Video-watching behavior vs student performance

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Objectives

- Understand student’s performance on in-video quizzes from student video-watching behavior on online course

- Predict whether user will be CFA (correct on first attempt) in answering question from student performance in MOOC (massive open online courses)

Overview

1. Dataset
2. Problem 1: How well can students be naturally grouped or clustered by their video-watching behavior?
    a. Models discussed: t-SNE, K-means
3. Problem 2: Can student's video-watching behavior be used to predict student's performance?
    a. Models discussed: Polynomial ridge regression, simple neural network
4. Problem 3: How well can you predict a student's performance on a particular in-video quiz question?
    a. Models discussed: Random Forest

Dataset

Features examined for a student – video pair: userID, videoID, fracSpent, fracComp, fracPaused, numPauses, avgPBR, numRWs, numFFs, s

- fracSpent: total time spent watching video divided by length of video
- fracComp: fraction of video watched (0 to 1)
- fracPaused: time student paused on video divided by length of video
- numPauses: number of times student paused video
- avgPBR: average playback rate (0.5x to 2.0x)
- numRWs: number of times student rewinds
- numFFs: number of times student fast forwards
- s: student answered question correct or incorrect (1 or 0) immediately after video

3976 students, 0-92 videos, 29,304 student-video pairs in dataset

Problem 1: How well can students be naturally grouped or clustered by video-watching behavior?

Only students that completed at least 5 videos were used.
t-SNE model used: t-distributed stochastic neighbor embedding (sklearn Python package)

- t-SNE is technique that helps in visualizing complex, high-dimensional data by reducing it to two or three dimensions while preserving the structure and relationships in the data.
- Step 1) Pairwise-similarities
- Step 2) Lower-dimensional representation
- Step 3) Optimization Algorithm
- Benefits of model:
  - Preserves local structures: similar points in high-dimensional space remain close together in lower-dimensional space
  - Helps uncover patterns / clusters / outliers in high-dimensional space
- Limitations:
  - Can be slow, especially for larger datasets
  - Not deterministic: stochastic nature so different results on different runs

