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Due Apr 13 11:59pm   Available from Apr 7   45 points possible

32 Replies, 13 Unread

# Unit 4: Discussion

## Directions

Based on the assigned readings, write 2 well-thought-out paragraphs describing how you plan to use SHAP in your analytics projects in general. Also address any concerns how have about the methodology and when it might not be appropriate.

## Initial Post (DUE: Thursday 11:59 p.m. CT)

- In the initial post you will do the following:
  - Uses the weekly materials to construct an academic argument that addresses the discussion question in a thorough and logical manner.
  - Correctly uses key terms and concepts. Thoroughly addresses all components of the prompt. Ideas are clear and on-topic.
  - Follows grammar conventions. The writing is concise and easy to read.

- Writes approximately 200 words.

## Response to Two Peers (DUE: Sunday, 11:59 CT)

Respond to two posts with your viewpoints on their discussion.

- In each response, you will do the following:
  - Furthers the conversation by asking thoughtful questions, responding directly to statements of others, and contributing additional analysis. Builds on peers' contributions by presenting logical viewpoints or challenges.
  - Follows grammar conventions. The writing is concise and easy to read.
  - Writes approximately 100 words.

Please review the rubric for this assignment before beginning to ensure that you earn full credit. Contact me if you have any questions.

Reply

PN Pravalika Naathi (https://canvas.park.edu/courses/85581/users/110436)

Apr 11 11:58pm | Last edited Apr 12 12:21am | Last reply Apr 12 12:40pm

Hello class,

In analytics projects, SHAP (SHapley Additive exPlanations) It mainly provides a strong foundation to improve the understanding of machine learning models. To make sure to take down complex models and explain the importance of each specific and It mainly shows how it impacts individual predictions, I planned to use SHAP, This is most important for stakeholders who need badly to understand why an approach gets to a particular occur, fostering confidence and facilitating simple adoption of these models. For example In a credit risk framework, SHAP can identify which variables such as income and credit history have a greater effect on loan trust and how they react. If using SHAP, i will plan to go beyond "black-box" forecasts and facilitate improved predictive modeling and decision-making.

I have some doubts about the methods. In particular actual time or large-scale scenarios, the computational price can be calculating the SHAP values may be prohibitive, mainly when dealing with complex models or large datasets with high dimensions. SHAP values, however while SHAP values provide a more accurate measure of feature importance than a few other options, it may be hard non-technical people to understand. It defiantly not be suitable in some situations where the people don't know the technical skills needed to understand SHAP outputs or if model clarity is not the primary concern, such as in fully automated systems where the focus is only on predicted accuracy.

**References:**

Lundberg, S. M., & Lee, S.-I. (2017). A unified approach to interpreting model predictions. *Advances in Neural Information Processing Systems*, 30. https://proceedings.neurips.cc/paper_files/paper/2017/file/8a20a8621978632d76c43dfd28b67767-Paper.pdf

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Akhil Muvva (https://canvas.park.edu/courses/85581/users/125122)

Apr 11 10:07pm

Hi All

## Leveraging SHAP for Model Interpretability in Analytics Projects

For my subsequent analytics projects, I will use SHAP (SHapley Additive exPlanations) as a prime tool for interpreting complex machine learning models. The provision by SHAP to attribute consistent and locally accurate importance values to all model features is important when using black-box algorithms like ensemble methods and deep learning models. I will use SHAP to provide better explainability to stakeholders who lack technical expertise, making models more transparent and trustworthy. As an illustration, in a project on credit scoring, SHAP values can show exactly how particular features like income, age, or credit history contribute to a customer's risk rating. This form of explainability is particularly significant when applied to regulated sectors like finance and healthcare because model choices can carry important real-world implications (Lundberg & Lee, 2017).

Despite SHAP's benefits, I have issues with its scalability and computational expense, particularly when used with huge datasets or very complex models. SHAP values can be computationally costly, mostly with tree- or deep neural networks without efficient algorithms. In addition, there are instances when SHAP might not be the ideal tool—for instance, when there are highly correlated datasets on which attribution will be misleading because of multicollinearity. In this scenario, the interpretability would be compromised since SHAP does not inherently capture the difference between causation and correlation (Slack et al., 2020). Hence, though SHAP is an efficient tool for model interpretability, it should be applied with care and with the support of domain knowledge and alternative interpretability methods when necessary.

