

N/A

**Auteur :** Saulas, Adrien

**Promoteur(s) :** Debruyne, Christophe

**Faculté :** Faculté des Sciences appliquées

**Diplôme :** Master : ingénieur civil en science des données, à finalité spécialisée

**Année académique :** 2023-2024

**URI/URL :** <http://hdl.handle.net/2268.2/21035>

---

*Avertissement à l'attention des usagers :*

*Tous les documents placés en accès ouvert sur le site le site MatheO sont protégés par le droit d'auteur. Conformément aux principes énoncés par la "Budapest Open Access Initiative"(BOAI, 2002), l'utilisateur du site peut lire, télécharger, copier, transmettre, imprimer, chercher ou faire un lien vers le texte intégral de ces documents, les disséquer pour les indexer, s'en servir de données pour un logiciel, ou s'en servir à toute autre fin légale (ou prévue par la réglementation relative au droit d'auteur). Toute utilisation du document à des fins commerciales est strictement interdite.*

*Par ailleurs, l'utilisateur s'engage à respecter les droits moraux de l'auteur, principalement le droit à l'intégrité de l'oeuvre et le droit de paternité et ce dans toute utilisation que l'utilisateur entreprend. Ainsi, à titre d'exemple, lorsqu'il reproduira un document par extrait ou dans son intégralité, l'utilisateur citera de manière complète les sources telles que mentionnées ci-dessus. Toute utilisation non explicitement autorisée ci-avant (telle que par exemple, la modification du document ou son résumé) nécessite l'autorisation préalable et expresse des auteurs ou de leurs ayants droit.*

---

## A Application as a Proof of Concept

The first part of this appendix will be dedicated to the different components that were developed to create the application associated with this thesis. As part of the internship at Intech related to my final year project, we had to develop an application serving as a proof of concept. This application will be a draft of the project and will allow Intech to demonstrate to their clients the kind of application Intech is capable of creating. According to Intech, we developed the application using Dash by Plotly. Dash by Plotly is a framework that allows us to create the front end of our application directly in Python. This ensures that if the project is continued later by another Intech collaborator, they will have no difficulty understanding the front end, having a data scientist profile and thus skills in Python. Additionally, Plotly enables the creation of callbacks, linking user input values with displayed values (e.g., selecting a variable to display on a graph). All parts of the application can be found in the Application folder.

### A.1 Model Selection

The first feature of our application simply shows the user the different results of the models on the test set after training, as seen in Figure 21. Furthermore, as shown in the red box in Figure 21, users can input the costs of different errors that the models might make. Based on these inputs, we select the most suitable pre-trained model implementation for the specified costs. At Intech’s request, for each model, we specify whether the model is interpretable and indicate the associated costs based on its errors.

### A.2 Prediction and Interpretability

Once we select the model, we move to the second page of our application where we can find information related to the model’s predictions. At Intech’s request, it is possible to select a time period that will define the data represented on the graphs. On this page, we can find several pieces of information listed below:

1. First, on Figure 25 we can see a graph representing the number of predicted transactions over time, with fraudulent transactions in black and legitimate transactions in orange. Additionally, the same block contains statistics on the predictions.
2. Then on Figure 23 we can see, if an interpretable model was selected on the previous page, it is possible to interpret the results of a prediction. By clicking on a prediction on the graph, it will be locally interpreted in the second block. Note that due to time constraints, we were unable to incorporate SHAP values into the application.
3. After selecting the model, it is possible to manually input values for the different variables to determine if a transaction would be classified as fraud or legitimate by the model. Moreover, if the selected model is interpretable, we will have the local explanation of the model’s prediction as we can see on Figure 24.
4. If the selected model is Explainable Boosting, we can access graphs of the variable weights specific to this model. These graphs provide great interpretability of the results. as we can see on Figure 26
5. Finally, we display the global average weights of the different variables for all models as we can see on Figure 27.

## B Tabular

This section contains all the tables that may be useful for reading this thesis but are not essential and do not provide any major insights.

<b>VIF</b>	<b>Variable</b>
12.11	Amount
4.42	V2
2.91	V7
2.80	V5
2.51	Intercept
2.39	V20
1.62	V1
1.56	V6
1.53	V3
1.15	V23
1.13	V21
1.12	V8
1.12	V10
1.11	V4
1.05	V22
1.03	V19
1.02	V25
1.02	V9
1.01	V18
1.01	V14
1.01	V27
1.00	V28
1.00	V12
1.00	V17
1.00	V13
1.00	V24
1.00	V16
1.00	V26
1.00	V15
1.00	V11

Table 8: VIF and corresponding variables

<b>Model</b>	<b>AUC</b>	<b>Accuracy</b>	<b>F1</b>	<b>Precision</b>	<b>Recall</b>	<b>PR AUC</b>
Random Forest	0.948	0.999	0.837	0.967	0.738	0.853
XGBoost	0.978	1.000	0.857	0.940	0.788	0.864
LightGBM	0.615	0.993	0.186	0.117	0.450	0.284
EBM	0.986	1.000	0.869	0.969	0.788	0.879

Table 9: Model performance with original data

<b>Model</b>	<b>AUC</b>	<b>Accuracy</b>	<b>F1</b>	<b>Precision</b>	<b>Recall</b>	<b>PR AUC</b>
Random Forest	0.950	0.999	0.876	0.957	0.807	0.882
XGBoost	0.985	1.000	0.890	0.958	0.831	0.895
LightGBM	0.638	0.996	0.241	0.195	0.313	0.255
EBM	0.981	1.000	0.885	0.945	0.831	0.888

Table 10: Model performance for the data without duplicates

<b>Model</b>	<b>AUC</b>	<b>Accuracy</b>	<b>F1</b>	<b>Precision</b>	<b>Recall</b>	<b>PR AUC</b>
Random Forest	0.948	0.999	0.837	0.967	0.738	0.853
XGBoost	0.981	1.000	0.863	0.955	0.788	0.871
LightGBM	0.767	0.998	0.454	0.370	0.588	0.479
EBM	0.986	1.000	0.869	0.969	0.788	0.879

Table 13: Model performance with minmax scaler

<b>Model</b>	<b>AUC</b>	<b>Accuracy</b>	<b>F1</b>	<b>Precision</b>	<b>Recall</b>	<b>PR AUC</b>
Random Forest	0.948	0.999	0.837	0.967	0.738	0.853
XGBoost	0.978	1.000	0.857	0.940	0.788	0.864
LightGBM	0.351	0.984	0.046	0.026	0.225	0.126
EBM	0.986	1.000	0.869	0.969	0.788	0.879

Table 14: Model performance with standard scaler

<b>Model</b>	<b>AUC</b>	<b>Accuracy</b>	<b>F1</b>	<b>Precision</b>	<b>Recall</b>	<b>PR AUC</b>
Random Forest	0.948	0.999	0.837	0.967	0.738	0.853
XGBoost	0.978	1.000	0.857	0.940	0.788	0.864
LightGBM	0.669	0.996	0.301	0.230	0.438	0.334
EBM	0.986	1.000	0.869	0.969	0.788	0.879

Table 15: Model performance with robust scaler

<b>Model</b>	<b>AUC</b>	<b>Accuracy</b>	<b>F1</b>	<b>Precision</b>	<b>Recall</b>	<b>PR AUC</b>
Random Forest	0.981	0.998	0.182	1.000	0.100	0.551
XGBoost	0.971	0.998	0.182	1.000	0.100	0.551
LightGBM	0.499	0.998	0.000	0.000	0.000	0.001
EBM	0.663	0.998	0.025	1.000	0.013	0.507

Table 11: Model Performance without the outliers (Z-score)

<b>Model</b>	<b>AUC</b>	<b>Accuracy</b>	<b>F1</b>	<b>Precision</b>	<b>Recall</b>	<b>PR AUC</b>
Random Forest	0.984	0.999	0.580	0.690	0.500	0.595
XGBoost	0.962	0.998	0.239	0.917	0.138	0.528
LightGBM	0.392	0.997	0.000	0.000	0.000	0.001
EBM	0.768	0.998	0.087	0.333	0.050	0.193

Table 12: Model performance without the outliers (Isolation Forest)

<b>Model</b>	<b>AUC</b>	<b>Accuracy</b>	<b>F1</b>	<b>Precision</b>	<b>Recall</b>	<b>PR AUC</b>
Random Forest	0.951	0.999	0.848	0.859	0.838	0.848
XGBoost	0.982	0.999	0.855	0.861	0.850	0.856
LightGBM	0.983	0.999	0.852	0.880	0.825	0.853
EBM	0.987	0.999	0.830	0.835	0.825	0.830

Table 16: Model performance with original\_random\_under\_sampling

<b>Model</b>	<b>AUC</b>	<b>Accuracy</b>	<b>F1</b>	<b>Precision</b>	<b>Recall</b>	<b>PR AUC</b>
Random Forest	0.957	0.999	0.807	0.779	0.838	0.808
XGBoost	0.980	0.999	0.863	0.863	0.863	0.863
LightGBM	0.979	0.999	0.834	0.819	0.850	0.835
EBM	0.991	0.999	0.834	0.819	0.850	0.835

Table 17: Model performance with standard\_random\_under\_sampling

<b>Model</b>	<b>AUC</b>	<b>Accuracy</b>	<b>F1</b>	<b>Precision</b>	<b>Recall</b>	<b>PR AUC</b>
Random Forest	0.961	0.999	0.805	0.786	0.825	0.806
XGBoost	0.978	0.999	0.741	0.642	0.875	0.759
LightGBM	0.974	0.999	0.817	0.775	0.863	0.819
EBM	0.985	0.999	0.817	0.775	0.863	0.819

Table 18: Model performance with standard\_cluster\_under\_sampling

<b>Model</b>	<b>AUC</b>	<b>Accuracy</b>	<b>F1</b>	<b>Precision</b>	<b>Recall</b>	<b>PR AUC</b>
Random Forest	0.957	0.999	0.843	0.848	0.838	0.843
XGBoost	0.984	0.999	0.857	0.852	0.863	0.857
LightGBM	0.981	0.999	0.830	0.835	0.825	0.830
EBM	0.989	0.999	0.848	0.859	0.838	0.848

Table 19: Model performance with robust\_random\_under\_sampling

<b>Model</b>	<b>AUC</b>	<b>Accuracy</b>	<b>F1</b>	<b>Precision</b>	<b>Recall</b>	<b>PR AUC</b>
Random Forest	0.955	1.000	0.884	0.970	0.813	0.891
XGBoost	0.984	1.000	0.872	0.895	0.850	0.873
LightGBM	0.974	1.000	0.873	0.885	0.863	0.874
EBM	0.983	1.000	0.880	0.943	0.825	0.884

Table 20: Model performance with original\_random\_over\_sampling

<b>Model</b>	<b>AUC</b>	<b>Accuracy</b>	<b>F1</b>	<b>Precision</b>	<b>Recall</b>	<b>PR AUC</b>
Random Forest	0.970	0.999	0.861	0.872	0.850	0.861
XGBoost	0.984	0.999	0.863	0.863	0.863	0.863
LightGBM	0.985	0.999	0.836	0.812	0.863	0.837
EBM	0.980	0.999	0.829	0.810	0.850	0.830

Table 21: Model performance with original\_smote

<b>Model</b>	<b>AUC</b>	<b>Accuracy</b>	<b>F1</b>	<b>Precision</b>	<b>Recall</b>	<b>PR AUC</b>
Random Forest	0.970	0.999	0.850	0.850	0.850	0.850
XGBoost	0.987	0.999	0.863	0.863	0.863	0.863
LightGBM	0.961	0.999	0.812	0.788	0.838	0.813
EBM	0.982	0.999	0.814	0.782	0.850	0.816

Table 22: Model performance with original\_adasyn

<b>Model</b>	<b>AUC</b>	<b>Accuracy</b>	<b>F1</b>	<b>Precision</b>	<b>Recall</b>	<b>PR AUC</b>
Random Forest	0.942	1.000	0.877	0.970	0.800	0.885
XGBoost	0.985	1.000	0.882	0.931	0.838	0.884
LightGBM	0.972	1.000	0.868	0.917	0.825	0.871
EBM	0.983	1.000	0.872	0.942	0.813	0.877

Table 23: Model performance with original\_borderline\_smote

<b>Model</b>	<b>AUC</b>	<b>Accuracy</b>	<b>F1</b>	<b>Precision</b>	<b>Recall</b>	<b>PR AUC</b>
Random Forest	0.948	1.000	0.871	0.955	0.800	0.878
XGBoost	0.981	1.000	0.857	0.940	0.788	0.864
LightGBM	0.967	0.999	0.834	0.887	0.788	0.838
EBM	0.982	1.000	0.878	0.956	0.813	0.884

Table 24: Model performance with original\_svm\_smote

<b>Model</b>	<b>AUC</b>	<b>Accuracy</b>	<b>F1</b>	<b>Precision</b>	<b>Recall</b>	<b>PR AUC</b>
Random Forest	0.954	1.000	0.875	0.984	0.788	0.886
XGBoost	0.977	1.000	0.896	0.932	0.863	0.898
LightGBM	0.968	0.999	0.854	0.870	0.838	0.854
EBM	0.983	1.000	0.892	0.971	0.825	0.898