Analogy: It is like flattening a crumpled piece of paper

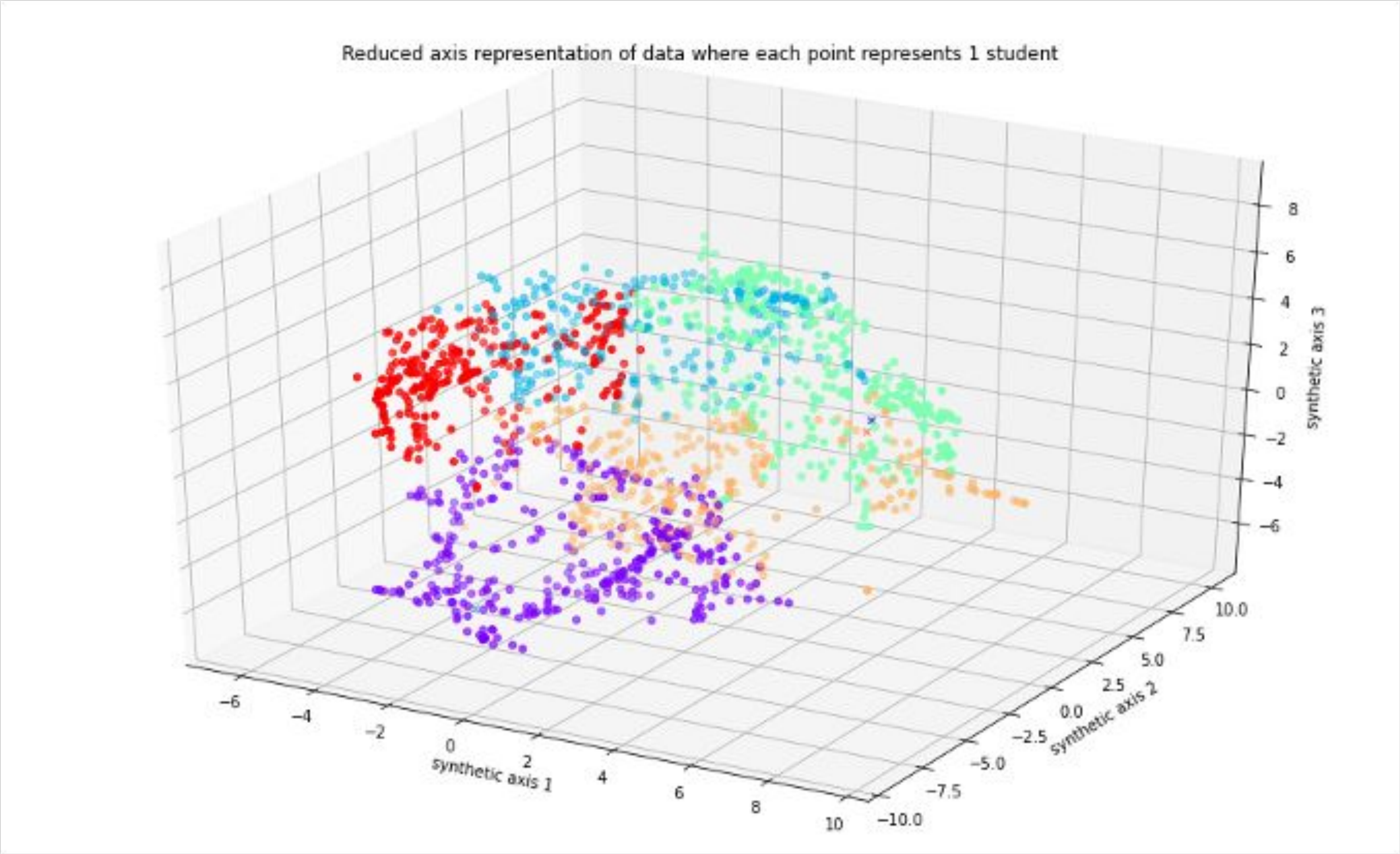


Figure 1: TSNE representing video-watching behavior features reduced to 3 dimensions

K-means

Clustering algorithm used to partition dataset into k distinct clusters based on feature similarity

Goal: group similar data points together

How it works:

- Randomly select k initial centroids
- Assign each data point to nearest centroid based on distance
- Calculate new centroids by taking mean of data points assigned to each cluster
- Repeat the assignment and update steps until convergence