**References**

Lundberg, S. M., & Lee, S.-I. (2017). A unified approach to interpreting model predictions. *Advances in Neural Information Processing Systems*, *30*, 4765–4774. https://doi.org/10.48550/arXiv.1705.07874

Slack, D., Hilgard, S., Jia, E., Singh, S., & Lakkaraju, H. (2020). Fooling LIME and SHAP: Adversarial attacks on post hoc explanation methods. *Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society*, *2020*, 180–186. https://doi.org/10.1145/3375627.3375830

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NP

Nandhan Nayak Porika (https://canvas.park.edu/courses/85581/users/122876)

Apr 11 2:37pm | Last reply Apr 11 10:28pm

Hello All,

Understanding SHAP (SHapley Additive exPlanations) through decision trees, as explored in the readings, has equipped me with a powerful tool for model interpretability. I plan to use SHAP in analytics projects involving tree-based models like XGBoost and Random Forests to quantify each feature's contribution to predictions. Tree SHAP's ability to isolate individual and joint feature effects like in the XOR and AND+boost examples makes it ideal for validating model behaviour and communicating insights, especially in high-stakes domains like marketing or healthcare.

Looking ahead to my goal of becoming a product manager at Tesla or another top tech company, I see SHAP playing a crucial role in model transparency. For example, when analysing smart vehicle sensor data or user behaviour to optimize features, SHAP could help identify why certain segments prefer specific functionalities. This clarity builds trust with stakeholders and enables data-driven decisions.

However, I am cautious of SHAP's limitations particularly its computational intensity in high-dimensional models and the risk of misinterpreting correlation as causation. SHAP reflects the model's logic, not true causal relationships. I will therefore use it as a diagnostic and exploratory aid, supported by domain knowledge and other interpretability tools.

**References:**


Gross, K. (2020, April 6). *Tree-Based Models: How they work (In Plain English!)*. https://blog.dataiku.com/tree-based-models-how-they-work-in-plain-english

Molnar, C. (2023, October 31). Should we stop interpreting ML models because XAI methods are imperfect? *Mindful Modeler*. https://mindfulmodeler.substack.com/p/should-we-stop-interpreting-ml-models

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Avinash Bunga (https://canvas.park.edu/courses/85581/users/111811)

Apr 11 10:28pm

Hi Nandhan,

Your goal of becoming a product manager at Tesla is inspiring, and the way you connected that with SHAP's use in understanding model behavior was very well thought out. Your example of using SHAP to interpret smart vehicle sensor data was interesting (Alomari & Andó, 2024). I agree that this insight can help improve how electric vehicles perform and how users experience them.

There is one area in which I am curious to hear more about how SHAP might help when evaluating battery performance and charging habits in electric cars. For example:

- Can SHAP help us understand how the age of a battery affects its range or performance?
- Could it show how much the battery has been used, like usage behavior or patterns
- Can SHAP identify how many charge cycles were done using fast charging, which may wear out the battery faster?

These details are essential for people thinking about buying a used Tesla. Do you think SHAP can help them make better choices by showing the real condition of the battery (Valdes, 2025)?

You did a great job explaining SHAP's strengths and limitations. Keep it up!

All The Best,

Avinash Bunga

**References**

Alomari, Y., & Andó, M. (2024). SHAP-based insights for aerospace PHM: Temporal feature importance, dependencies, robustness, and interaction analysis. *Results in Engineering, 21*, 101834. https://doi.org/10.1016/j.rineng.2024.101834

Divya, G., Mustare, N. B., Swarupa, M. L., & Phani Kumar, K. S. V. (2025). Improving electric vehicle battery health management with explainable AI. *E3S Web of Conferences, 616*, 03030. https://doi.org/10.1051/e3sconf/202561603030

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KK

Kouame Hermann Kouame (https://canvas.park.edu/courses/85581/users/123444)