Table 25: Model performance with minmax\_random\_over\_sampling

<b>Model</b>	<b>AUC</b>	<b>Accuracy</b>	<b>F1</b>	<b>Precision</b>	<b>Recall</b>	<b>PR AUC</b>
Random Forest	0.961	1.000	0.884	0.970	0.813	0.891
XGBoost	0.981	1.000	0.889	0.932	0.850	0.891
LightGBM	0.965	0.999	0.848	0.859	0.838	0.848
EBM	0.985	1.000	0.865	0.941	0.800	0.871

Table 26: Model performance with standard\_random\_over\_sampling

<b>Model</b>	<b>AUC</b>	<b>Accuracy</b>	<b>F1</b>	<b>Precision</b>	<b>Recall</b>	<b>PR AUC</b>
Random Forest	0.967	1.000	0.869	0.969	0.788	0.879
XGBoost	0.982	1.000	0.895	0.944	0.850	0.897
LightGBM	0.973	1.000	0.866	0.883	0.850	0.867
EBM	0.985	1.000	0.886	0.957	0.825	0.891

Table 27: Model performance with robust\_random\_over\_sampling

<b>Model</b>	<b>AUC</b>	<b>Accuracy</b>	<b>F1</b>	<b>Precision</b>	<b>Recall</b>	<b>PR AUC</b>
Random Forest	0.954	1.000	0.890	0.985	0.813	0.899
XGBoost	0.986	1.000	0.870	0.905	0.838	0.872
LightGBM	0.976	0.999	0.841	0.857	0.825	0.841
EBM	0.980	1.000	0.864	0.854	0.875	0.864

Table 28: Model performance with robust\_borderline\_smote

<b>Model</b>	<b>AUC</b>	<b>Accuracy</b>	<b>F1</b>	<b>Precision</b>	<b>Recall</b>	<b>PR AUC</b>
Random Forest	0.963	0.999	0.857	0.892	0.825	0.859
XGBoost	0.983	0.999	0.864	0.854	0.875	0.864
LightGBM	0.979	0.999	0.826	0.793	0.863	0.828
EBM	0.978	0.999	0.817	0.775	0.863	0.819

Table 29: Model performance with original\_random\_under\_sampling\_random\_over\_sampling

<b>Model</b>	<b>AUC</b>	<b>Accuracy</b>	<b>F1</b>	<b>Precision</b>	<b>Recall</b>	<b>PR AUC</b>
Random Forest	0.969	0.999	0.841	0.821	0.863	0.842
XGBoost	0.986	0.999	0.811	0.747	0.888	0.818
LightGBM	0.979	0.999	0.819	0.769	0.875	0.822
EBM	0.984	0.999	0.814	0.761	0.875	0.818

Table 30: Model performance with original\_random\_under\_sampling\_borderline\_smote

<b>Model</b>	<b>AUC</b>	<b>Accuracy</b>	<b>F1</b>	<b>Precision</b>	<b>Recall</b>	<b>PR AUC</b>
Random Forest	0.955	0.999	0.831	0.802	0.863	0.833
XGBoost	0.986	0.999	0.838	0.805	0.875	0.840
LightGBM	0.979	0.999	0.833	0.795	0.875	0.835
EBM	0.987	0.999	0.817	0.775	0.863	0.819

Table 31: Model performance with original\_random\_under\_sampling\_svm\_smote

<b>Model</b>	<b>AUC</b>	<b>Accuracy</b>	<b>F1</b>	<b>Precision</b>	<b>Recall</b>	<b>PR AUC</b>
Random Forest	0.957	0.999	0.838	0.838	0.838	0.838
XGBoost	0.981	0.999	0.812	0.767	0.863	0.815
LightGBM	0.974	0.999	0.807	0.758	0.863	0.810
EBM	0.977	0.999	0.810	0.773	0.850	0.811

Table 32: Model performance with minmax\_random\_under\_sampling\_random\_over\_sampling

<b>Model</b>	<b>AUC</b>	<b>Accuracy</b>	<b>F1</b>	<b>Precision</b>	<b>Recall</b>	<b>PR AUC</b>
Random Forest	0.970	0.999	0.795	0.729	0.875	0.802
XGBoost	0.987	0.999	0.683	0.560	0.875	0.718
LightGBM	0.982	0.999	0.667	0.538	0.875	0.707
EBM	0.978	0.997	0.494	0.351	0.838	0.594

Table 33: Model performance with minmax\_random\_under\_sampling\_smote



<b>Model</b>	<b>AUC</b>	<b>Accuracy</b>	<b>F1</b>	<b>Precision</b>	<b>Recall</b>	<b>PR AUC</b>
Random Forest	0.955	0.999	0.829	0.810	0.850	0.830
XGBoost	0.972	0.999	0.758	0.676	0.863	0.770
LightGBM	0.968	0.997	0.543	0.397	0.863	0.630
EBM	0.977	0.994	0.335	0.208	0.863	0.535

Table 34: Model performance with minmax\_cluster\_under\_sampling\_random\_over\_sampling

<b>Model</b>	<b>AUC</b>	<b>Accuracy</b>	<b>F1</b>	<b>Precision</b>	<b>Recall</b>	<b>PR AUC</b>
Random Forest	0.972	0.999	0.773	0.693	0.875	0.784
XGBoost	0.984	0.998	0.598	0.455	0.875	0.665
LightGBM	0.976	0.998	0.593	0.449	0.875	0.662
EBM	0.987	0.996	0.419	0.274	0.888	0.581

Table 35: Model performance with minmax\_cluster\_under\_sampling\_smote

<b>Model</b>	<b>AUC</b>	<b>Accuracy</b>	<b>F1</b>	<b>Precision</b>	<b>Recall</b>	<b>PR AUC</b>
Random Forest	0.970	0.999	0.823	0.833	0.813	0.823
XGBoost	0.982	0.999	0.836	0.812	0.863	0.837
LightGBM	0.977	0.999	0.812	0.767	0.863	0.815
EBM	0.975	0.999	0.805	0.764	0.850	0.807

Table 36: Model performance with standard\_random\_under\_sampling\_random\_over\_sampling

<b>Model</b>	<b>AUC</b>	<b>Accuracy</b>	<b>F1</b>	<b>Precision</b>	<b>Recall</b>	<b>PR AUC</b>
Random Forest	0.956	0.999	0.828	0.844	0.813	0.828
XGBoost	0.988	0.999	0.798	0.724	0.888	0.806
LightGBM	0.978	0.999	0.800	0.737	0.875	0.806
EBM	0.984	0.999	0.723	0.622	0.863	0.742

Table 37: Model performance with standard\_random\_under\_sampling\_borderline\_smote

<b>Model</b>	<b>AUC</b>	<b>Accuracy</b>	<b>F1</b>	<b>Precision</b>	<b>Recall</b>	<b>PR AUC</b>
Random Forest	0.979	0.999	0.821	0.784	0.863	0.823
XGBoost	0.985	0.999	0.795	0.729	0.875	0.802
LightGBM	0.976	0.999	0.767	0.690	0.863	0.776
EBM	0.986	0.999	0.724	0.612	0.888	0.750

Table 38: Model performance with standard\_random\_under\_sampling\_svm\_smote

<b>Model</b>	<b>AUC</b>	<b>Accuracy</b>	<b>F1</b>	<b>Precision</b>	<b>Recall</b>	<b>PR AUC</b>
Random Forest	0.957	0.999	0.850	0.890	0.813	0.852
XGBoost	0.981	0.999	0.848	0.824	0.875	0.849
LightGBM	0.978	0.999	0.838	0.805	0.875	0.840
EBM	0.977	0.999	0.824	0.800	0.850	0.825

Table 39: Model performance with robust\_random\_under\_sampling\_random\_over\_sampling

<b>Model</b>	<b>AUC</b>	<b>Accuracy</b>	<b>F1</b>	<b>Precision</b>	<b>Recall</b>	<b>PR AUC</b>
Random Forest	0.961	0.999	0.845	0.968	0.750	0.859
XGBoost	0.980	1.000	0.857	0.940	0.788	0.864
LightGBM	0.627	0.997	0.332	0.252	0.488	0.370
EBM	0.986	1.000	0.861	0.969	0.775	0.872

Table 40: Model performance with original

## C Figures

This section contains all the figures that may be useful for reading this thesis but are not essential and do not provide any major insights.