Output: k clusters and each data point assigned to a cluster

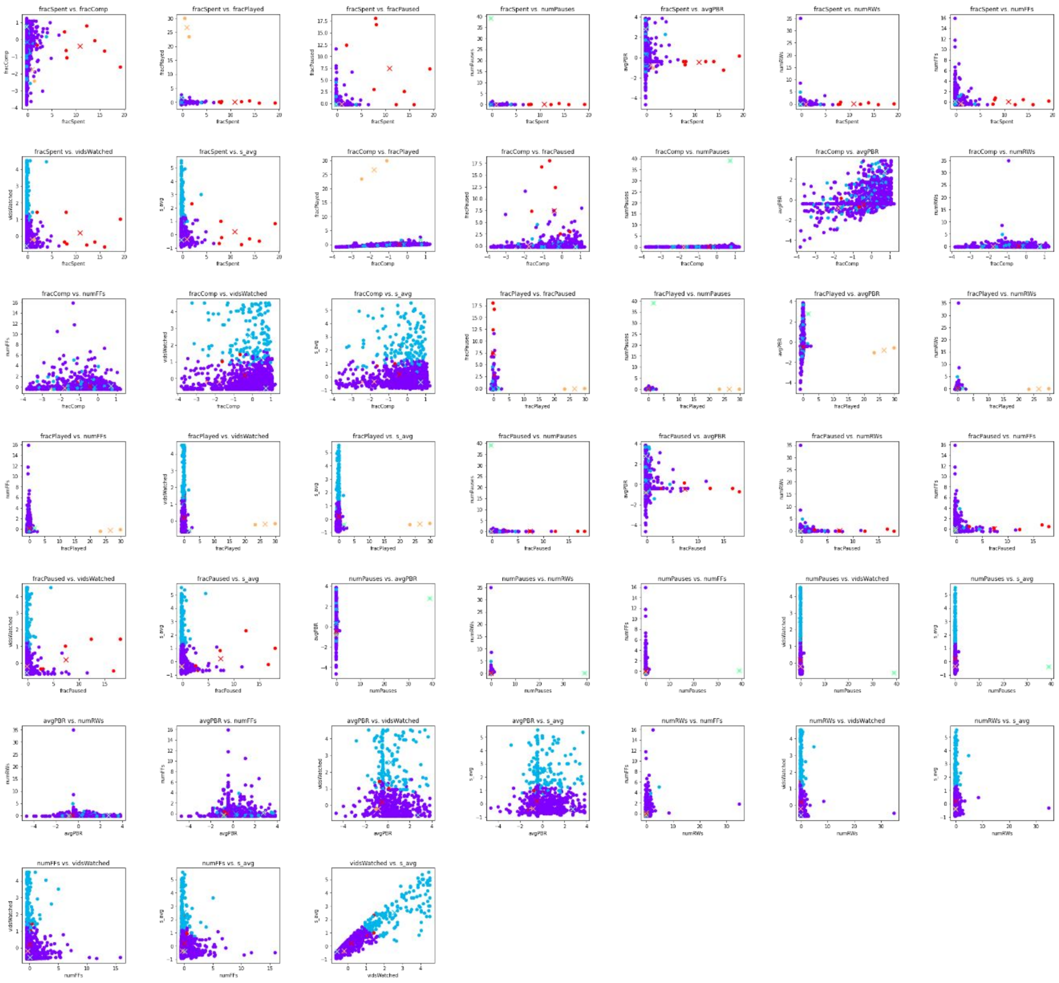


Figure 2: K means output plotting video-watching behavior features against each other

Problem 2: Can student's video-watching behavior be used to predict student's performance?

- All students that complete at least half of quizzes were used (students who watch at least half of total videos)
- Polynomial ridge regression model to predict future student's performance given video-watching behavior parameters
  - Purpose: Polynomial model while applying ridge regularization to control for overfitting
    - Polynomial regression: model relationship between input features and output as an nth degree polynomial
    - Ridge regression: linear regression that includes regularization term (lambda) to prevent overfitting
    - Cost function has an added penalty term
  - Benefits of model:
    - Preventing overfitting
    - Generalizes better to unseen data
    - Fit non-linear relationships
  - Limitations:
    - complex with higher degree polynomials

$$\text{Cost} = \sum_{i=1}^{m}(y_i - \hat{y}_i)^2 + \lambda\sum_{j=1}^{n}\beta_j^2$$

$$y = \beta_0 + \beta_1 x + \beta_2 x^2 + \beta_3 x^3 + \ldots + \beta_n x^n + \epsilon$$

Develop / Train model

Step 1) Import libraries

- import matplotlib.pyplot as plt
- import numpy as np
- import seaborn as sns
- from sklearn.pipeline import make_pipeline
- from sklearn.linear_model import Ridge
- from sklearn.preprocessing import PolynomialFeatures

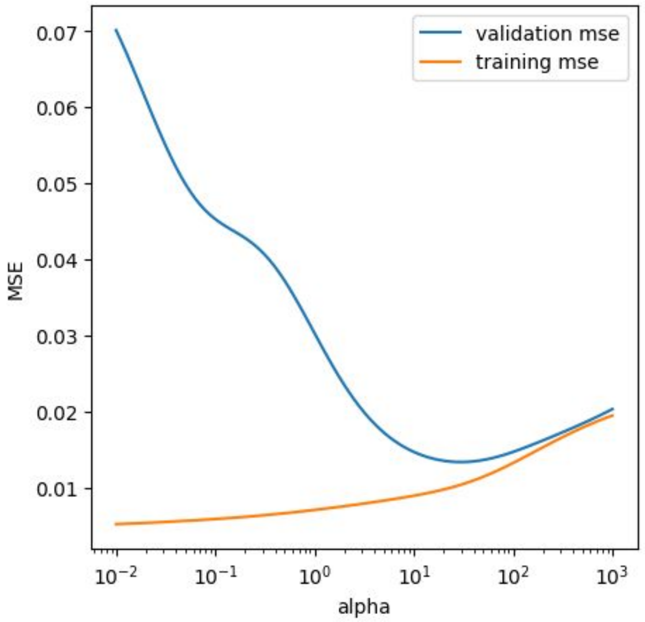
Step 2) Working with dataset

- Get dataset and split into training, testing dataset

Step 3) create polynomial and ridge regression model

- transform original input features into polynomial features
- use ridge regression on transformed polynomial feature set