Apr 10 11:37pm | Last reply Apr 11 8:51pm

Hello Class, here is my discussion post for this week !SHAP (SHapley Additive ExPlanations) is a powerful framework for interpreting machine learning models, attributing the prediction of each instance to the contribution of each feature. Based on cooperative game theory, SHAP values provide a unified measure of feature importance by fairly distributing the impact of each feature across all possible combinations. In my analytics projects, I will plan to use SHAP to improve model interpretability, especially for complex tree-based models such as XGBoost, LightGBM, and CatBoost.(Wang, 2024). For example, I will use TreeExplainer to calculate SHAP values and generate visualizations such as summary charts, dependency diagrams, and force diagrams. These visualizations help stakeholders understand which features influence predictions, identify potential biases, and validate model behavior against domain knowledge. Additionally, SHAP interaction values can reveal the influence of feature pairs on predictions, which is useful in scenarios such as churn analysis or credit risk modeling, where interactions between variables (e.g., income and loan term) are crucial.
Although SHAP is a robust tool, it is important to note some limitations for the sake of transparency and acknowledge that our model may also have limitations. First, its computational cost can be prohibitive for large datasets or high-dimensional models, as SHAP calculations necessarily require evaluating all feature permutations. The SHAP kernel, a model-independent approximation, mitigates this problem but sacrifices accuracy for speed. Second, SHAP assumes that features are independent, which is not always the case in reality.(O'Sullivan, 2023)

Sources:

O'Sullivan, C. (2023, March 12). The limitations of SHAP - TDS Archive - Medium. *Medium*. https://medium.com/data-science/the-limitations-of-shap-703f34061d86

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GK George Kumi (https://canvas.park.edu/courses/85581/users/117082)

Apr 10 10:17pm

Hello Class,

Kindly find below my discussion for week 4.

In my analytics projects, I plan to incorporate SHAP (SHapley Additive exPlanations) to provide transparent, model-agnostic interpretations, especially when working with complex tree-based models like XGBoost or Random Forest. SHAP offers a theoretically grounded framework derived from cooperative game theory to quantify each feature's contribution to a model's prediction (Lundberg & Lee, 2017). This is particularly beneficial in projects that require stakeholder trust and model explainability common needs in areas like finance, healthcare, and government analytics. For example, if I am evaluating risk scores in a public sector project, SHAP values would allow me to justify why a specific individual received a certain risk score, fostering transparency and fairness in decision-making. The insights from the "Tree-Based Models" material further support SHAP's compatibility with gradient-boosted trees and its efficiency in visualizing local and global feature importance.

However, I remain cautious about potential concerns. One major limitation of SHAP is its computational cost when dealing with very large datasets or deep ensemble models, which may hinder real-time applications. Additionally, SHAP assumes feature independence, which can lead to misleading interpretations in datasets with highly correlated variables. In such cases, it might be more appropriate to complement SHAP with other interpretability techniques, like Partial Dependence Plots or permutation importance, to triangulate insights (Molnar, 2022). Thus, while SHAP is a powerful interpretability tool, it is not universally appropriate and should be applied with a critical understanding of its assumptions and constraints.

**References**

Lundberg, S. M., & Lee, S.-I. (2017). A Unified Approach to Interpreting Model Predictions. *Advances in Neural Information Processing Systems*, 30.

Molnar, C. (2022). *Interpretable Machine Learning: A Guide for Making Black Box Models Explainable* (2nd ed.). https://christophm.github.io/interpretable-ml-book/

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Battulga Bolormaa (https://canvas.park.edu/courses/85581/users/68062)

Apr 10 8:10pm | Last edited Apr 10 8:12pm

Hello class,

In the future, I will consider using SHAP (SHapley Additive exPlanations) to better understand how different features in a dataset influence model predictions. SHAP values offer a clear and consistent way to interpret complex machine learning models by showing how much each input variable contributes to a prediction. This is especially useful in projects involving stakeholders who may not have technical backgrounds but need to trust the outcomes. For example, if I develop a model to predict customer churn, SHAP can help explain why the model thinks a certain customer might leave by highlighting key factors like low engagement or frequent complaints. This kind of transparency can help organizations take meaningful action and improve decision-making.

A simple case might be predicting house prices: SHAP can clearly show that a house's location, number of bedrooms, and square footage contribute positively to the final predicted price, while proximity to noisy areas reduces it. This kind of transparency helps both analysts and business users understand the logic behind predictions and build trust in the model.