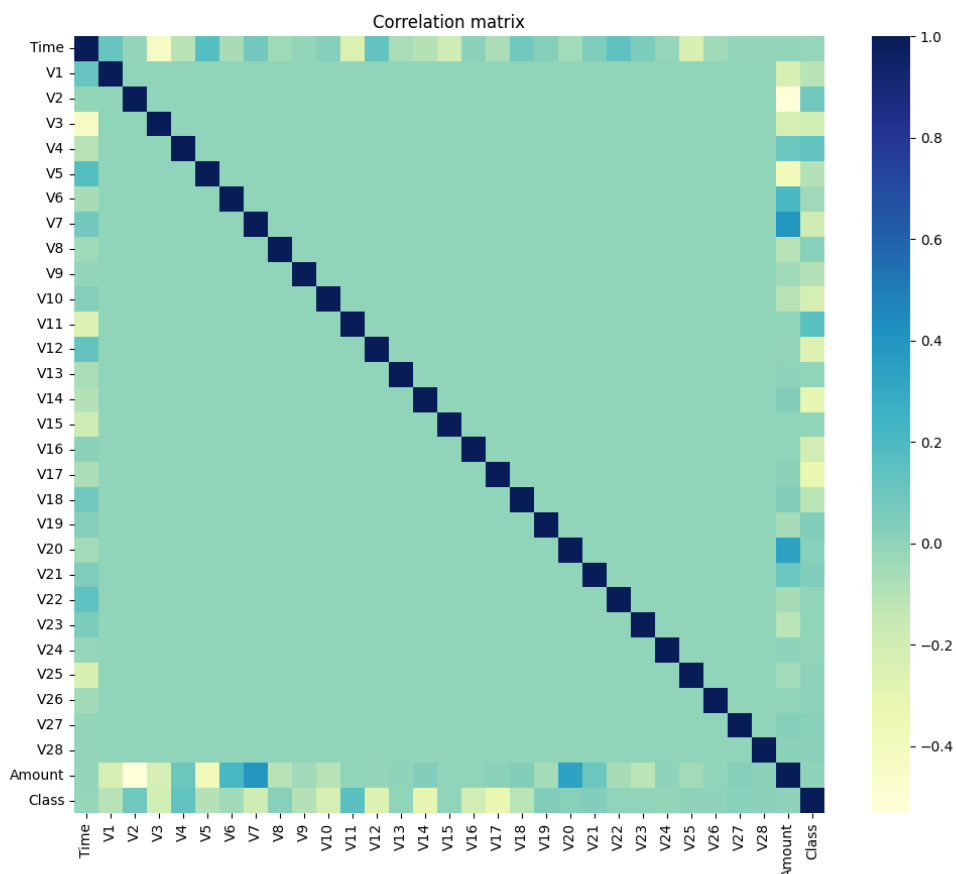


Figure 18: Correlation Matrix

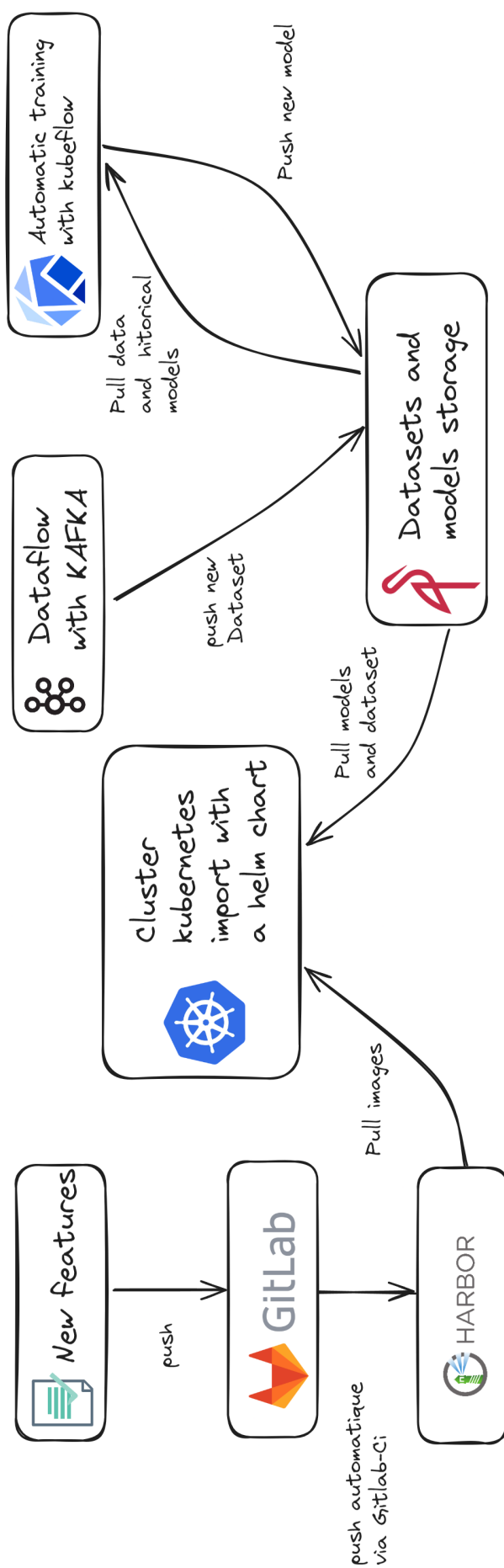


Figure 19: Complete architecture of the fraud detection platform

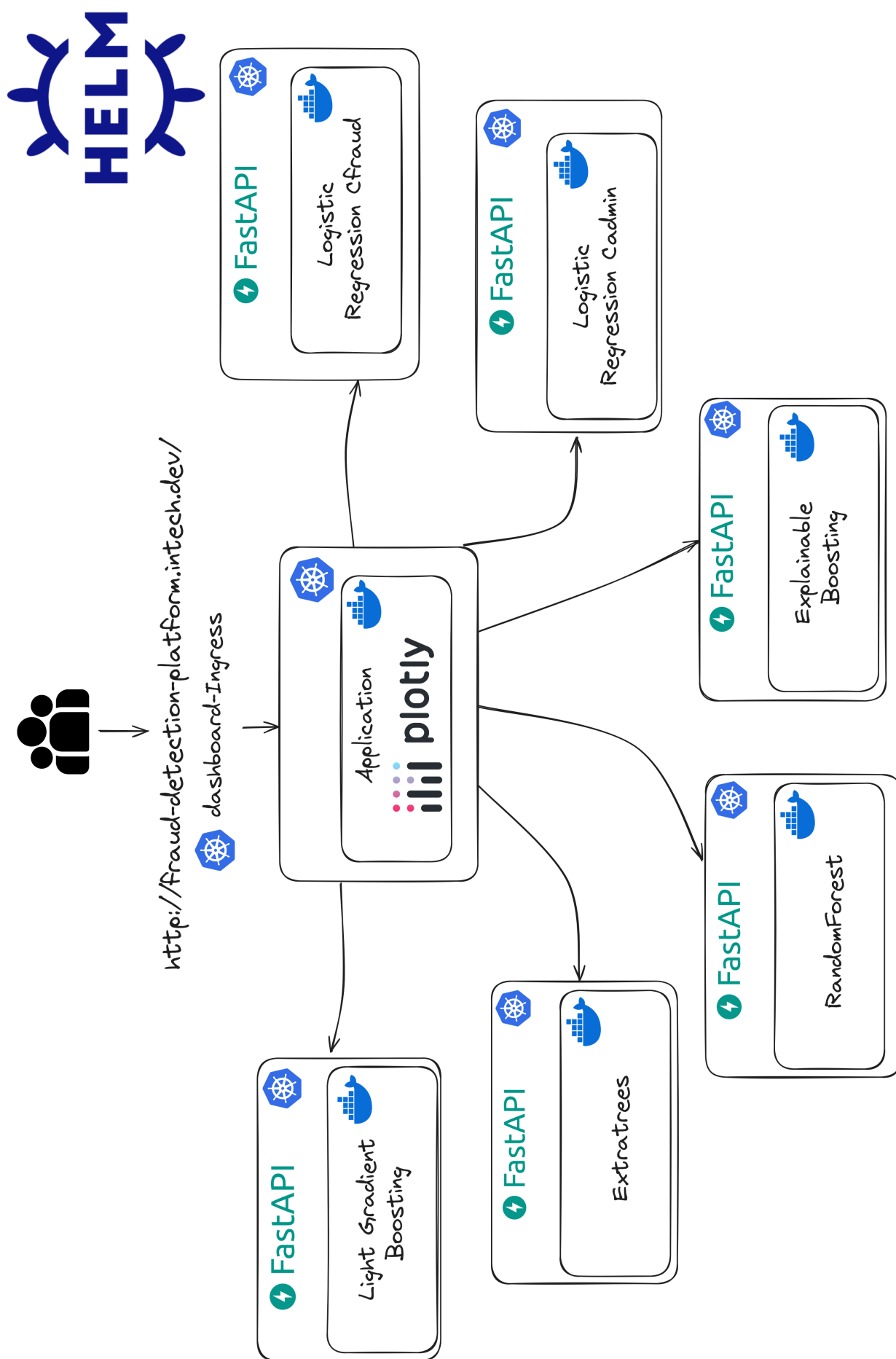


Figure 20: Complete architecture of the kubernetes cluster of the fraud detection platform



