Assignment: Feature attribution methods and their evaluation
Due: Nov 21, 2024

Note: I had permission from the professor for an extension of a few days after the date, so I'm submitting this assignment on the 23rd.

Objective

The goal of this assignment is to explore how various feature attribution methods provide explanations for model predictions and to assess their effectiveness using quantitative metrics.

Dataset

Tabular Dataset: Used the Bank Marketing Dataset from UCI on OpenML. The dataset is related with direct marketing campaigns of a Portuguese banking institution. The marketing campaigns were based on phone calls. Often, more than one contact to the same client was required, to access if the product (bank term deposit) would be ('yes') or not ('no') subscribed.

Model

To make predictions on this dataset, a specific 2 layer simple feedforward neural network was implemented.

Tasks

1. **Model Training:** Prepared and trained the model on the chosen dataset.

```
FeedForwardNetwork(
  (network): Sequential(
    (0): Linear(in_features=16, out_features=32, bias=True)
    (1): ReLU()
    (2): Linear(in_features=32, out_features=2, bias=True)
  )
)

Epoch 1, Loss: 0.2548, Accuracy: 0.8934
Epoch 2, Loss: 0.2377, Accuracy: 0.8992
Epoch 3, Loss: 0.2333, Accuracy: 0.8994
Epoch 4, Loss: 0.2311, Accuracy: 0.8994
Epoch 5, Loss: 0.2299, Accuracy: 0.9022
Epoch 6, Loss: 0.2287, Accuracy: 0.9018
Epoch 7, Loss: 0.2278, Accuracy: 0.9020
Epoch 8, Loss: 0.2266, Accuracy: 0.9039
Epoch 9, Loss: 0.2263, Accuracy: 0.9026
Epoch 10, Loss: 0.2267, Accuracy: 0.9033
Epoch 11, Loss: 0.2249, Accuracy: 0.9044
Epoch 12, Loss: 0.2254, Accuracy: 0.9023
Epoch 13, Loss: 0.2250, Accuracy: 0.9033
Epoch 14, Loss: 0.2247, Accuracy: 0.9046
Epoch 15, Loss: 0.2237, Accuracy: 0.9048
Epoch 16, Loss: 0.2240, Accuracy: 0.9049
Epoch 17, Loss: 0.2238, Accuracy: 0.9041
Epoch 18, Loss: 0.2234, Accuracy: 0.9046
Epoch 19, Loss: 0.2230, Accuracy: 0.9036
Epoch 20, Loss: 0.2229, Accuracy: 0.9038
Epoch 21, Loss: 0.2234, Accuracy: 0.9046
Epoch 22, Loss: 0.2232, Accuracy: 0.9043
Epoch 23, Loss: 0.2220, Accuracy: 0.9054
Epoch 24, Loss: 0.2224, Accuracy: 0.9051
Epoch 25, Loss: 0.2227, Accuracy: 0.9044
Test Accuracy: 0.8964
```

   1. **Explainability Analysis:**
      a. Evaluated explanations generated by the following methods: LIME, Gradient, InputXGradient, and IntegratedGradients.

b. Implemented several XAI models to monitor explainability:
   i. LIME – from [Github](). I did not find the one from Captum to work well, hence decided on using the original implementation from Github.
   ii. GradientSHAP – from [Captum]()
   iii. InputXGradients – from [Captum]()
   iv. IntegratedGradients – from [Captum]()

