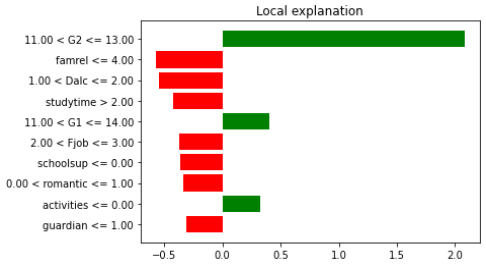
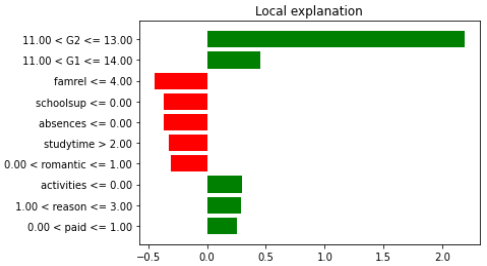
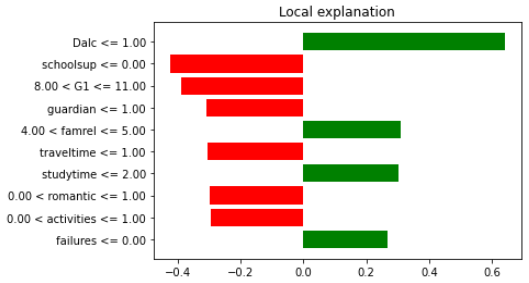
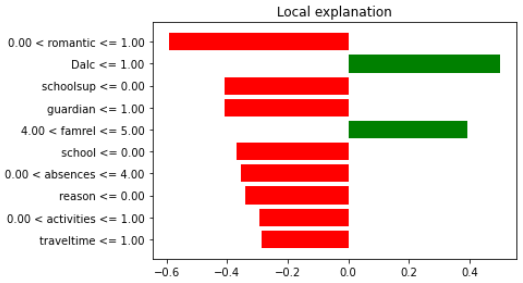
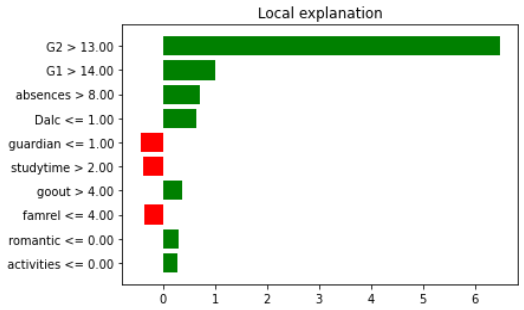
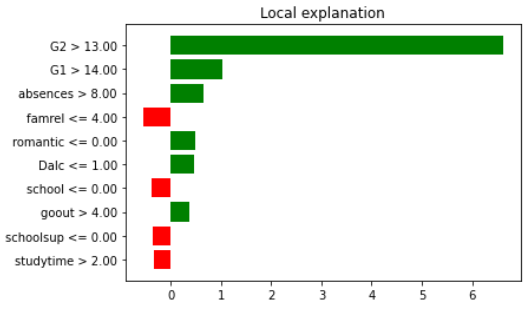
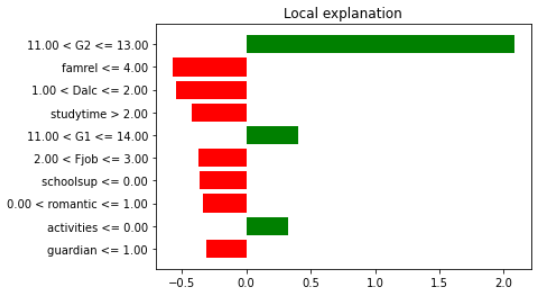
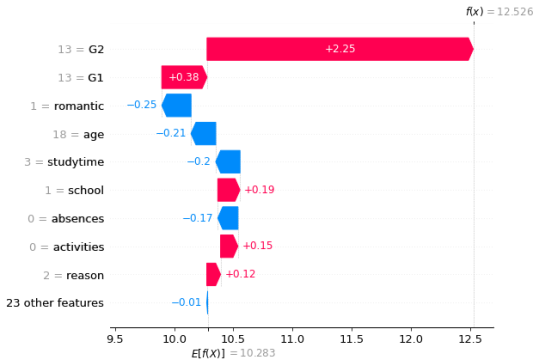
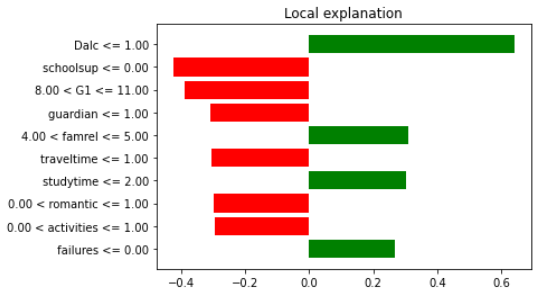
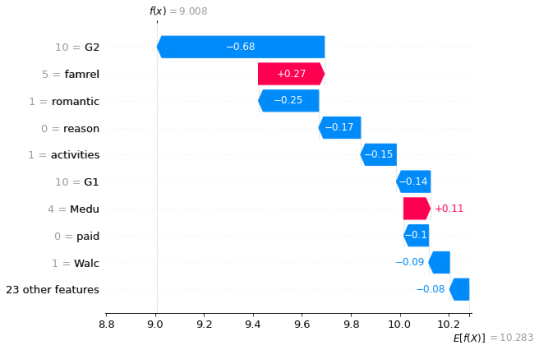
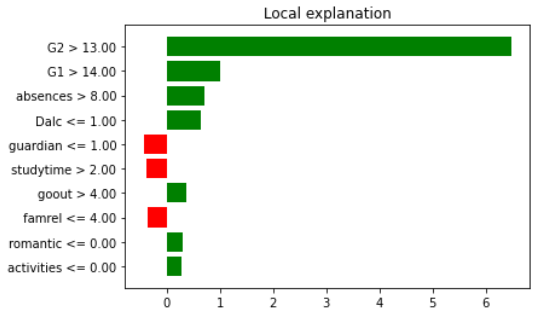
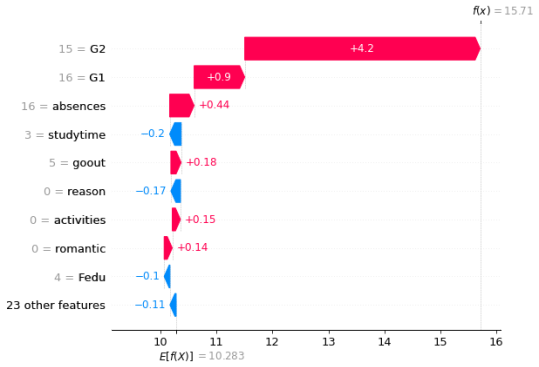
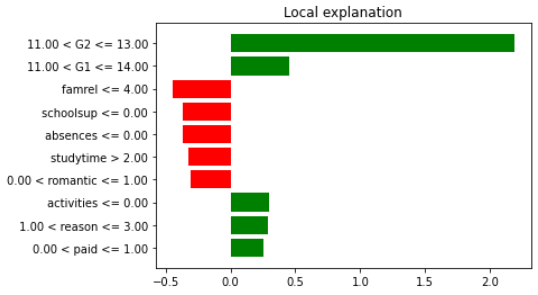
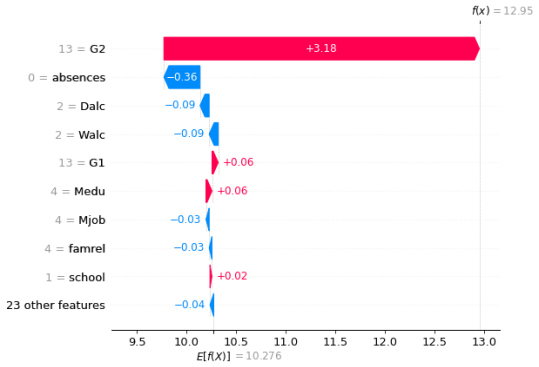
3. Compare LIME for various observations in the dataset. How stable are these explanations?
5. Compare LIME between at least two different models. Are there any systematic differences across many observations?