Step 4) Train / tune model



Evaluation of model

- MSE (mean squared error) is metric used to evaluate regression models
  - Measures the average of the squares of the errors

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y_i})^2$$

n = number of samples in training dataset

y_i = ground truth

$\hat{y_i}$ = predicted value

  - Lower MSE indicates better model
  - From polynomial regression model, MSE = 0.0097

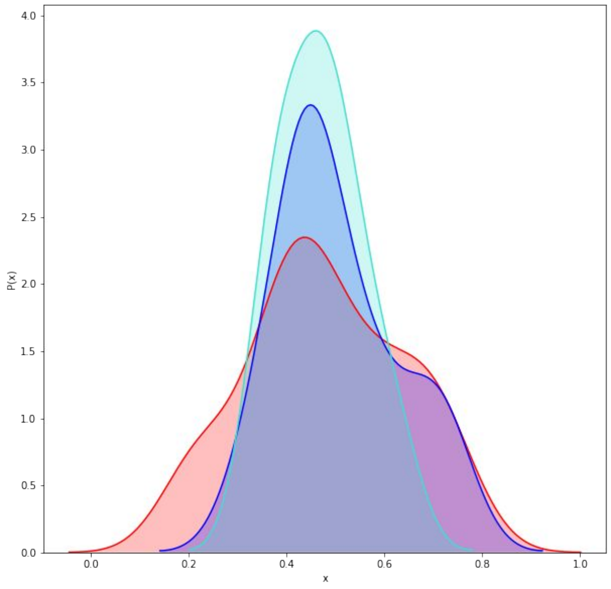


Figure 4: Polynomial Ridge Regression Probability Distribution

(Red: Training, Blue: Testing, Turquoise: Predicted)

Problem 2: Can student's video-watching behavior be used to predict student's performance?

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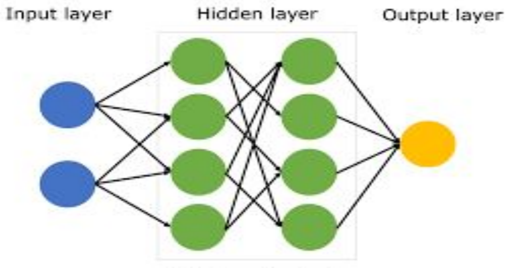
Simple Neural Network

- A neural network is a sequence of layered neurons in which each neuron is a linear function with a non-linear activation function.
- Key feature is neurons can learn from process called back propagation which uses an error/loss function to guide network in its learning process
- Allows model to fit non-linear features of dataset
- Result: MSE = 0.0065



Conclusion: From both approaches, there is a relationship between students' video watching behavior and their overall performance on video quizzes considering low MSE values.

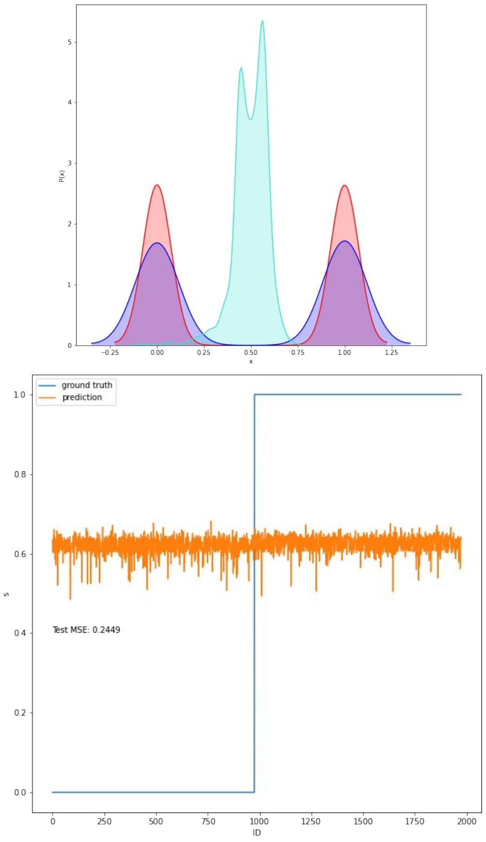
Problem 3: How well can you predict a student's performance on a particular in-video quiz question?

