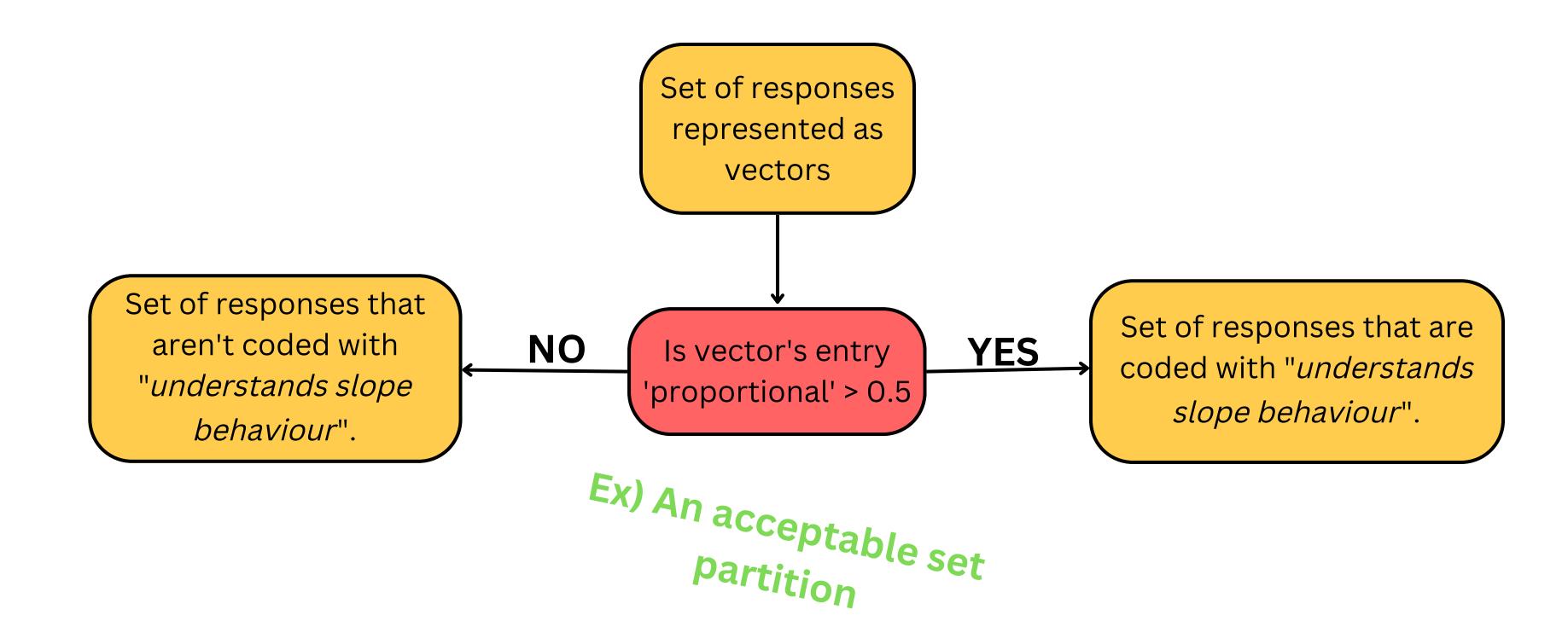
Gradient Boosting Machine Classification

- The GBM is a decision tree that classifies the vector data.
 - The GBMs classification attempts to properly sort the labeled input.
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 - The GBMs classification attempts to properly sort the labeled input.
 - It does this by partitioning the data with a one dimensional hyper-plane.
- Hundreds are built and discarded as a best classifier is iteratively designed.
 - Weak learners support the tree by reclassifying residuals.
- Separate, parallel GBMs must be trained for each code.
- Cross-validation grid search finds each model's best parameters:
 - oparameters: sample size, tree depth, number of estimators, learning rate.
- Using the trained model:
 - Influential tokens for partitioning can be examined.
 - New data can be automatically coded by the model.