Figure 21: Model selection page of Detection fraud application

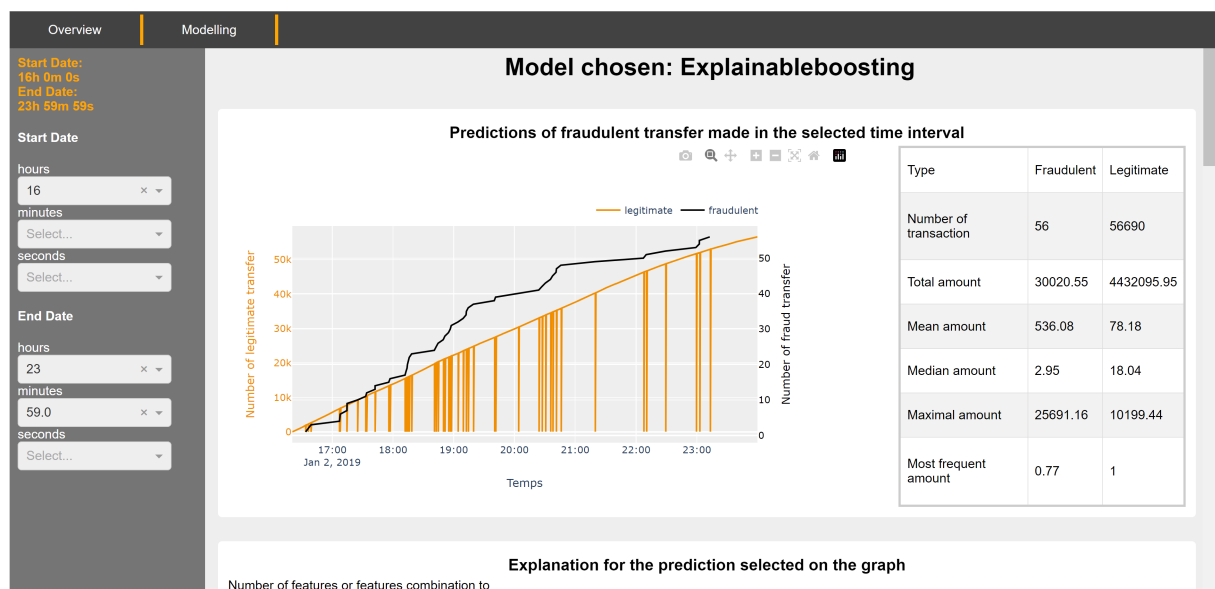


Figure 22: Prediction and explication page of Detection fraud application

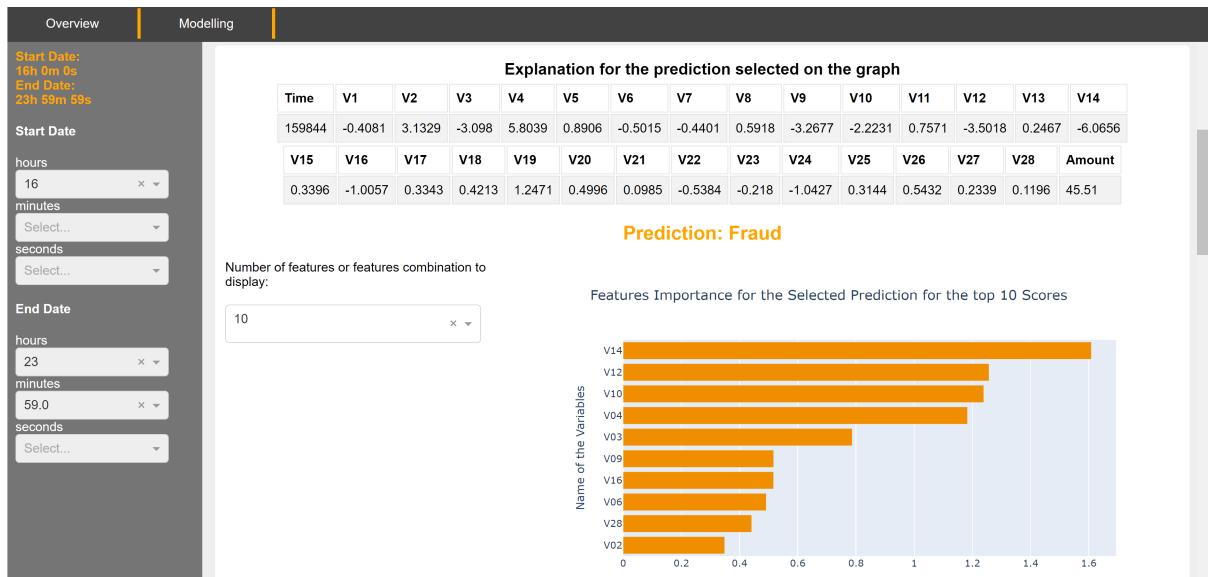


Figure 23: Prediction and explication page of Detection fraud application

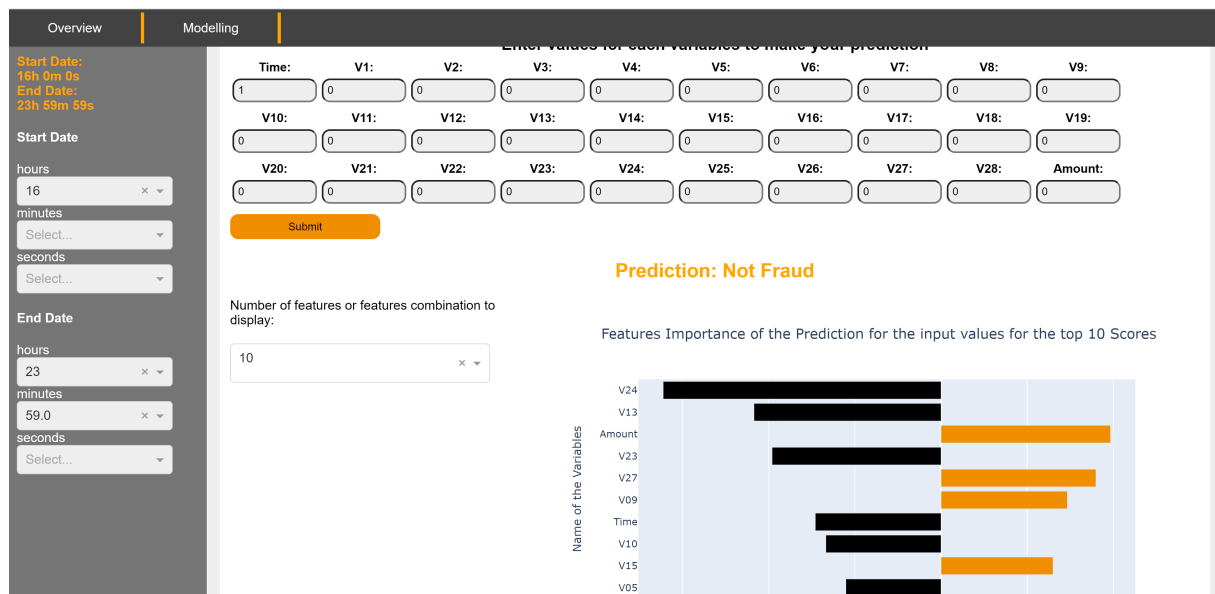


Figure 24: Prediction and explication page of Detection fraud application

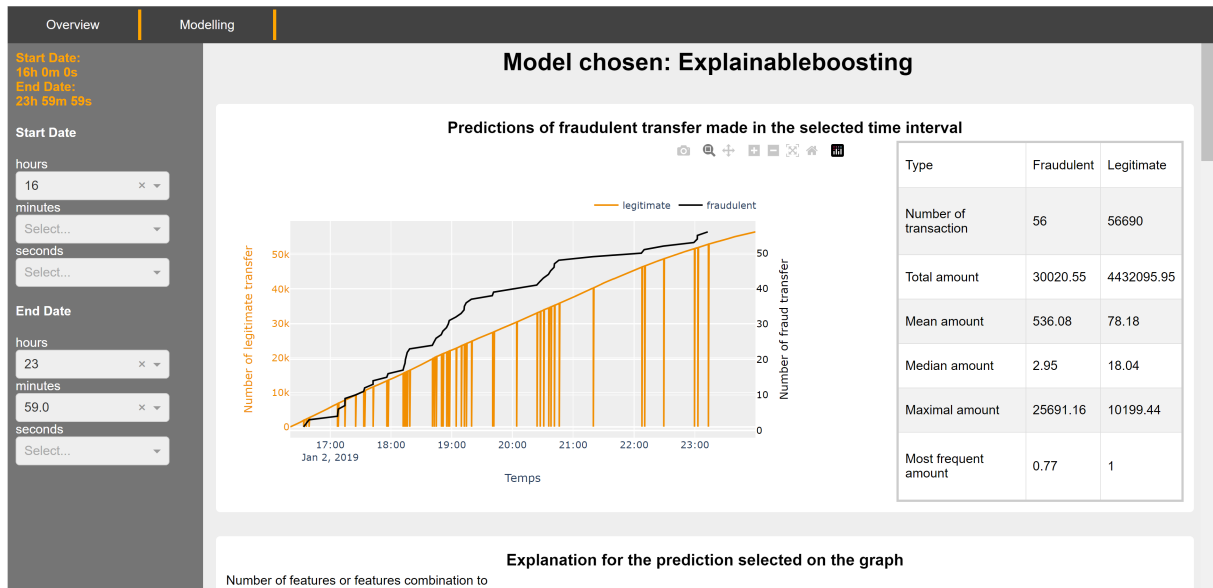


Figure 25: Prediction and explication page of Detection fraud application

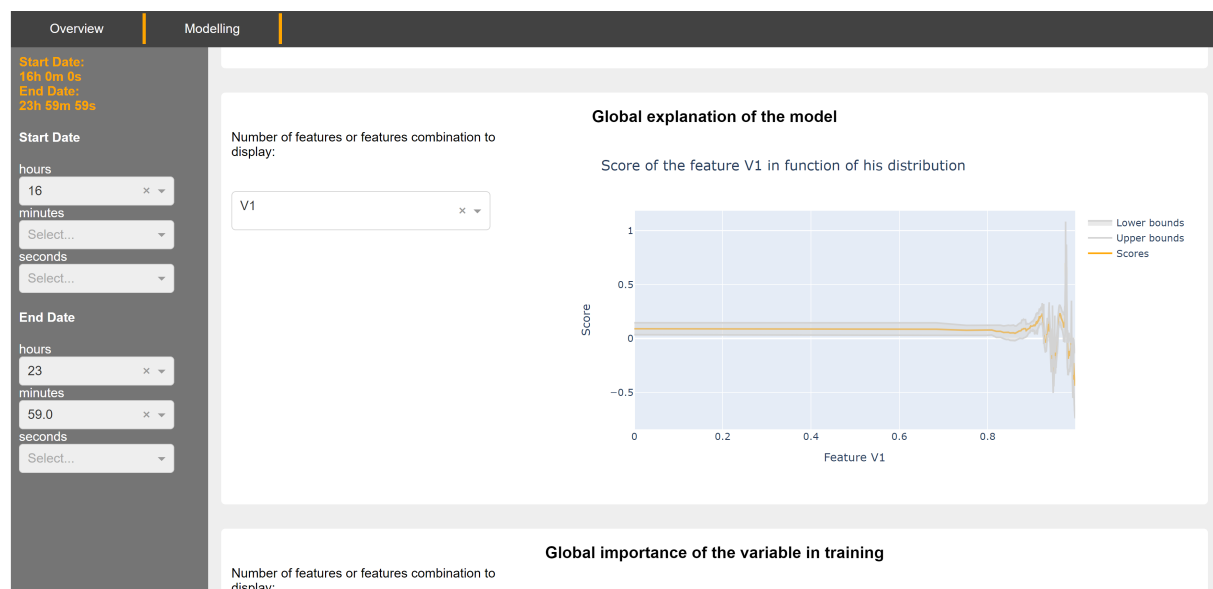


Figure 26: Prediction and explication page of Detection fraud application



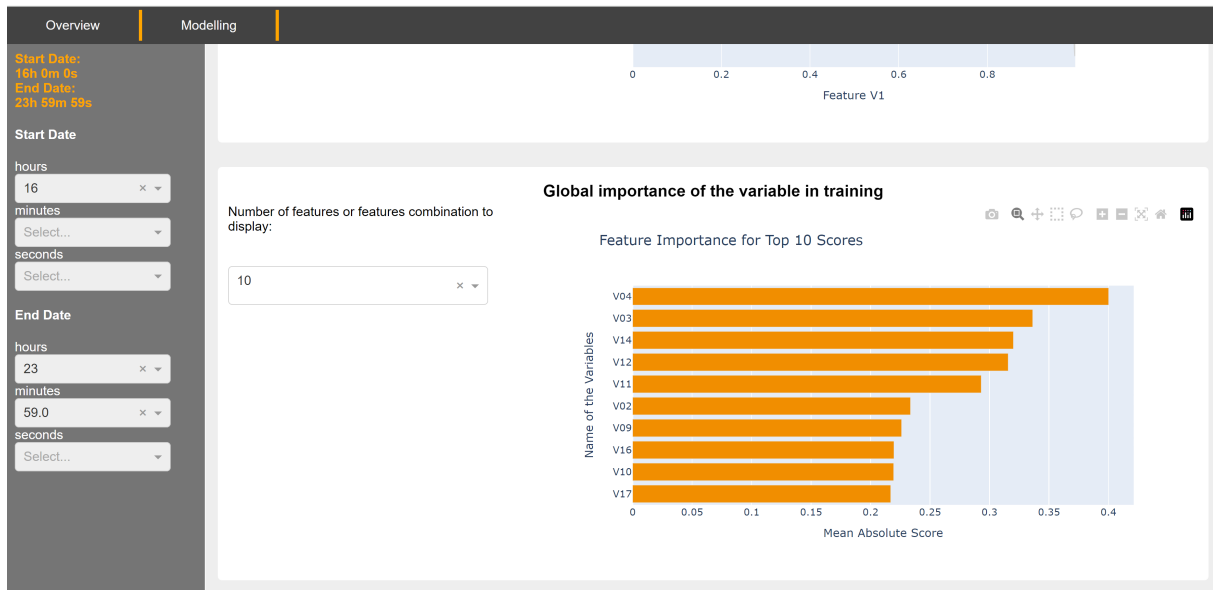


Figure 27: Prediction and explication page of Detection fraud application

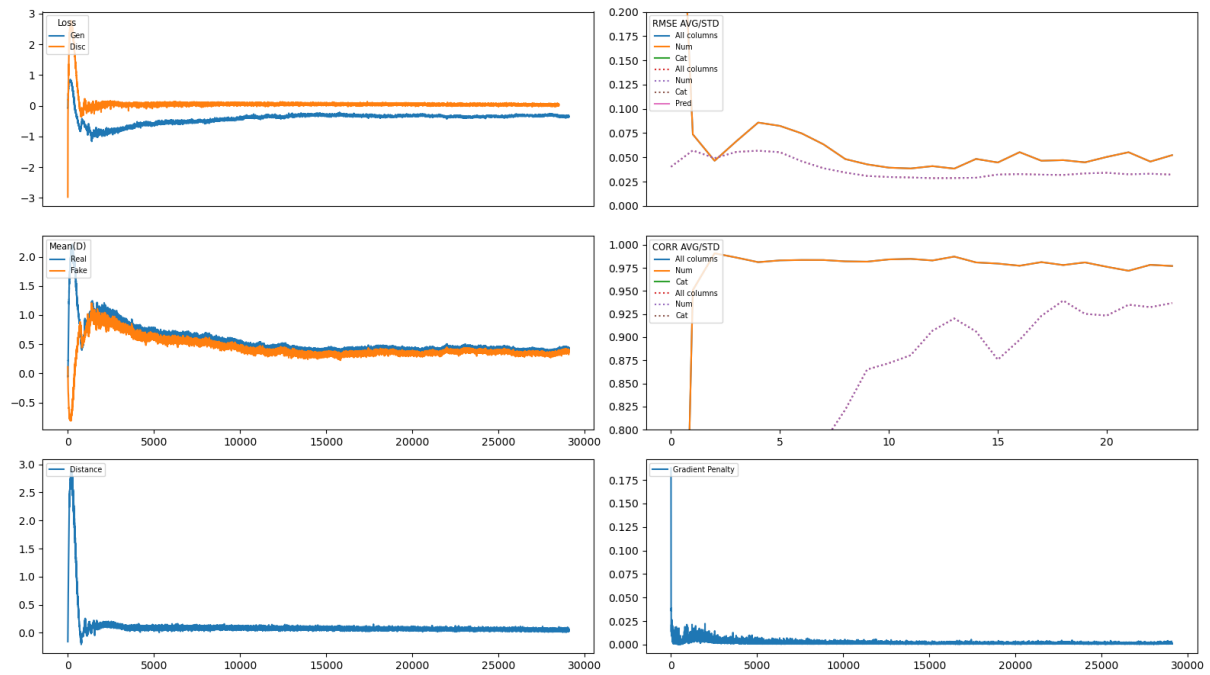
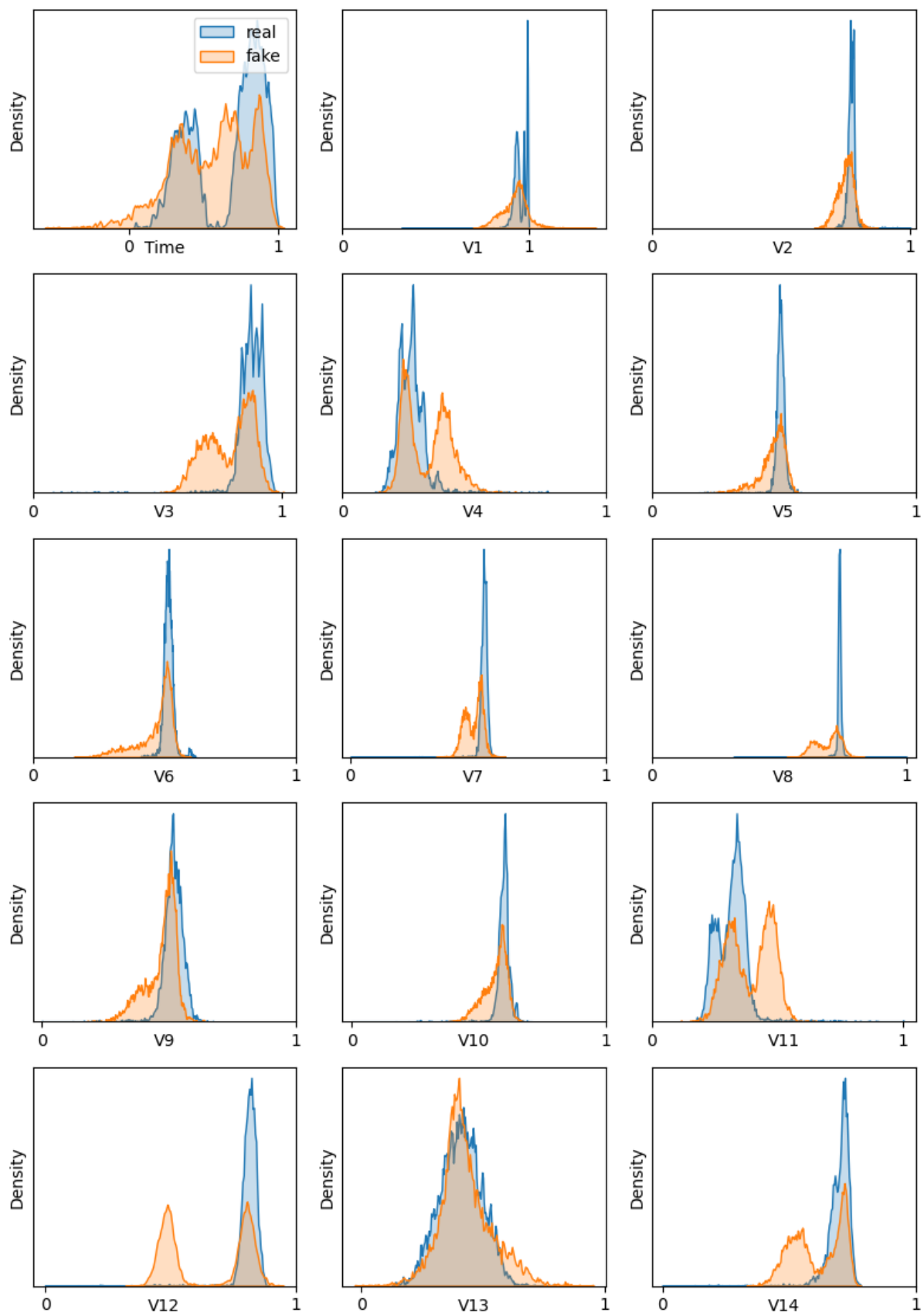


