COVID-19 Effect on Student Performance

Team 4
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COVID-19 RESPONSE

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Introduction

- Problem: COVID-19 and other factors' effect on test performance of students.

- Dataset we have (Portland Oregon):
  - 6 subject scores for 1400 Students over 6 semester (online and in-person semesters).
  - School, grade level, gender, covid infection, household income
  - Family size, parent education levels, free lunch, number of computers

- Methods:
  - Statistical Analysis – T-test, ANOVA
  - Predictive Methods – regression, decision tree, random forest, fixed effect model, interactive effect model
  - Exploratory and Causal Inference Methods – clustering, casual inference

- Challenges: Sample representation, characteristics of students is somewhat limited.

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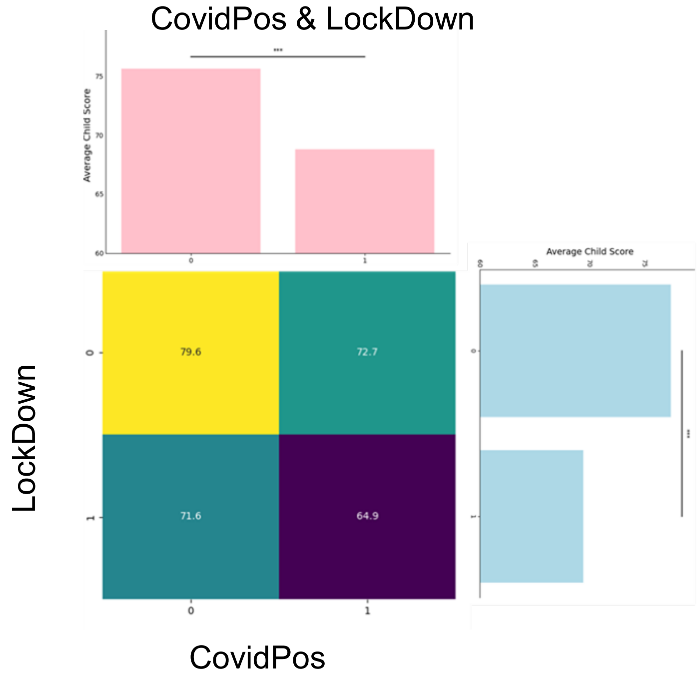
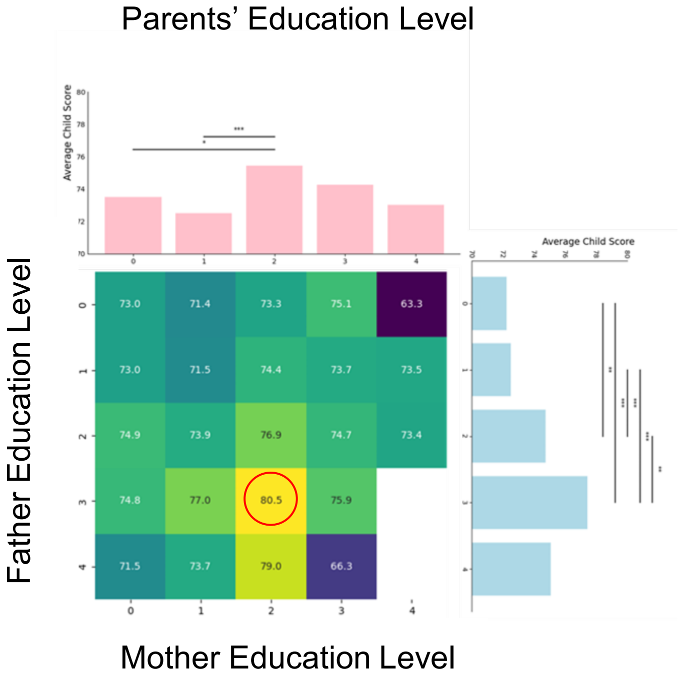
Statistical Analysis





- Apply one-way anova and Tukey's HSD test on 4 interesting inputs
- Parents education level has influence on students' score but not directly linearly correlated
- Lockdown and Covid positive significantly decreased the average score

Linear Regression & Logistic Regression

Table 3: Linear Regression Between Various Factors and Average Course Scores.