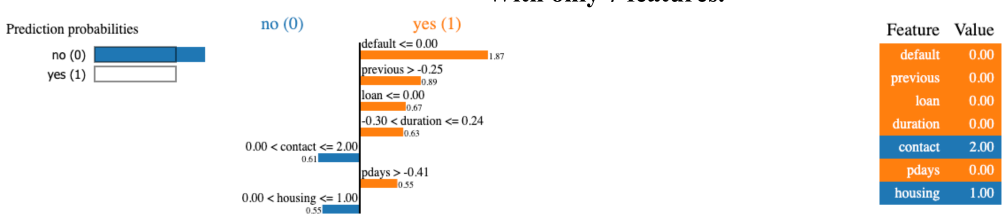
c. Confirmed the availability of these methods with the following command:
`quantus.AVAILABLE_XAI_METHODS_CAPTUM.`

```
Available XAI Methods: ['GradientShap', 'IntegratedGradients', 'DeepLift',
'DeepLiftShap', 'InputXGradient', 'Saliency', 'FeatureAblation',
'Deconvolution', 'FeaturePermutation', 'Lime', 'KernelShap', 'LRP',
'Gradient', 'Occlusion', 'LayerGradCam', 'GuidedGradCam',
'LayerConductance', 'LayerActivation', 'InternalInfluence',
'LayerGradientXActivation', 'Control Var. Sobel Filter', 'Control Var.
Constant', 'Control Var. Random Uniform']
```

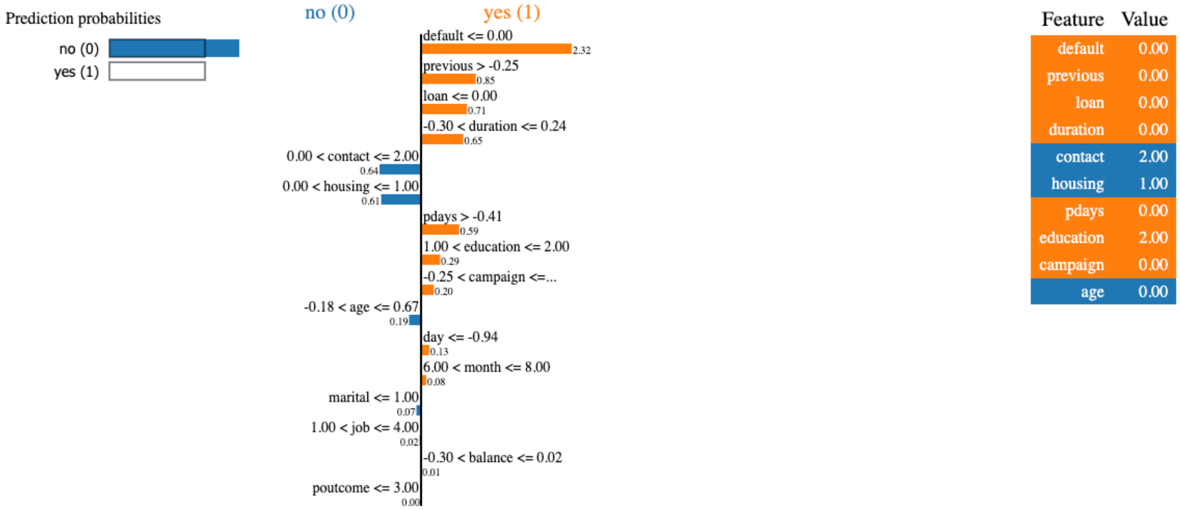
d. **Qualitative Analysis**
Generated Feature Importance Graphs for each explainable model.

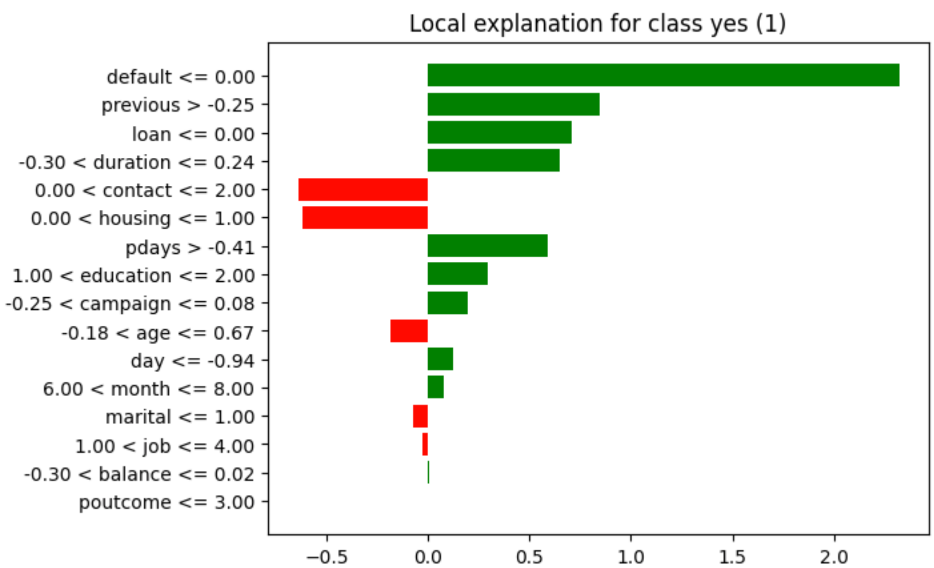
LIME:

With only 7 features.



With all 16 features.

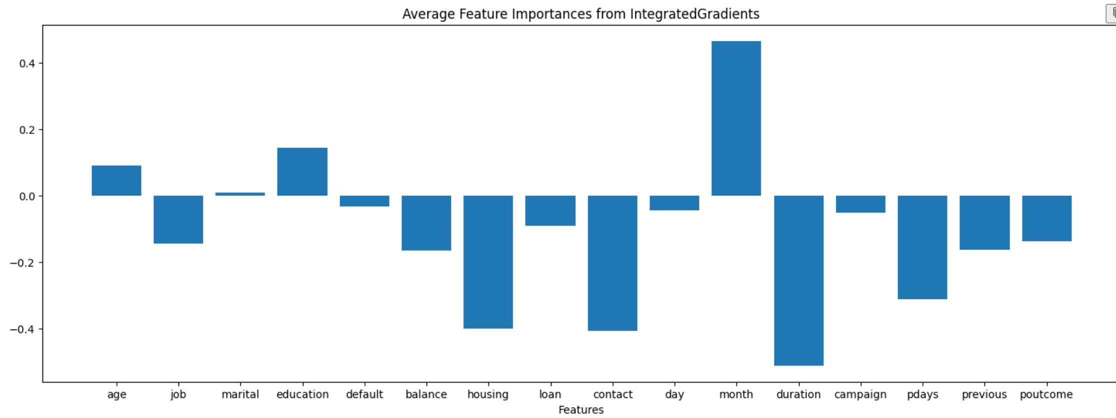




Integrated Gradients:

```
      dtype= object )
Average Feature Importances from IntegratedGradients
age :  0.091
job :  -0.144
marital :  0.010
education :  0.145
default :  -0.034
balance :  -0.167
housing :  -0.400
loan :  -0.092
contact :  -0.409
day :  -0.044
month :  0.467
duration :  -0.512
campaign :  -0.051
pdays :  -0.313
previous :  -0.163
poutcome :  -0.138
```

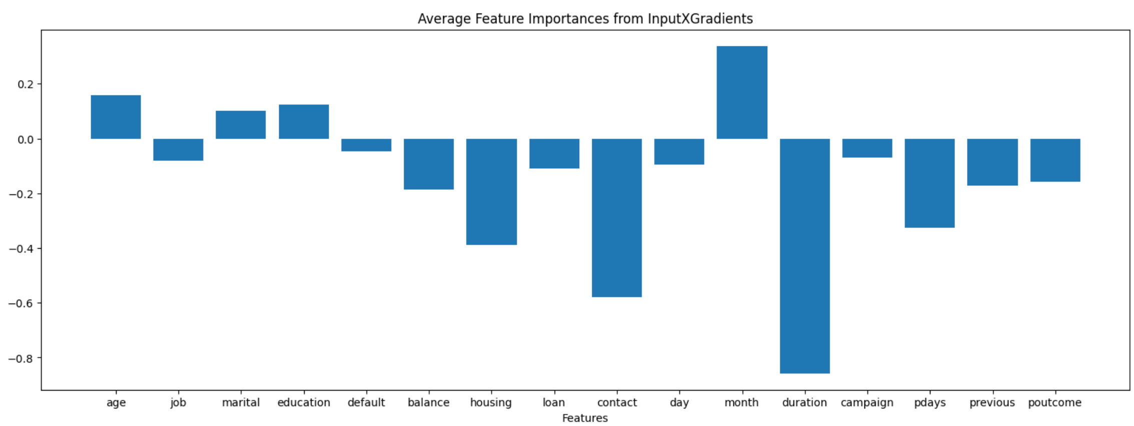
...