Figure 28: Loss function of the c-WGAN use for sampling



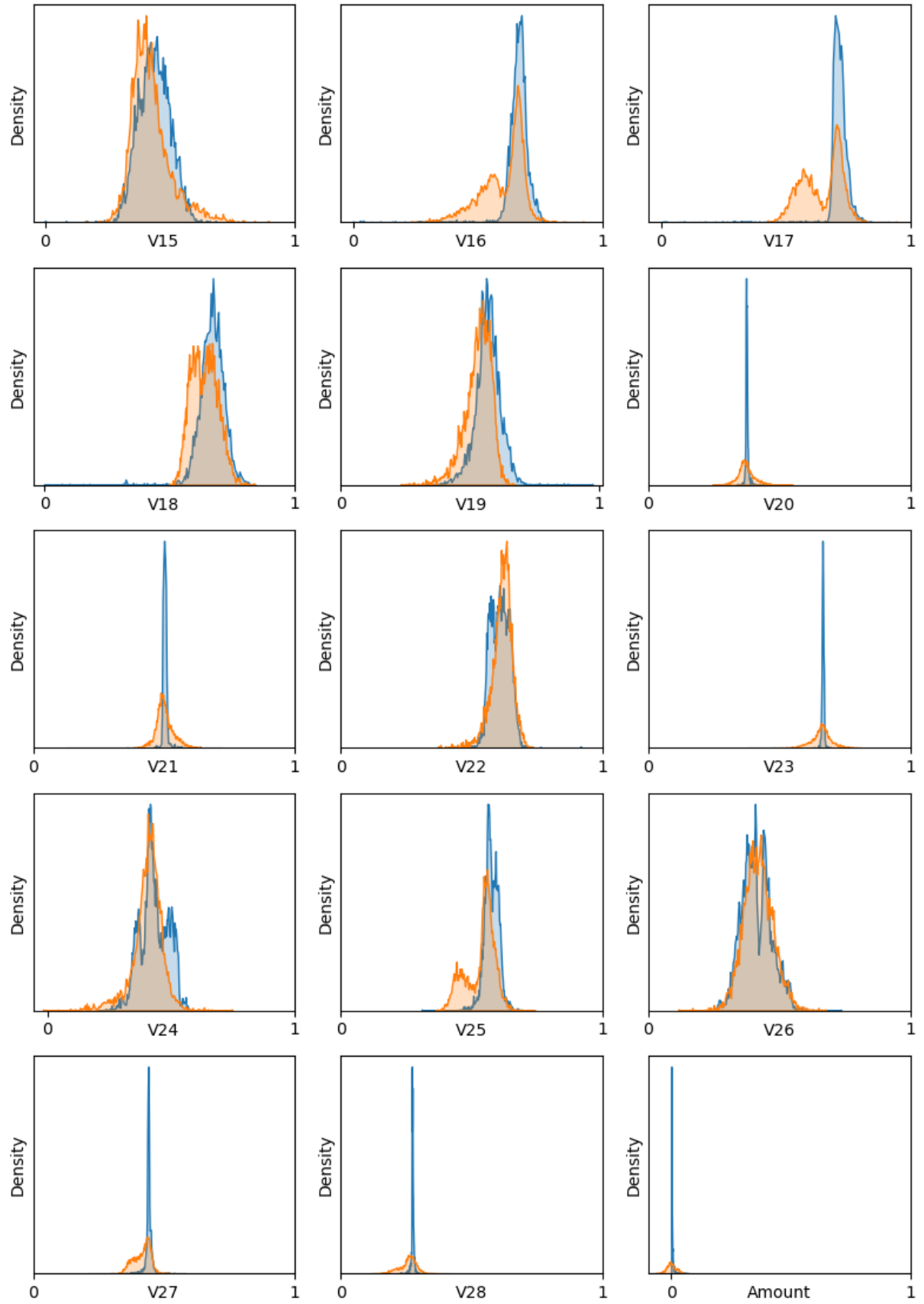
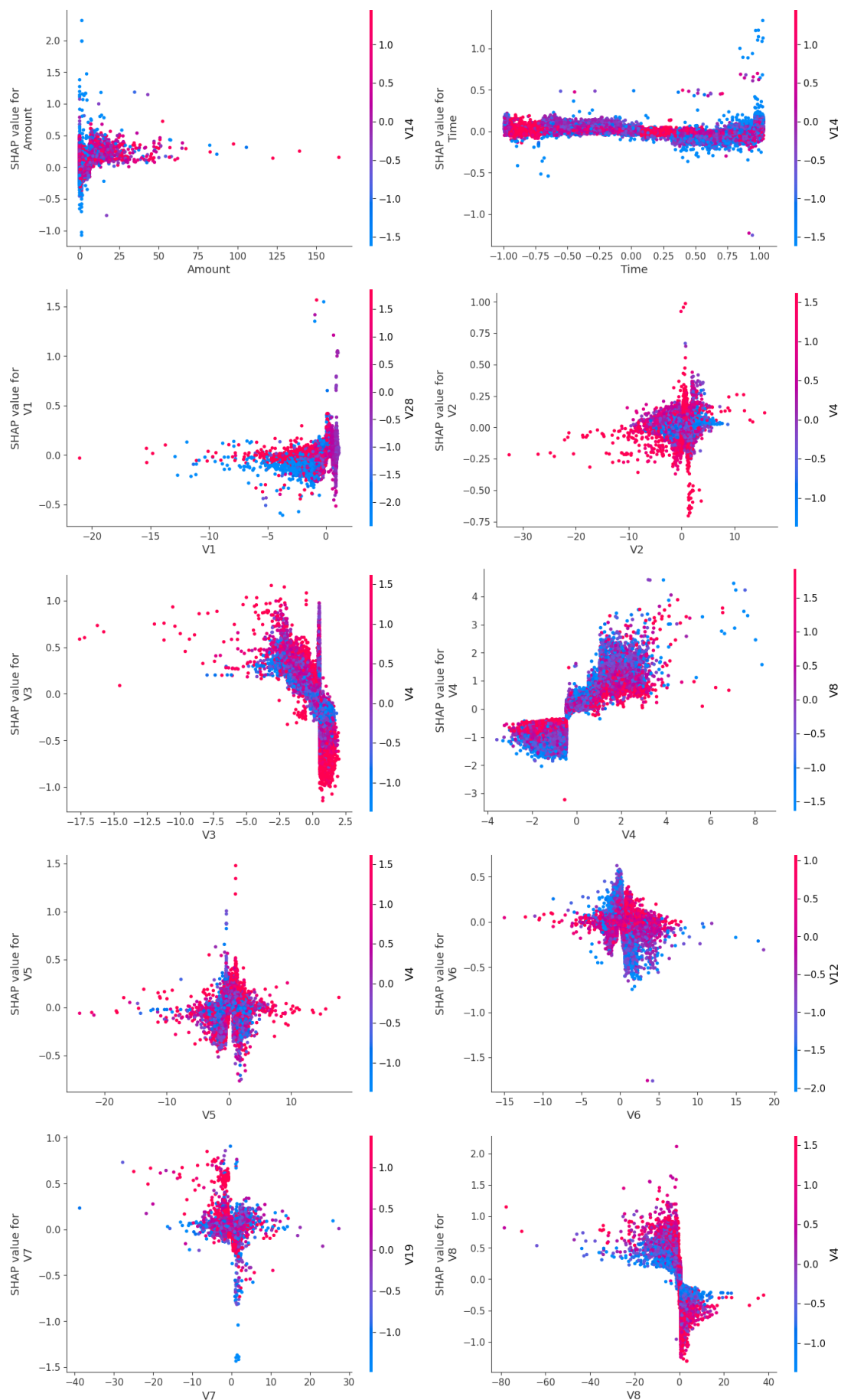
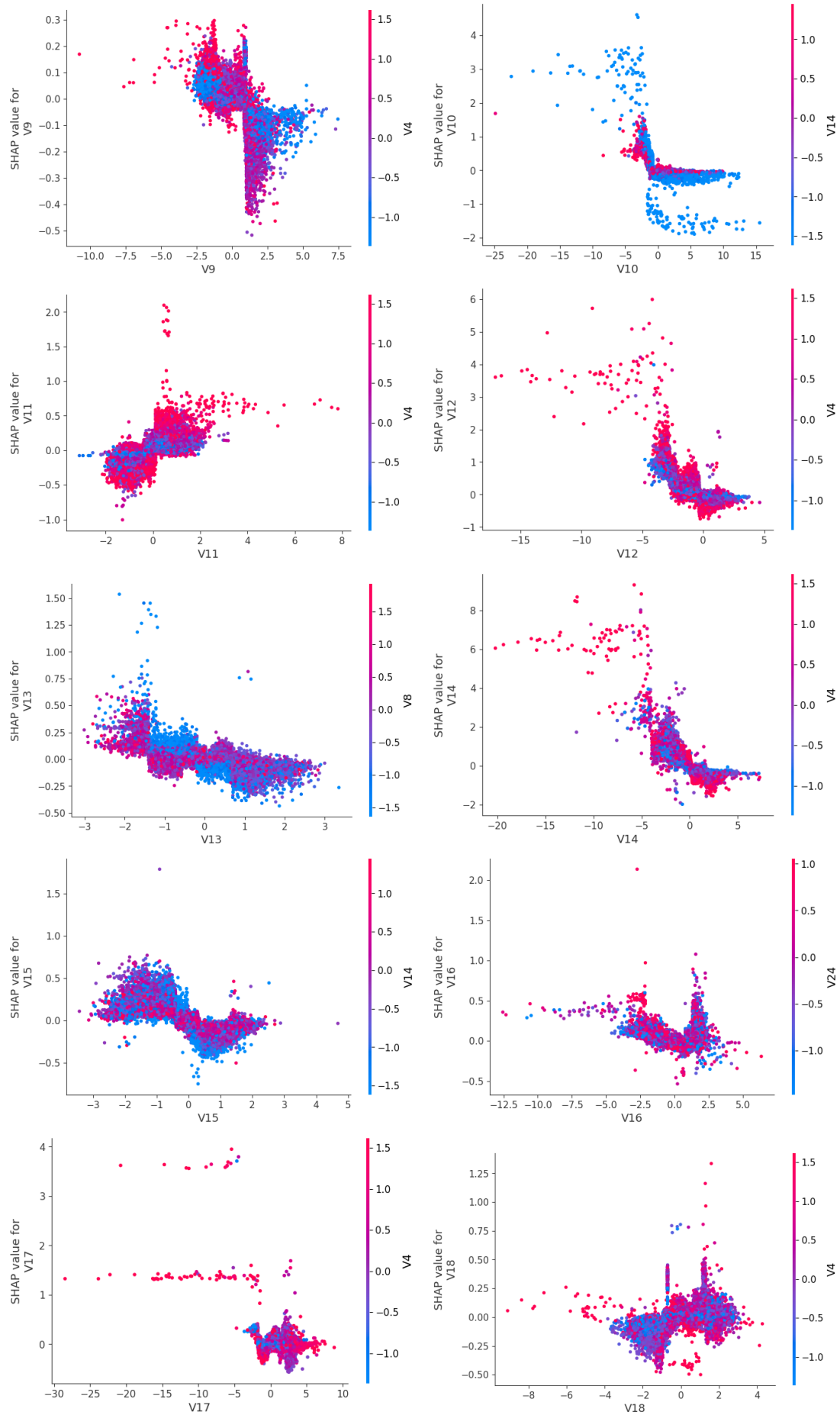


Figure 29: Distribution of the real and the synthetic distribution of the data create with the c-WGAN