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Factor	Pre-lockdown			Post-lockdown		
	Coef	Std Err	P-value	Coef	Std Err	P-value
const	73.4175	0.934	0.000***	65.3653	0.932	0.000***
school	-6.5033	0.435	0.000***	-6.2920	0.436	0.000***
gradelevel	0.0371	0.055	0.501	-0.0218	0.055	0.692
gender	0.4624	0.220	0.036**	0.2522	0.220	0.252
covidpos	-2.7809	0.254	0.000***	-2.5538	0.254	0.000***
householdincome	9.8695	0.981	0.000***	10.1047	0.982	0.000***
freelunch	0.5032	0.348	0.149	0.8220	0.349	0.019**
numcomputers	0.0703	0.079	0.374	0.0745	0.079	0.347
familysize	-0.4493	0.105	0.000***	-0.3729	0.105	0.000***
fathereduc	1.4546	0.135	0.000***	1.7225	0.140	0.000***
mothereduc	1.0320	0.134	0.000***	0.7025	0.131	0.000***

Table 4: Logistic Regression Between Various Factors and Average Course Scores.

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Factor	Pre-lockdown			Post-lockdown		
	Coef	Std Err	P-value	Coef	Std Err	P-value
const	-4.2208	0.978	0.000***	-2.4253	0.952	0.011**
school	-2.7584	0.378	0.000***	-2.7925	0.377	0.000***
gradelevel	0.0798	0.058	0.172	-0.0424	0.057	0.455
gender	0.3660	0.230	0.111	-0.0221	0.223	0.921
covidpos	-1.6358	0.256	0.000***	-1.4687	0.250	0.000***
householdincome	6.4237	1.123	0.000***	6.6083	1.110	0.000***
freelunch	0.4038	0.422	0.339	0.2675	0.401	0.505
numcomputers	0.0510	0.082	0.535	-0.0002	0.081	0.998
familysize	-0.0181	0.110	0.870	-0.2675	0.109	0.014**
fathereduc	0.8125	0.147	0.000***	1.0420	0.150	0.000***
mothereduc	0.5351	0.141	0.000***	0.4047	0.133	0.002***

- Significant factors: school type, COVID-19 infection, household income, and parental education levels
- The lockdown **enhanced** the influence of **household income** and **father's education level** but **reduced** the impacts of **COVID-19 infection** and **mother's education level**.

Interaction and Fixed Effect Model

$$Grade = \beta_0\, Covid + \beta_1\, Female + \epsilon$$

$$\frac{\partial\, Grade}{\partial\, Female} = \beta_1$$

$$Grade = \beta_0\, Covid + \beta_1\, Female + \beta_3\, Covid \times Female + \upsilon$$

With Interactions:

$$\frac{\partial\, Grade}{\partial\, Female} = \beta_1 + \beta_3\, Covid$$

$$Grade = \beta_0\, Online\ Semester + \beta\, Student\ Dummys + \epsilon$$

Fig. 5. Fixed Effect regression on Average Course Scores. Standard errors are in the parenthesis.

	Model 1	Model 2
Online (=1)		-8.008***(0.141)
Constant	76.199***(2.693)	80.203***(2.389)
Individual Fixed Effect	✓	✓
R2	.47	.637
Observations	8,400	8,400

*p < 0.1, **p < 0.05, ***p < 0.01

	(1) scoreSL	(2) readingsco~L	(3) writingsco~L	(4) mathscoreSL
COVID (=1)	-3.238*	-2.947**	-3.307**	-3.460*
	(0.0675)	(0.0142)	(0.0357)	(0.252)
Female (=1)	-3.335**	-3.301**	-3.188***	-3.517*
	(0.0242)	(0.0152)	(0.00397)	(0.0840)
Poor School	-0.844*	-1.309*	-2.079	0.856*
	(0.0598)	(0.0645)	(0.164)	(0.0495)
HHIncome	0.0767**	0.0880**	0.0711**	0.0708***
	(0.000563)	(0.000523)	(0.00111)	(0.0000598)
Female X Covid	0.323	0.292	0.145	0.531
	(0.141)	(0.0613)	(0.0512)	(0.537)
Poor School X Covid	0.0946	-0.103*	0.193	0.193**
	(0.00764)	(0.00562)	(0.0179)	(0.000567)
Female X Poor School	0.537	0.545*	0.566*	0.499
	(0.0444)	(0.0322)	(0.0366)	(0.202)
Poor School X HHIncome	-0.0699**	-0.0799**	-0.0618*	-0.0680**
	(0.000774)	(0.000556)	(0.00137)	(0.000399)
Constant	72.09**	70.58**	74.05**	71.63***
	(0.336)	(0.234)	(0.849)	(0.0759)
R2	.551	.353	.306	.234
Observations	8,400	8,400	8,400	8,400
Time Fixed Effect	Yes	Yes	Yes	Yes
Father's Education FE	Yes	Yes	Yes	Yes
Mother's Education FE	Yes	Yes	Yes	Yes