InputXGradients:

```
Average Feature Importances from InputXGradients
age :  0.158
job :  -0.082
marital :  0.102
education :  0.125
default :  -0.047
balance :  -0.187
housing :  -0.387
loan :  -0.109
contact :  -0.579
day :  -0.094
month :  0.339
duration :  -0.858
campaign :  -0.070
pdays :  -0.327
previous :  -0.172
poutcome :  -0.159
```

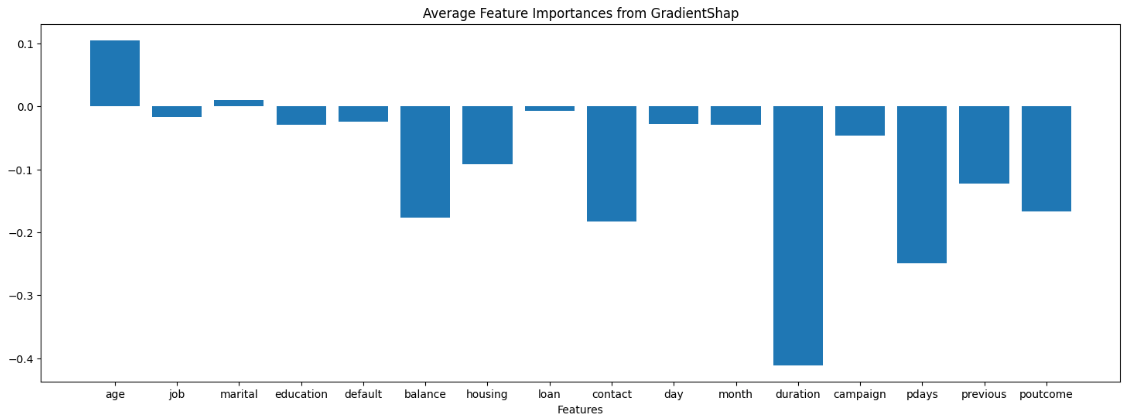
...



GradientSHAP:

```
Average Feature Importances from GradientShap
age :  0.105
job :  -0.018
marital :  0.010
education :  -0.029
default :  -0.025
balance :  -0.177
housing :  -0.092
loan :  -0.008
contact :  -0.183
day :  -0.028
month :  -0.030
duration :  -0.411
campaign :  -0.046
pdays :  -0.250
previous :  -0.122
poutcome :  -0.167
```

...



Observations

1. **LIME**:
   - LIME focuses on individual, datapoints rather than larger regions of interest.
   - In a bank marketing dataset, this might be useful to understand the predictions made for a single person, but in a different domain such as images, it might be irrelevant.
   - In my case, LIME for a singular instance gave a strong probability score for it to predict 'No' for a bank term deposit based on just 5 random features.
   - Later I used 16 features to understand the impact on a different output and it still gave me a good explanation for which features are the most useful.
2. **IntegratedGradients**:
   - This method highlights broader, continuous regions, capturing global dependencies and relationships among various features in a tabular dataset
   - For instance, in this specific case, IG demonstrated **'age', 'education' and 'month' and 'marital status'** as positive indicators to predict whether the product (bank deposit) would be subscribed or not.
   - Indeed, as a human insight, education and age holds significant importance in predicting whether an individual will make a bank term deposit. This is shown in the graph as positive values for **education** at **0.145** and **age** at **0.091**. The **most important feature** was the **month** feature with a attribution score of **0.467**
   - It effectively balances relevance across the entire object, making it suitable for comprehending the general significance of all features in the tabular dataset.