That said, there are some situations where SHAP may not be the best choice. For example, when working with very large datasets or real-time systems, SHAP can be slow or resource-heavy because it needs to calculate the contribution of each feature for every prediction. Also, SHAP's assumption that features are independent might not always reflect real-world data relationships, which could affect the reliability of its explanations. In these cases, simpler techniques like feature importance from decision trees or LIME may offer faster, though less detailed, alternatives. Still, when interpretation and accountability are important, I believe SHAP is one of the most powerful tools available to make machine learning more explainable.

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AA

Atit Adhikari (https://canvas.park.edu/courses/85581/users/126504)

Apr 10 7:58pm | Last reply Apr 12 9:31am

Hi everyone! In my last week's assignment, I worked with an insurance dataset from Kaggle that included information like age, sex, BMI, number of children, smoking status, and region. I used this dataset to apply different regression models such as linear, Ridge, Lasso, Elastic Net, and logistic regression. This week, I will continue using the same dataset and apply tree-based models like Random Forest and XGBoost and use SHAP to help explain how these models make predictions.

SHAP is useful because it shows how each feature (like smoking status or age) affects the prediction for every individual. This is helpful when we want to understand why the model made a certain prediction and explain it to others in a simple way. However, SHAP can be slow when working with large datasets or complex models (Massed Compute, n.d.). Also, it assumes that features are independent, which is not always true in real-world data and can lead to incorrect interpretations (O'Sullivan, 2022). Even with these concerns, I believe SHAP is a powerful tool for making machine learning models more understandable and trustworthy, especially when we need to explain results clearly to business users or decision-makers.

One of the best parts of using SHAP is that it allows us to go beyond general model accuracy and see how different features influence outcomes for each person in the dataset (DataCamp, 2023). This is especially important in areas like insurance pricing or healthcare predictions, where fairness and transparency matter. For example, using SHAP with my insurance data will help identify whether the model is unfairly favoring or penalizing certain groups based on features like region or gender. This makes SHAP not only a technical tool but also a way to check for bias and promote responsible AI practices.

References

DataCamp. (2023, June 28). *An introduction to SHAP values and machine learning interpretability*. https://www.datacamp.com/tutorial/introduction-to-shap-values-machine-learning-interpretability (https://www.datacamp.com/tutorial/introduction-to-shap-values-machine-learning-interpretability)

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Avinash Bunga (https://canvas.park.edu/courses/85581/users/111811)

Apr 10 5:04pm | Last edited Apr 10 5:04pm | Last reply Apr 10 10:57pm

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**Avinash Bunga**

**Information Systems and Business Analytics, Park University**

**CIS625HOS2P2025 Machine Learning for Business**

**Professor: Abdelmonaem Jornaz**

**April 10, 2025**

*Unit 4: Discussion*

## SHAP in Car Price and Loan Predictions

In my analytics projects, I plan to use SHAP (SHapley Additive exPlanations) to bring transparency and trust into machine learning models, mainly when predicting outcomes in the automobile domain. For example, if I build a model that estimates the resale price of used cars, SHAP can show how each feature, such as mileage, brand, or accident history, affects the final predicted price. Suppose the average used car price is $15,000, and my model predicts $17,500 for a 2024 Toyota Camry (Acerta, 2021). SHAP could explain it like this:

| Feature | SHAP Impact on Price | Explanation |
| --- | --- | --- |
| Year = 2024 | +$1,500 | A newer model year increases the value |
| Brand = Toyota | +$400 | A reliable brand reputation adds value |
| Mileage = 40,000 | +$300 | Low mileage suggests less wear and tear |
| No Accident History | +$200 | Clean record improves resale confidence |

| | | |
|---|---|---|
| Automatic Transmission | +$100 | More popular with buyers, especially in cities |
| Fuel = Gasoline | $0 | Common fuel type with a neutral effect |
| Total SHAP Effect | +$2,500 | Final prediction increase from base price |

This breakdown makes it easier for customers or dealers to understand what drives the price prediction, building trust in the system. SHAP allows each feature to "speak for itself" in the prediction, which is particularly useful in high-stakes industries like automotive pricing

That said, I do have concerns about SHAP's limitations. It can be computationally expensive on large datasets and assumes that features are independent of each other, which may not always be true in real-world data. For instance, in predicting car loan approvals, income level and employment type are often correlated. In such cases, SHAP might misattribute the influence of these features. However, when model explainability is a priority, especially in customer-facing applications, SHAP offers an intuitive and powerful way to interpret model behavior (Dev, 2024).