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

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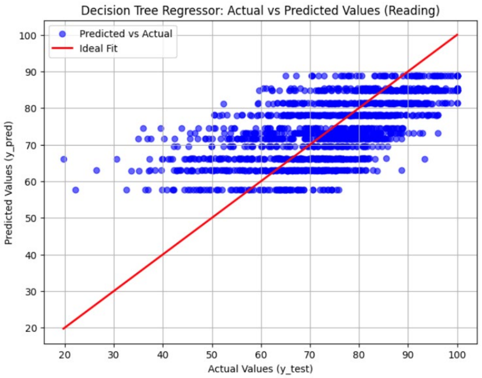
AVGB: average score before the lockdown
AVGA: average score after the lock down

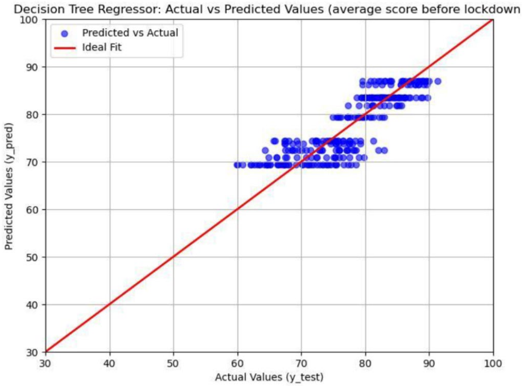
Decision Tree & Random Forest

Table 5: Performance metrics for decision tree and random forest

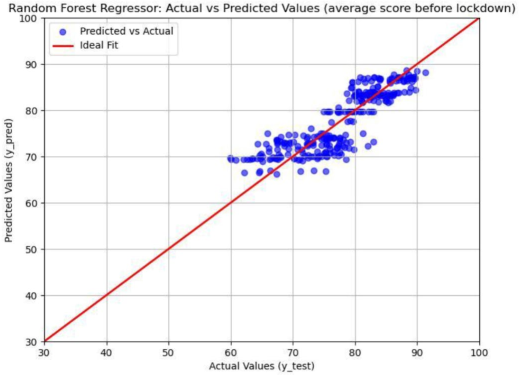
Model	Decision Tree								Random Forest	
Metric	Read	Write	Math	RSL	WSL	MSL	**AVGB**	**AVGA**	**AVGB**	**AVGA**
MSE	111.13	128.86	131.19	123.38	120.88	153.11	**14.34**	14.86	13.71	**13.05**
R^2	0.37	0.34	0.27	0.33	0.28	0.21	**0.73**	0.70	**0.74**	0.74