3. **InputXGradient**:
    - In an image, InputXGradient emphasizes **edges and fine details**. In the context of a **tabular dataset**, the method evaluates how changes in individual input features impact the model's output by computing the gradient of the output with respect to each input feature.
    - In my case, I have aggregated the impact into a single feature importance graph.
    - **Scale Dependency:** Inputx gradients can be influenced by the scale of input features, so normalization is often required. This is the reason for normalizing my dataset before applying XAI models on the dataset.
    - In my case, the graph is almost so **identical with IntegratedGradients**. However, the attribution values are slightly larger in comparison for some features.
    - Moreover, it solidifies education as a important predictor and confirms the findings of IntegratedGradients as both gave 'education', 'age' and 'month' higher significance.
    - All these features are important predictors in the real world of finance, thus the model is working well in predicting the output.

4. **Gradient (GradientSHAP)**:
    - Gradients focus on **edge cases** and highlight similar regions as InputXGradient but with **higher noise** and less smoothness.
    - Rightly so, in my case, GradientSHAP gave a **varying output** compared to the other three XAI models.
    - In this particular case, GradientSHAP used a normal baseline and the same parameters as the other model and yet, gave only **'age'** a positive attribution score.

XAI methods such as LIME, IntegratedGradients, InputXGradient, and GradientSHAP provide insights into model predictions. LIME and IntegratedGradients highlight individual features, while InputXGradient and GradientSHAP emphasize edges and fine details. These methods demonstrate the significance of education, age, and month in predicting bank term deposit subscriptions. Integrated Gradients excels in highlighting global explainability that captures critical object features. InputXGradient focuses on finer details, offering precise explanations but introducing slight noise. LIME, however, produced accurate point-based locally explainable graphs for feature importance. Gradient-based SHAP explanations are noisier and less interpretable than Integrated Gradients and InputXGradient. In comparison, InputXGradients and IntegratedGradients performed significantly better in explaining the model compared to the other methods.

Note: For Quantitative analysis, my code was written for tabular data as I wanted to keep my assignment unique. and I didn't find any supplemnraty material for using these specific metrics for tabular. All of them were mostly used for images online. I did try to do it for tabular which can be found in my previous github commits. Please look at them and let me know if I was on right track or not. I did ask Raghu and Dip but still couldn't figure it out for tabular. I'll be happy to add them after I figure out how to do them for tabular.

e. **Quantitative Analysis**

i. For each explanation method, evaluated the following metrics:

1. **Faithfulness Correlation:** Measures how well the explanation aligns with the model's predictions. Link: https://quantus.readthedocs.io/en/latest/docs_api/quantus.metrics.faithfulness.faithfulness_correlation.html

2. **Relative Input Stability:** Evaluates the robustness of explanations under slight input perturbations. The lower, the better. Link: https://quantus.readthedocs.io/en/latest/docs_api/quantus.metrics.robustness.html

3. **Sparsity:** Assesses the simplicity of explanations by checking how many features contribute significantly. Link: https://quantus.readthedocs.io/en/latest/docs_api/quantus.metrics.complexity.sparseness.html

ii. After computing these metrics, analyze the results. Consider the following questions:
   1. Which explanation method scores highest for faithfulness, stability, and sparsity?
   2. Is any method consistently the best across all metrics, or do trade-offs exist?
   3. Does the quantitative evaluation align with the qualitative observations?

f. Points to remember:

i. Always perform analyses on correctly classified samples to ensure meaningful and reliable insights.

ii. When calculating metrics, average the results over 500/1000 correctly classified samples to obtain robust quantitative evaluations.

Submission

Submit a report with your findings, including heat maps or tables, and a detailed analysis of each explanation method's effectiveness based on both qualitative and quantitative metrics.