**References**

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Michael Oduro (https://canvas.park.edu/courses/85581/users/112167)

Apr 10 12:10pm | Last reply Apr 12 11:18am

Hello Class,

My discussion for the week.

SHAP (SHapley Additive exPlanations) is a powerful interpretability tool I plan to integrate into my analytics projects to better understand and communicate model predictions. I will use SHAP to explain how different features contribute to individual predictions in machine learning models, especially tree-based ones like XGBoost or Random Forests. This is crucial in business contexts where stakeholders require transparency and trust in predictive models, such as when justifying why a loan application was denied. By visualizing SHAP values, I can highlight the most influential drivers of outcomes, allowing for more targeted interventions or strategic decisions. I also plan to use SHAP for feature selection and debugging, as it can help identify redundant or misleading features that may be inflating model complexity or introducing bias.

However, I do have some concerns about SHAP's limitations, especially when applied to complex or correlated data. SHAP assumes feature independence in many of its approximations, which can result in misleading explanations when strong multicollinearity exists between variables. Additionally, SHAP can be computationally expensive for large datasets or deep models, which may make real-time or large-scale deployment impractical. Reference

**Reference**


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SS

Selorm Kwaku Soga (https://canvas.park.edu/courses/85581/users/73415)

Apr 10 11:24am | Last edited Apr 10 3:29pm | Last reply Apr 11 11:58pm

I'm going to use SHAP (SHapley Additive exPlanations) for better model interpretability in my analytical projects, specifically for critical areas like healthcare and finance. To give an example, if I'm building a predictive model that assesses the readmission risk among patients, I will use SHAP values to quantify what age, previous diagnoses, and treatment adherence contribute to this risk. This improves the understanding among clinicians regarding what the model is suggesting so that their decisions are more data-driven and transparent. I, too, would apply SHAP for overall feature selection. Since this will help me to identify important features, I will focus on significant variables as they can serve to clear the noise out of my model. For tree-based models, I am using TreeSHAP, which efficiently calculates exact Shapley values to ensure the precise explanation of the model. This, particularly for the regulated industries, where models are required to have clear and audited justification regarding their predictions, will add to the credibility of the developed model. For example, in credit scoring or fraud detection, the provision of a reason on why every decision has been taken makes clear sense to both stakeholders and regulators.

Yes, SHAP is potent, but I am conscious that it cannot be without faults. For example, SHAP assumptions might give rise to errors in triangulating model insights on cases where features are highly correlated or not tree models. I will be testing some alternatives, such as LIME or counterfactual explanations, whenever necessary, to cover these disadvantages so that accurate insights will be ensured.

**Reference**

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IK

Ian Koskei (https://canvas.park.edu/courses/85581/users/122159)

Apr 10 11:20am | Last reply Apr 10 3:28pm

**UNIT 4 DISCUSSION**

Shap values (SHapley Additive exPlanations) is a method based on cooperative game theory and used to increase transparency and interpretability of machine learning models (Trevisan, 2022). In my future analytics projects, I plan to use SHAP (SHapley Additive exPlanations) as a core tool for interpreting model predictions, particularly when working with tree-based models. SHAP values provide a consistent and objective way to gain insights into how a machine learning model makes predictions and which features have the greatest influence (datacamp, 2023). The ability of SHAP to offer consistent and locally accurate attributions is one of its most potent features as it facilitates the explanation of complex models to stakeholders who are both technical and non-technical. In industries like healthcare where understanding feature contributions can be crucial for both model debugging and fostering end-user trust, this degree of awareness is extremely beneficial.

Even with its many benefits, I am still concerned about the SHAP methodology's drawbacks.  Its computational complexity is one issue, especially when working with extremely complicated models where obtaining SHAP values may require sampling or approximations. SHAP's interpretability may also deteriorate in situations involving complex feature interactions or in models that are fundamentally non-additive even while it offers concise summaries and visualizations for simpler or well-behaved models.  In many situations, the explanations may also be inaccurate because they oversimplify the actual underlying processes. Datacamp(2023) states that Machine learning models are powerful but hard to interpret. However, SHAP values can help you understand how model features impact predictions.