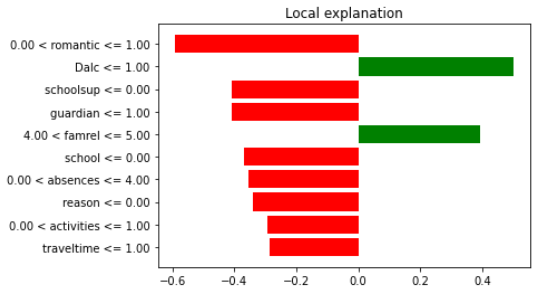
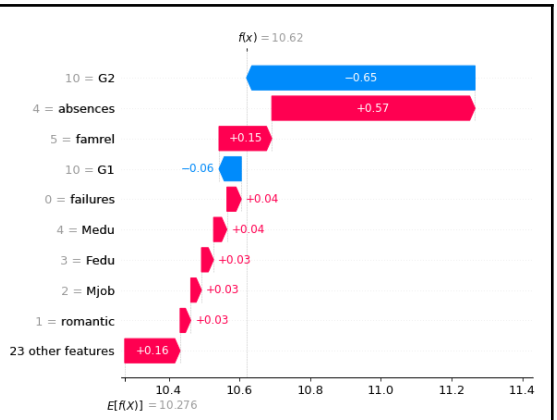
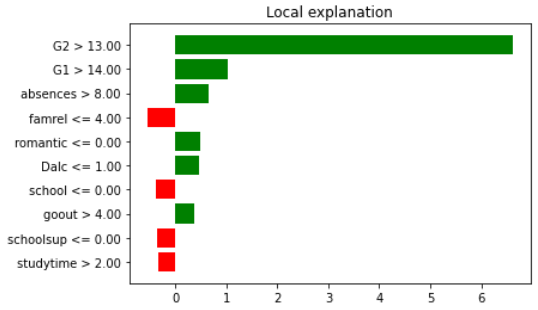
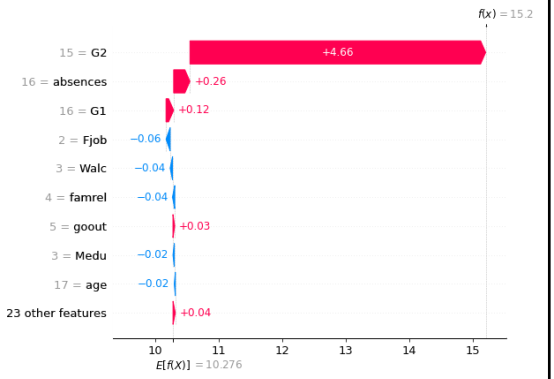
	Linear regression	Random forest
obs. 3		
obs. 33		
obs. 222		