(a) Reading



(a) Before Lockdown



(c) Before Lockdown

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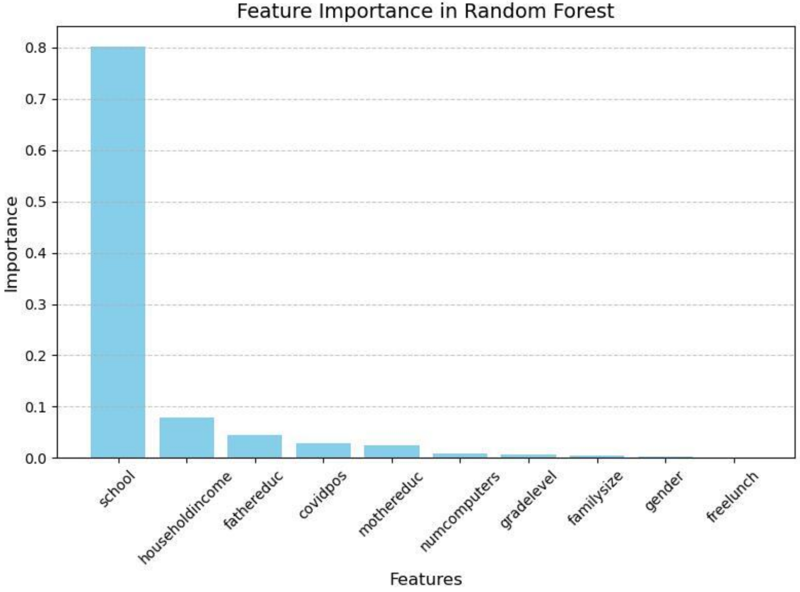
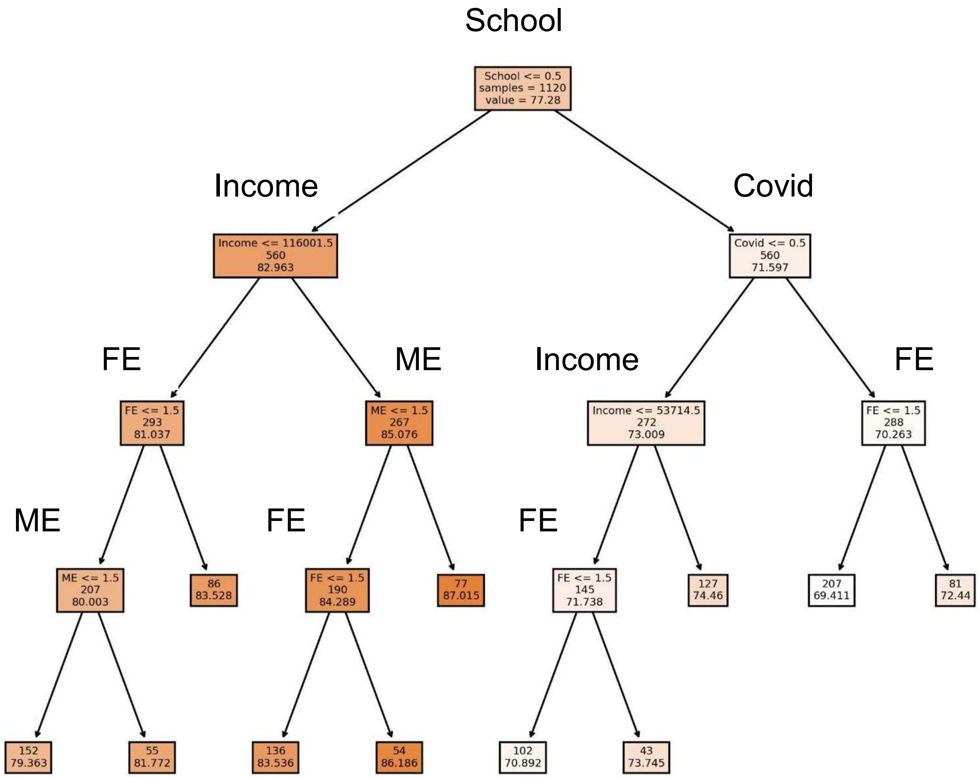
Decision Tree & Random Forest

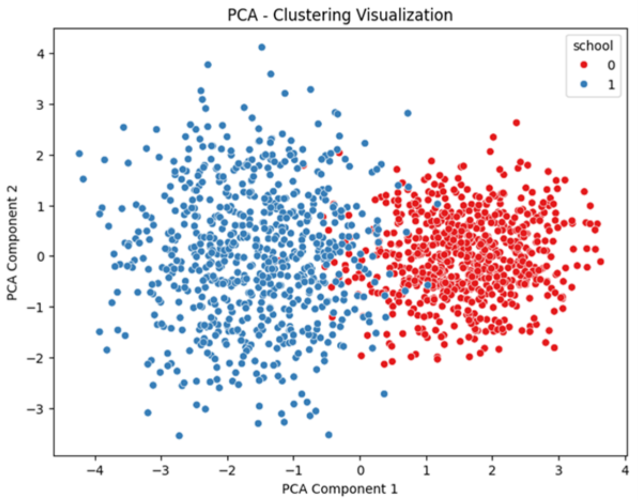
FE: father education level
ME: mother education level





Clustering

- School is a large factor in effectively differentiating student groups.
- Clusters show better accuracy to their school and the family's economic status than the student's learning method.