Random Forest classifier

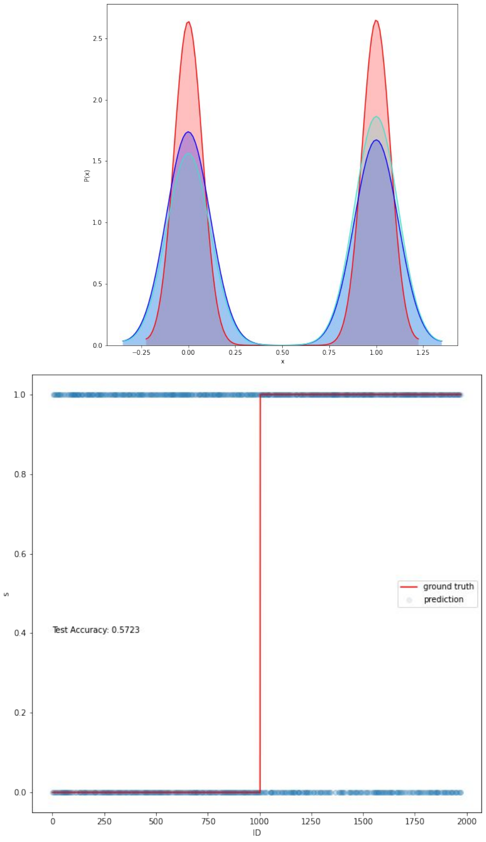
- Purpose: classification model from building a set of decision trees and outputs a class label (0 or 1 since we are interested in binary classification)
- Observations from model: combines multiple individual trees, each tree is trained on a random sample of training data
- Benefits of model:
  - high accuracy
  - less overfitting
- Limitations:
  - complex and computationally intensive

Other models tried:

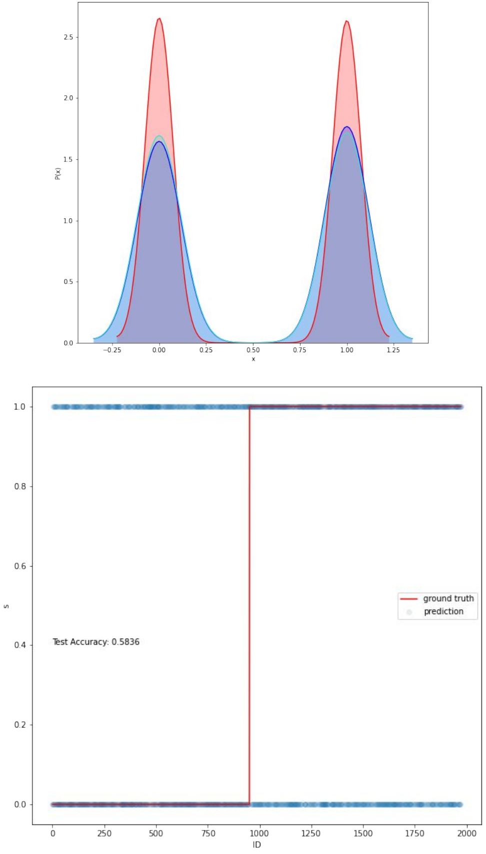
- Linear Ridge Regression model
- Logistic regression model
- Gaussian Bayes model
- kNN model
- Multinomial Naïve Bayes model
- Neural network



Linear Regression



Logistic Ridge Regression



Random Forest

Evaluation