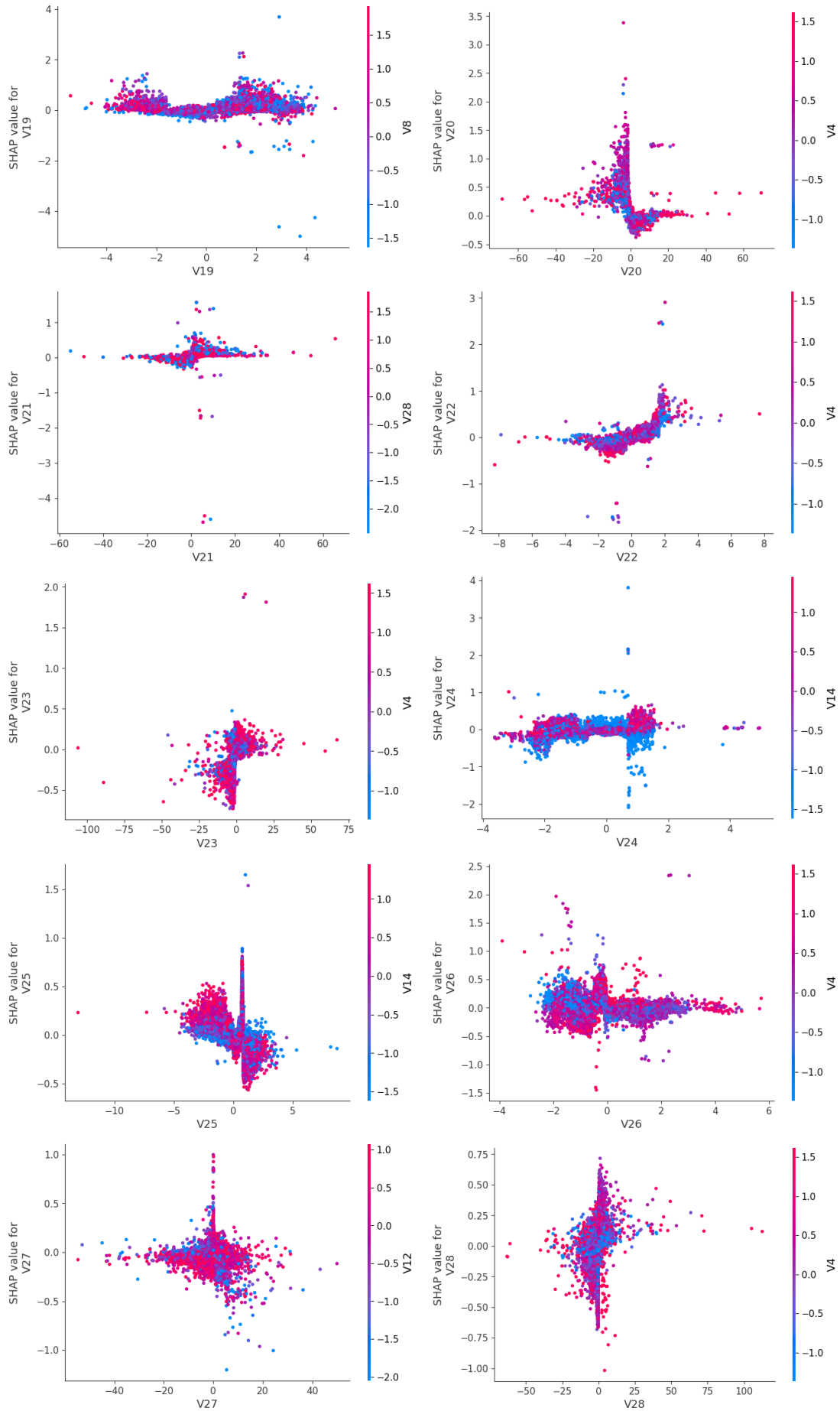
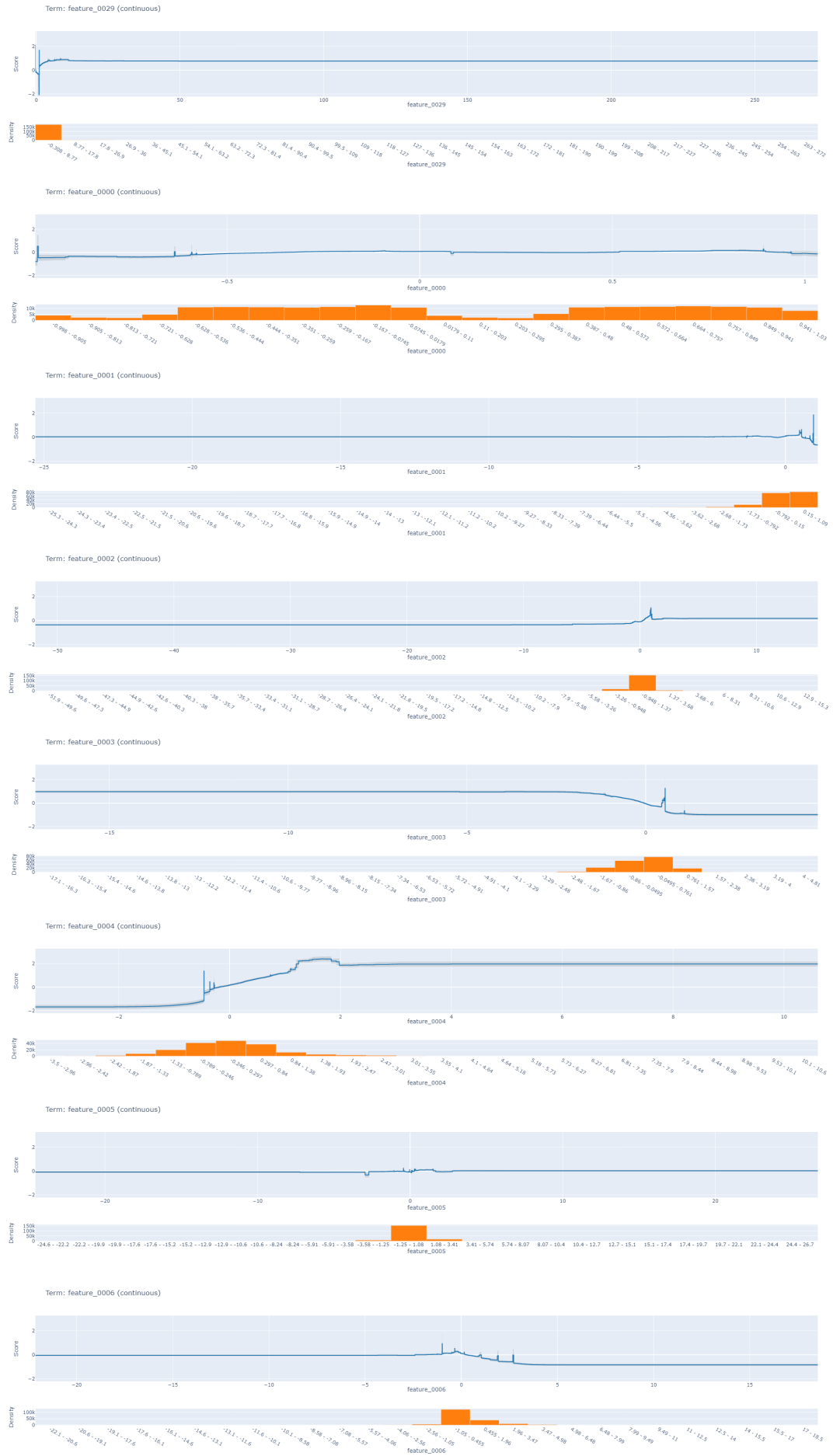
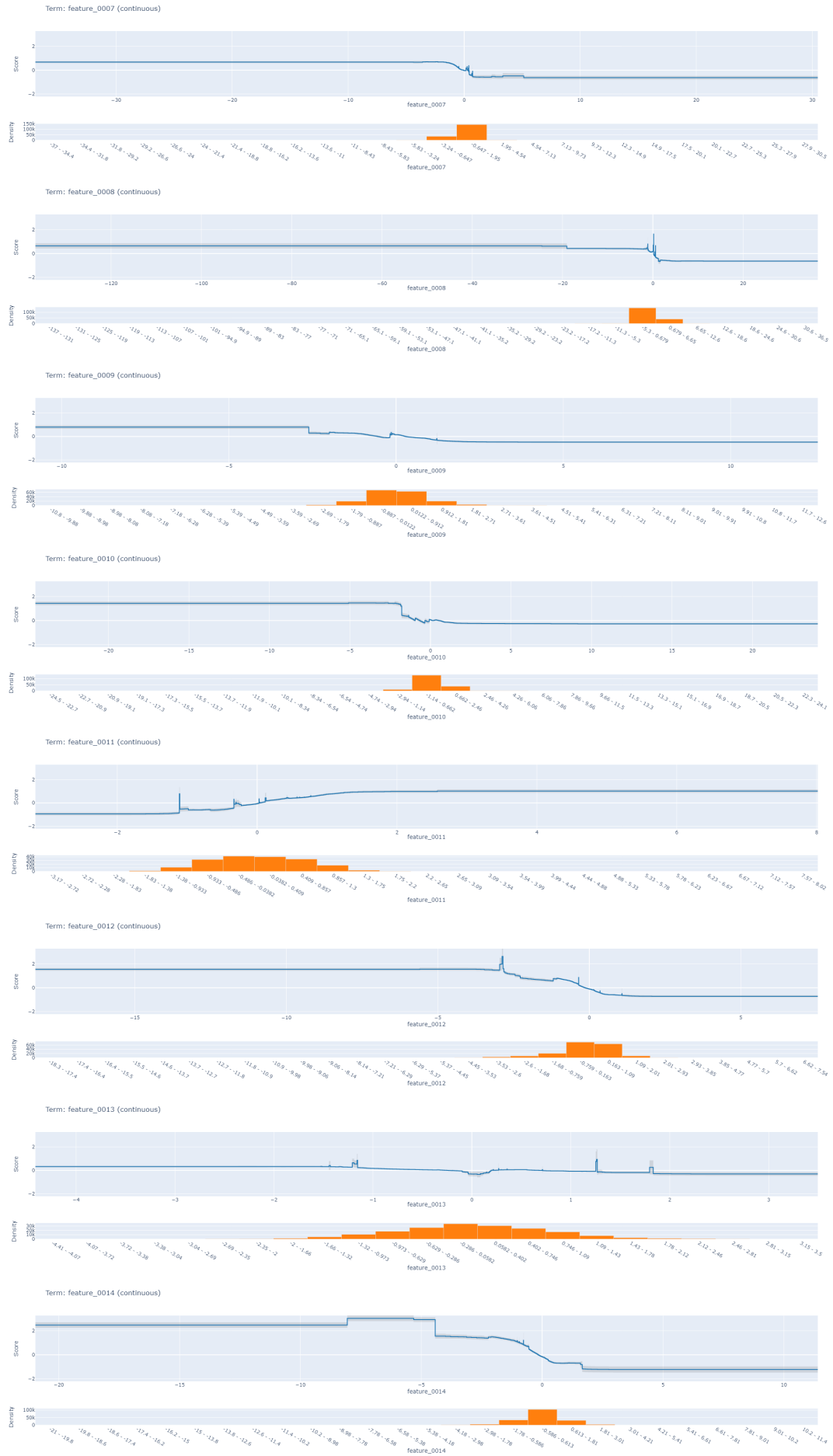
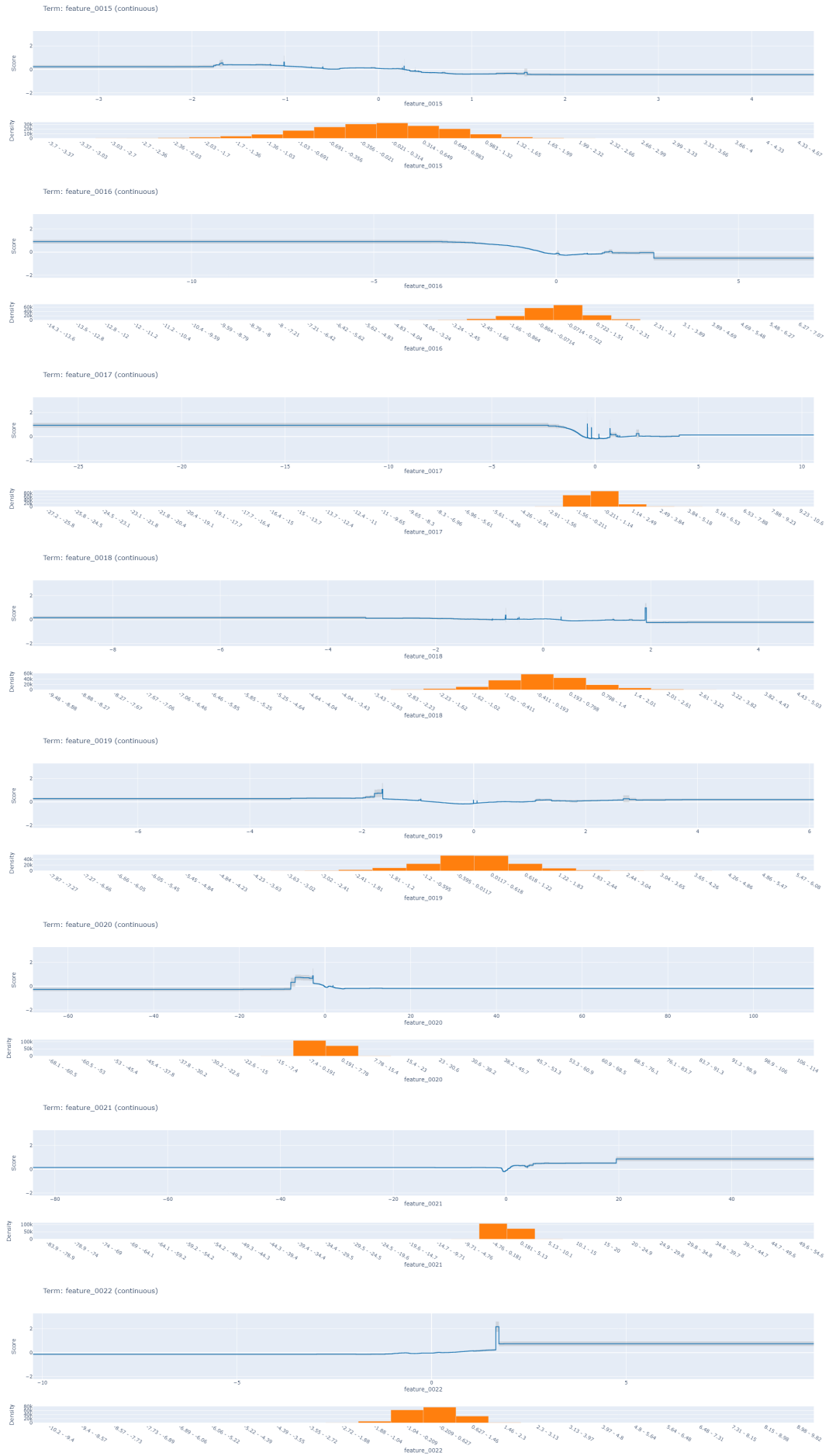