Most of the features selected by the explainer are similar for both models. In no case did the explainer choose a feature to have a positive influence on the outcome for one model and a negative for the other. Most features' influence and relevant value range are consistent between the two models. The most important feature for samples 3 and 222 have been found to be the same one and for sample 33 Dalc (daily alcohol consumption) is first or second most important. Grades from previous semesters expectedly are found to be important for two of the samples.

4. Compare LIME with the explanations obtained using SHAP. What are the main differences between them?

	LIME	SHAP
	Linear regression	

obs. 3		
obs. 33		
obs. 222		
	Random forest	
obs. 3		

obs. 33		
obs. 222		

The main difference between the explainers is that SHAP calculates importance for all features, while LIME selects the top 10 most influential. SHAP seems to give more definite answers and differences between the most influential features, when LIME's metric gives more comparable values for the features.
When it comes to the results, what stands out the most is the fact that for sample 33 SHAP has selected grades from previous semesters as most important, consistently with the other samples, while LIME did not select them as the top two features and in case of the random forest model, did not select them at all.

6. Comment on the results obtained in (3), (4) and (5).

Across all the comparisons the two explainer methods give slightly different, yet not exclusionary results. It may be beneficial to use both of them for analyses to have a better outlook on the model's decision process.
The explainers are also able to highlight the differences between models, which may be another possible use for them.