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KF

Kwame Frempong (https://canvas.park.edu/courses/85581/users/118427)

Apr 9 11:25pm | Last reply Apr 10 1pm

Hello class,

In my analytics projects, I plan to use SHAP (SHapley Additive exPlanations) to gain a more nuanced understanding of feature contributions in complex tree-based models. SHAP offers consistency and local accuracy, allowing me to explain individual predictions while maintaining a global perspective on feature importance. This dual capability is particularly useful in domains where interpretability is critical, such as finance or healthcare. By leveraging Tree SHAP, which is optimized for decision tree models like XGBoost or LightGBM, I can efficiently compute exact Shapley values and use them to identify key drivers of outcomes, detect potential data biases, and communicate model behavior transparently to stakeholders. The intuitive visualizations provided by SHAP also enhance stakeholder trust and support data-driven decision-making.

However, I am cautious about over-relying on SHAP in contexts where its assumptions may not hold or its outputs may be misinterpreted. One concern is that SHAP values can sometimes give a false sense of causal inference when they merely reflect associations within the model. Additionally, SHAP explanations can become less reliable when features are highly correlated or when the model is unstable. In these cases, feature attributions might be misleading, suggesting relationships that aren’t robust. Therefore, I will complement SHAP with domain expertise, sensitivity analyses, and alternative interpretability methods to ensure robust insights.

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JM

Joseph Maina (https://canvas.park.edu/courses/85581/users/118606)

Apr 9 10:09pm

Hello class

When dealing with machine learning techniques in decision-making processes, the interpretability of the model is important. Shapley additive explanation (SHAP) is a powerful tool for interpreting complex machine learning models where transparency and explainability are critical. SHAP can assign each feature an important value based on the game theory principle which makes it ideal for understanding how predictors are made. Grouped features from SHAP allow an easier understanding of the model without reconstruction of the model according to Nohara et al. (2021). In my analytics project, I would employ SHAP to interpret complex machine-learning models.  SHAP can be used to break down a model's decision by quantifying the contribution of factors that influence the target using independent variables. This will not only help stakeholders trust the model but also aid in debugging and improving it by identifying unexpected feature influences. SHAP will critique the model and evaluate its performance.

SHAP also has its limitations, it is in general unrealistic to compute exact SHAP scores (Huang & Marques-Silva, 2024). Data accessibility and availability are one of these restrictions regarding ethical and technical reasons as stated by Sahatova and Balabaeva (2022). The SHAP method does not assume feature independence, some of the approximation methods used to calculate the SHAP values do assume it. SHAP values do not show how the features contribute to the observations, but rather how the features contribute to the models' predictions for the observations. SHAP analysis does not quantify the importance of predictors in the real-world problem, but rather their importance to the model's predictions (Ponce-Bobadilla et al., 2024). I would hesitate to use SHAP in cases where the model itself is poorly calibrated which could amplify confusion rather than clarifying if the underlying predictions are unreliable.

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RN Robert Nyabiti (https://canvas.park.edu/courses/85581/users/93498)

Apr 9 9:21pm

SHapley Additive exPlanations (SHAP) was introduced by Lundberg and Lee (2017) as a tool for interpreting machine learning predictions, thereby enhancing accuracy and interpretability. As an aspiring data analyst and higher education consultant, I plan to utilize SHAP not only to make data-informed decisions but also to collaborate with other stakeholders in the education field. My goal is to identify various factors that contribute to challenges in student retention and graduation rates in community colleges. Using SHAP, higher education consultants will be able to predict with considerable accuracy the number of students who may struggle to continue their studies. Furthermore, this approach will help implement measures needed to ensure that these students not only remain at two-year colleges but also successfully graduate (Soesanto, 2024) and progress to four-year degree programs.

Yadav (2024) noted that SHAP can be applied across various industries today. Despite its benefits, SHAP requires human input to fully understand behaviors that may not be accurately computed or interpreted by machine tools. Like many AI tools, SHAP has the potential to reinforce biases in the field of higher education due to issues such as biased data inputs or incomplete datasets, which can lead to mistrust and harmful outcomes (Leslie, 2019). Additionally, SHAP may not be suitable for predicting simple relationships that can be effectively modeled using basic regression techniques.