Figure 30: dependence plot for the different variable with the variables with which they have the more interaction









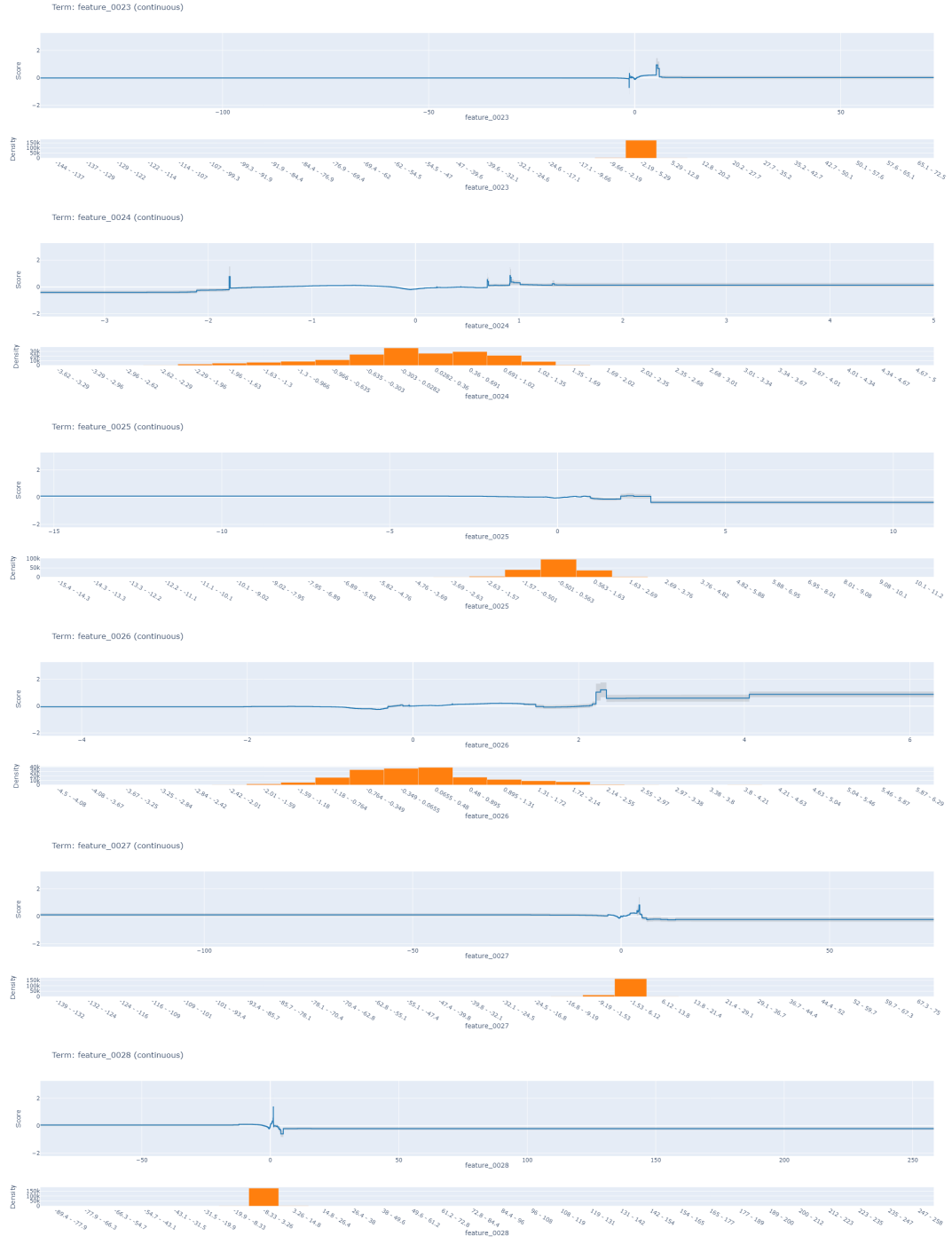
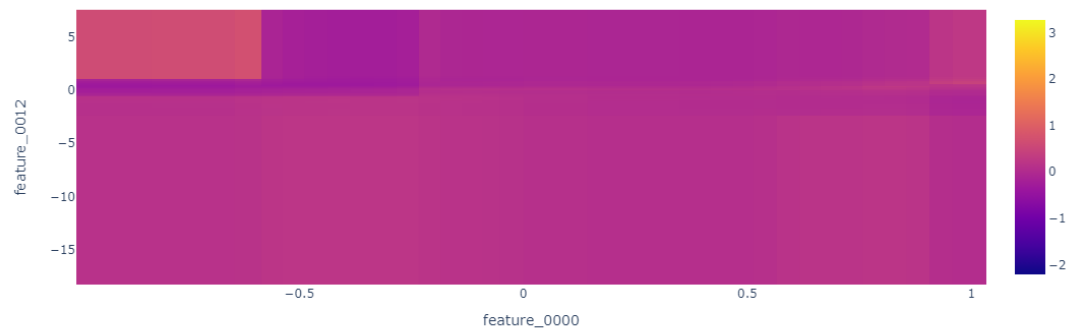


Figure 31: Global Explanation from explanation boosting on each variables

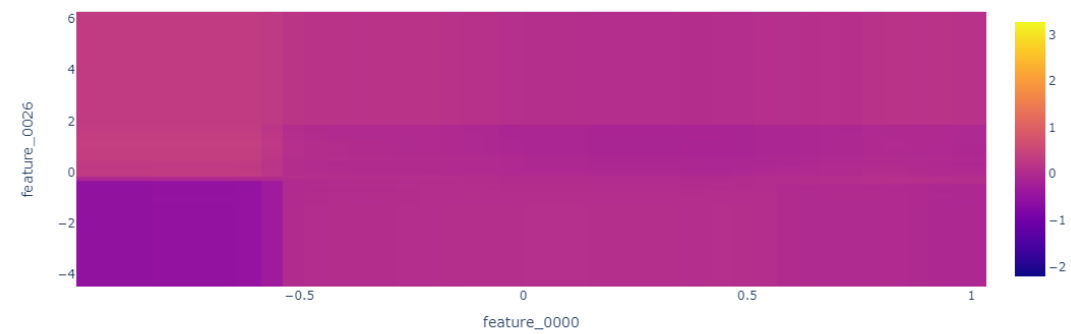
Term: feature\_0000 & feature\_0001 (interaction)



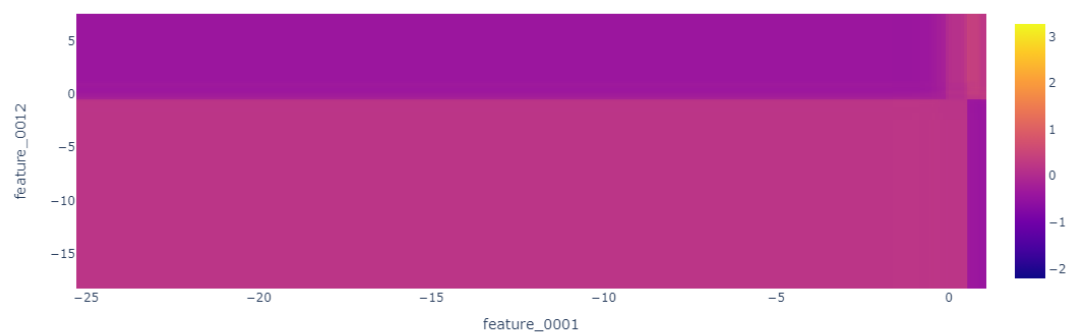
Term: feature\_0000 & feature\_0012 (interaction)



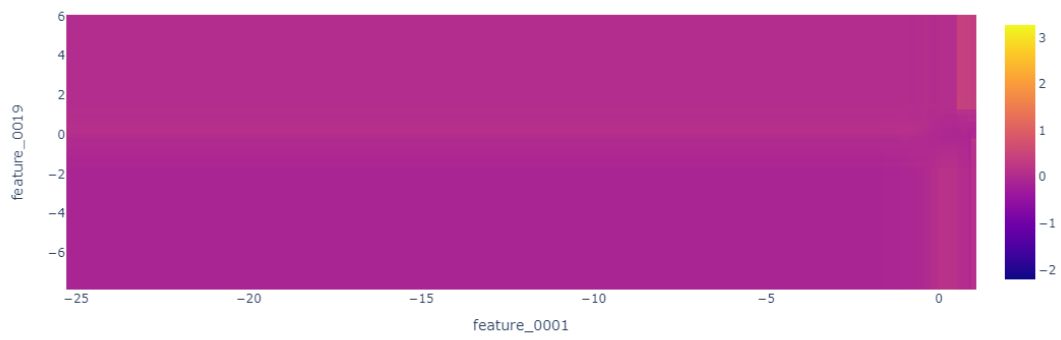
Term: feature\_0000 & feature\_0026 (interaction)



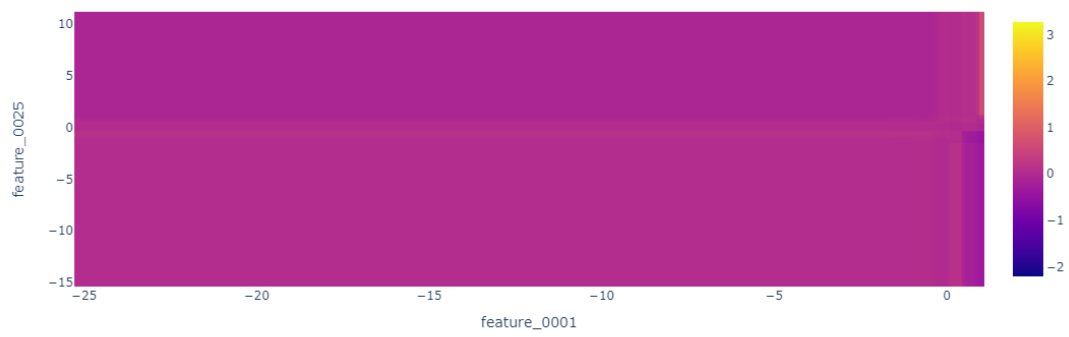
Term: feature\_0001 & feature\_0012 (interaction)



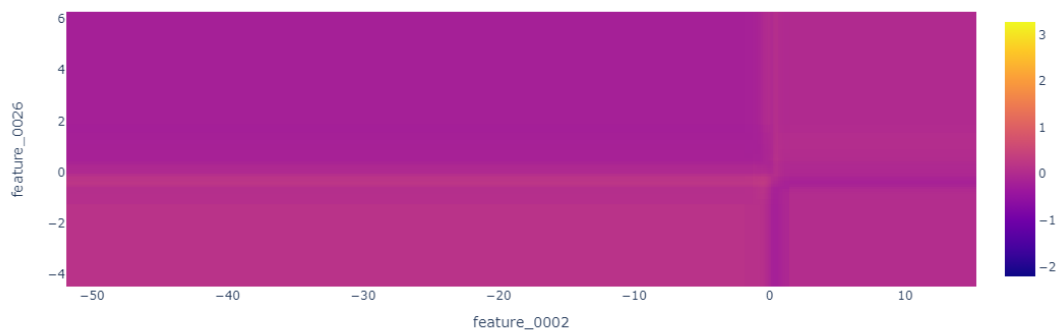
Term: feature\_0001 & feature\_0019 (interaction)



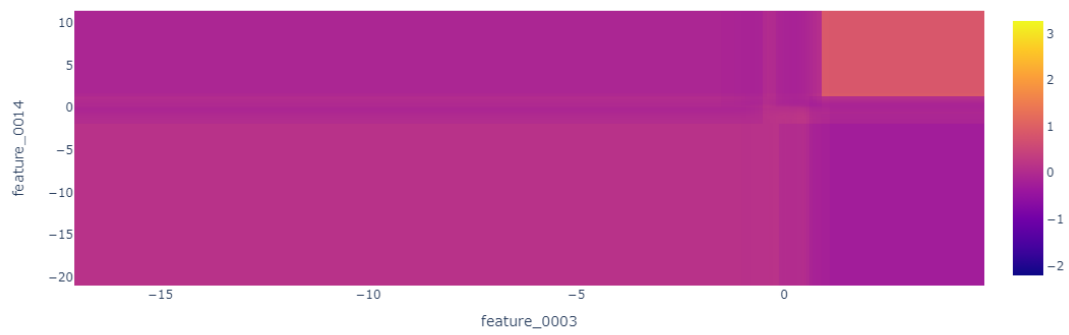
Term: feature\_0001 & feature\_0025 (interaction)