Predicted Cluster	Learning Mode		School		Income	
	In person	Online	0	1	High	Low
Cluster 0	3071	1808	3593	1286	3484	1395
Cluster 1	1129	2392	607	2914	716	2805

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Causal Inference

- We conducted causal inference using a **Directed Acyclic Graph (DAG)**
- We treated each factor as a **cause** while controlling other factors as **confounders**.
- The **backdoor criterion** identified causal effects, quantified by **linear regression**.
- A **placebo treatment** was used to assess robustness and rule out noise or bias.

Table 6: The Estimated Causal Effects and Placebo Treatment Results.

Factor	Pre-lockdown			Post-lockdown		
	Estimated Effect	Placebo Effect	P-value	Estimated Effect	Placebo Effect	P-value
school	-6.7524	-0.0124	0.94	-6.3525	0.0019	1.00
gradelevel	0.0275	-0.0025	0.98	-0.0474	-0.0018	0.92
gender	0.3739	-0.0189	0.76	0.2626	0.0245	0.96
covidpos	-2.6148	-0.0338	0.94	-2.4209	-0.0059	0.98
householdincome	9.9288	-9.9e-14	0.00	10.2544	-1.9e-13	0.00
freelunch	0.1505	-0.0184	0.78	0.5106	-0.0291	0.90
numcomputers	0.0418	-0.0003	0.98	0.0676	-0.0037	0.98
familysize	-0.4077	0.0082	0.78	-0.4205	0.0001	0.88
fathereduc	1.4483	-0.0036	0.88	1.7163	-0.0071	0.98
mothereduc	0.9779	-0.0018	0.98	0.6525	-0.0098	0.86

- The ratio of the estimated causal effect to the placebo effect for **household income** is significantly larger
- It indicates a robust causal relationship between **household income** and **student performance**.
- This effect is **further amplified** by the **COVID-19 lockdown**, highlighting **social inequities** during the crisis.

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Comparison

Table 7: The comparison of different regression methods.

Method	Pre-lockdown				Post-lockdown			
	MSE	R2	RSS	RSE	MSE	R2	RSS	RSE
Linear Regression	12.79	0.7388	3580	0.2224	12.33	0.7319	3451	0.2184
DecisionTree	14.34	0.7258	4014	1.6945	14.86	0.7039	4160	1.7251
RandomForest	13.71	0.7378	3839	1.6571	13.05	0.7398	3655	1.6169

Table 8: The comparison of different classification methods.

Method	Pre-lockdown				Post-lockdown			
	Accuracy	Precision	Recall	F1	Accuracy	Precision	Recall	F1
Logistic Regression	0.9393	0.94	0.94	0.9416	0.9107	0.91	0.91	0.9141
DecisionTree	0.8893	0.89	0.88	0.8864	0.9036	0.92	0.90	0.9078
RandomForest	0.9214	0.96	0.89	0.9225	0.9071	0.92	0.90	0.9110

- Decision trees are prone to **overfitting** but offer **good interpretability**.
- Random forests **improve performance** through ensemble methods but **lack interpretability**.
- Simple linear regression is effective and interpretable for **linear data** but fails with **non-linear data**.

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Conclusion

- Different methods consistently highlight the importance of **school type**, **household income**, **parental education**, and **COVID-19 infection**

- It underscores the **strong impact of economic and social conditions** on student performance.

- The COVID-19 lockdown **further amplified** these influences, exacerbating educational inequities.

- Policymakers should consider measures to **promote social fairness**, such as subsidies for low-income families and increased investment in public schools.

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Contribution

- Anubhav Dhakal: Interaction and Fixed effect analysis, Statistical Analysis
- Nick Li: Literature Review, PCA tests, Clustering, Conclusion
- Sihan Lyu: Statistical Analysis, Decision Trees, Random Forest, Conclusion
- Hung Anh Vu: Challenges, Statistical analysis, Decision Trees, Conclusion
- Yiqing Wang: Problem Statement, Statistical Analysis, Linear & Logistic Regression, Causal Inference, Conclusion

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Thank you for your attention!

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