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JK Jagadeesh Korukonda (https://canvas.park.edu/courses/85581/users/116942)

Apr 9 7:19pm | Last reply Apr 12 12:18pm

Hello Class,

In future analytics projects, I plan to use SHAP (SHapley Additive exPlanations) to interpret the predictions of machine learning models, especially tree-based models like XGBoost or Random Forest. SHAP values offer a unified, model-agnostic framework grounded in cooperative game theory, allowing us to fairly attribute contributions of each feature to a prediction. This is especially important when presenting results to non-technical stakeholders, as SHAP plots—such as force plots or summary plots—can intuitively show how specific features drive individual or global predictions. In projects like fraud detection or healthcare diagnostics, where interpretability is critical, SHAP can help explain why a model flagged a particular transaction or diagnosis, potentially leading to more trust and actionable insights.

However, I have some concerns about SHAP's computational complexity, especially for large datasets or deep models. While TreeSHAP improves efficiency for tree-based models, applying SHAP to neural networks or ensembles can still be computationally expensive. Additionally, SHAP assumes feature independence, which may not hold in real-world data where multicollinearity is common. In such cases, the attribution may be misleading. Therefore, I will be cautious about interpreting SHAP values in models with high feature correlation or when working under tight computational constraints.

**Reference:**

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Thank you,

Jagadeesh. K

> **1 Reply, 1 Unread** | Reply | Mark as Unread

Ashish Thapa (https://canvas.park.edu/courses/85581/users/79401)

Apr 9 8:46am

Hello Everyone,

SHapley Additive exPlanations (SHAP) in data science is the way to explain the outcome of any machine learning model. SHAP values show how each feature affects each final prediction, the significance of each feature compared to others, and the model's reliance on the interaction between features. (Awan, 2023) I have planned to use SHAP for a better understanding and better explanation of the predictions made by the models that I will use which are Random Forest and XGBoost. When handling the complex data these models are very useful but it is very hard to know and make an understanding of why those predictions are made for, this is where SHAP comes into the play and shows us how each feature contributes to the final output for overall as well as individual predictions. I see it as highly effective when the data-driven decisions are to be taken and the explanation of why that decision is taken when presenting the decisions to an interested party which includes parties that do not have expertise on data. Also the features from SHAP will help in identifying the key features and can explain the outliers as well.

The only concern I have for using SHAP is the time it may consume when using a large dataset since it runs many calculations for estimating the feature contributions. So, the time consuming process would be my factor of concern despite SHAP being a powerful tool for clarity.

Thanks

Reference:

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Licurgo Silveira Teixeira (https://canvas.park.edu/courses/85581/users/119244)

Apr 7 5:48pm | Last reply Apr 10 1:07pm

Hello everyone.

This is my SHAP interpretation for the weekly discussion post.

The individual plans to employ SHAP, particularly Tree SHAP, in analytics projects to interpret tree-based models such as random forests, leveraging its efficiency in elucidating predictions (SHAP Documentation). However, significant challenges and limitations arise. SHAP's computational intensity, especially for complex ensembles, poses a barrier in resource-constrained settings (Dataiku Blog). Tree-based models themselves exhibit limitations: single trees risk overfitting, while ensembles sacrifice interpretability, even with SHAP's assistance (Dataiku Blog). Furthermore, SHAP may prove inappropriate for noisy datasets or non-tree-based models like neural networks, necessitating less efficient alternatives such as Kernel SHAP (SHAP Documentation). These imperfections raise concerns, though Molnar advocates for pragmatic use of such methods despite their flaws (Mindful Modeler), suggesting a balanced approach to their application.

SHAP effectively identifies key variables, such as age in credit risk models, enabling the individual to prioritize influential factors (SHAP Documentation). Yet, its assumption of variable independence presents a critical limitation. Real-world correlations, such as between income and education, can skew SHAP values, yielding misleading interpretations (Mindful Modeler). Consequently, the individual intends to integrate SHAP with exploratory analyses to address multicollinearity, ensuring reliable identification of key variables when independence cannot be reasonably assumed.

Thank you.

Licurgo Silveira Teixeira.

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