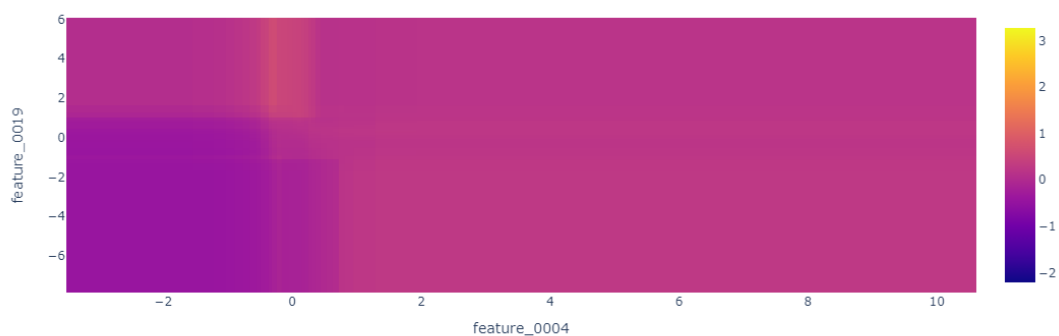
Term: feature\_0002 & feature\_0026 (interaction)



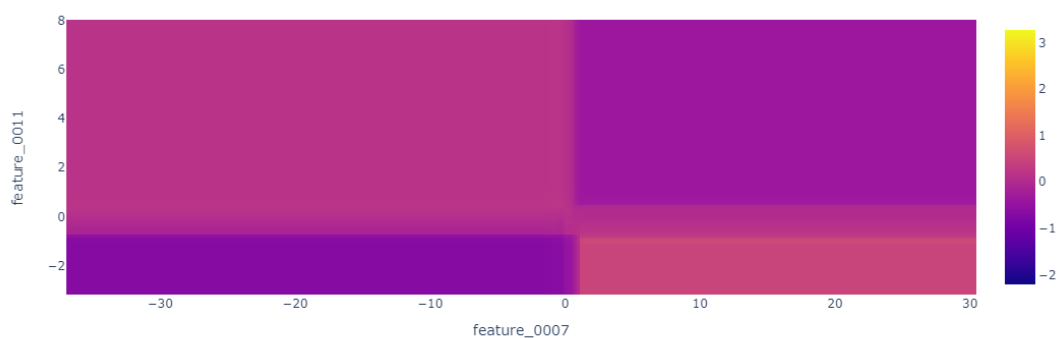
Term: feature\_0003 & feature\_0014 (interaction)



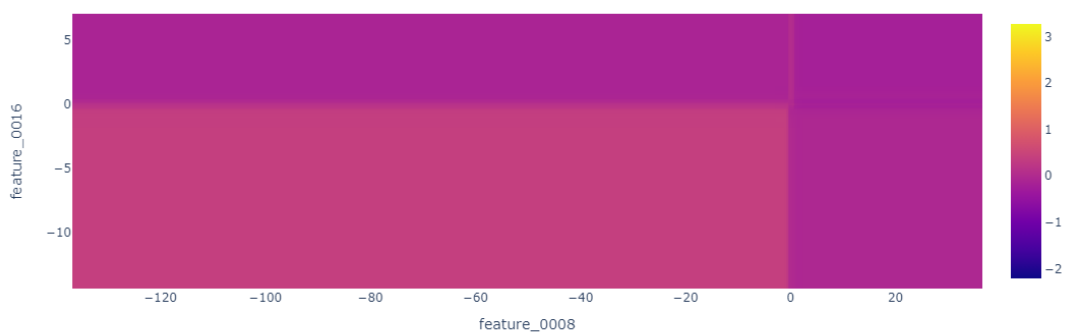
Term: feature\_0004 & feature\_0019 (interaction)



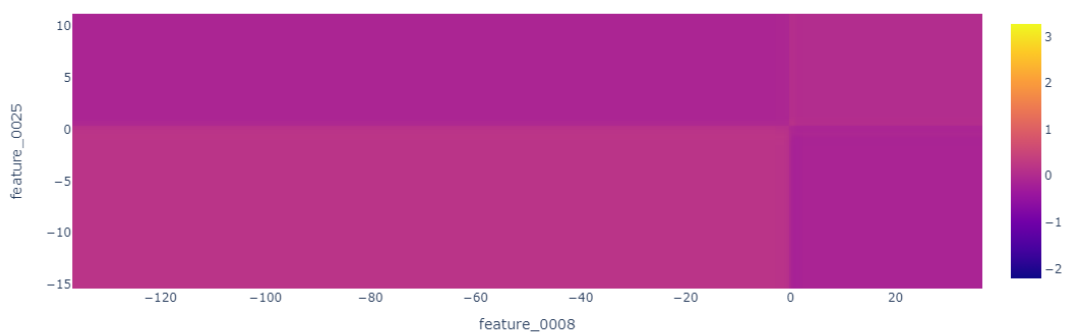
Term: feature\_0007 & feature\_0011 (interaction)



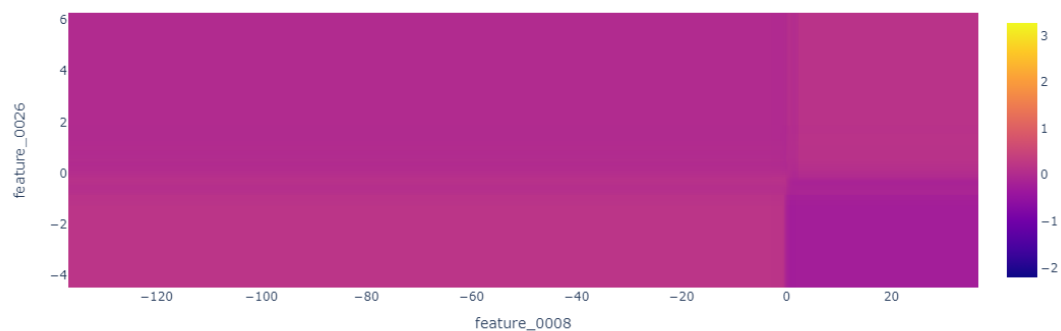
Term: feature\_0008 & feature\_0016 (interaction)



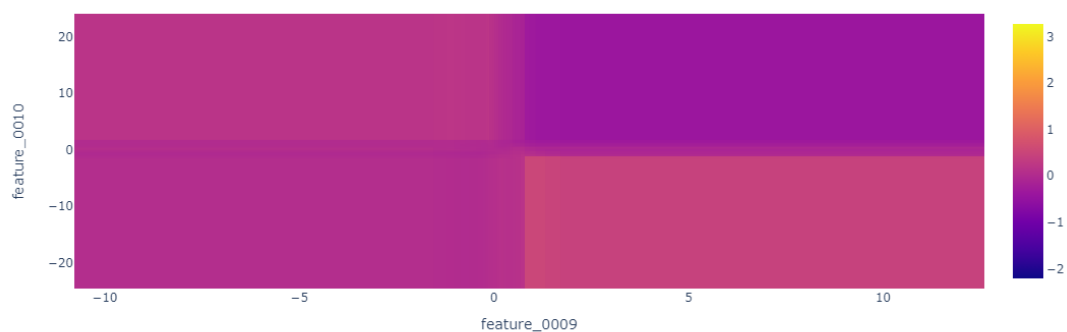
Term: feature\_0008 & feature\_0025 (interaction)



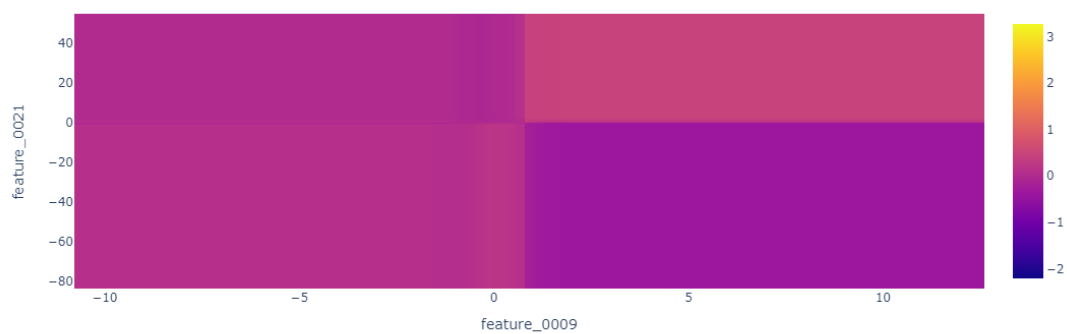
Term: feature\_0008 & feature\_0026 (interaction)



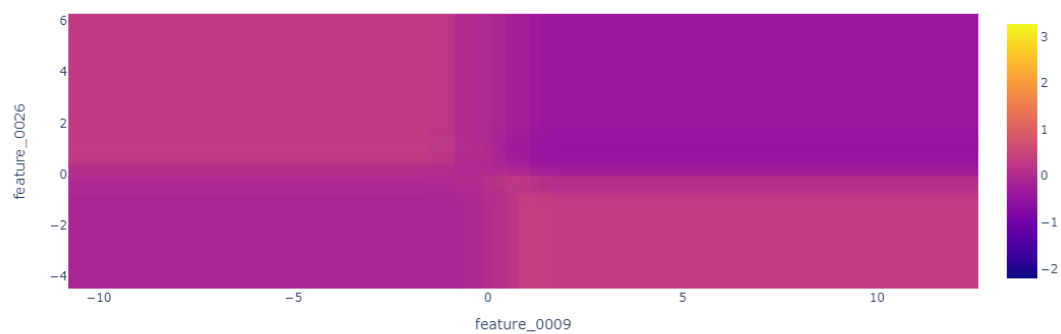
Term: feature\_0009 & feature\_0010 (interaction)



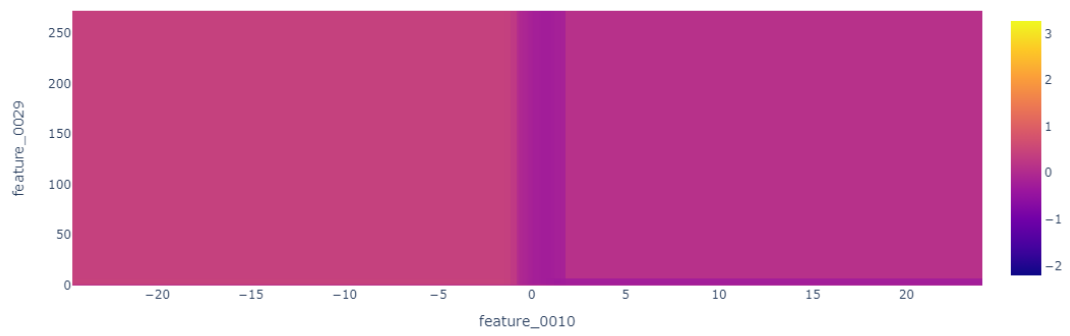
Term: feature\_0009 & feature\_0021 (interaction)



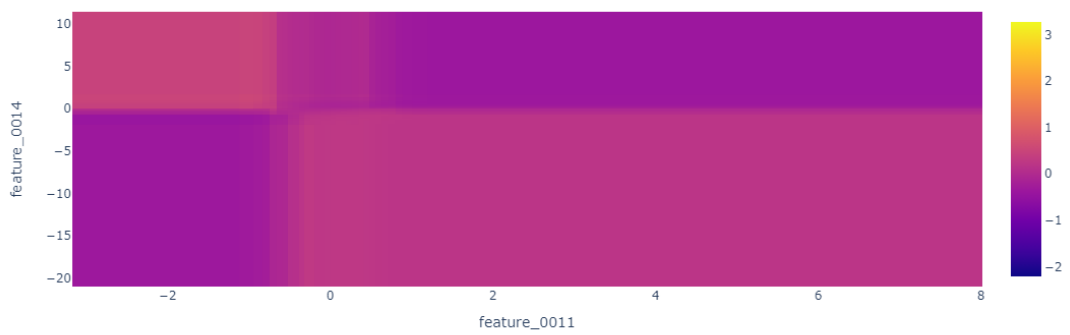
Term: feature\_0009 & feature\_0026 (interaction)



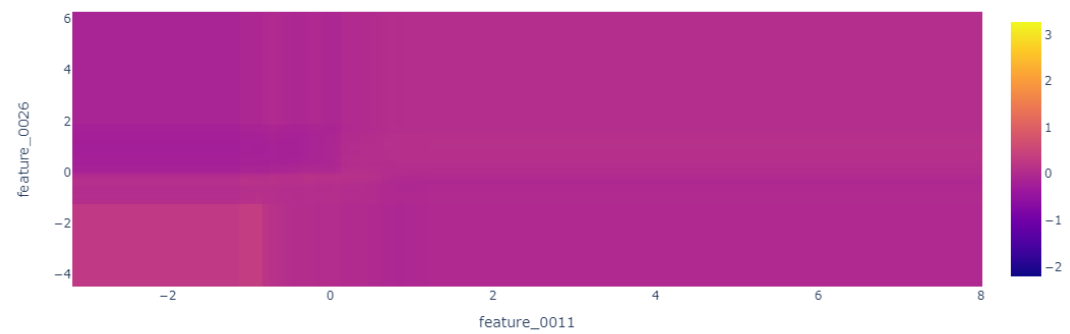
Term: feature\_0010 & feature\_0029 (interaction)



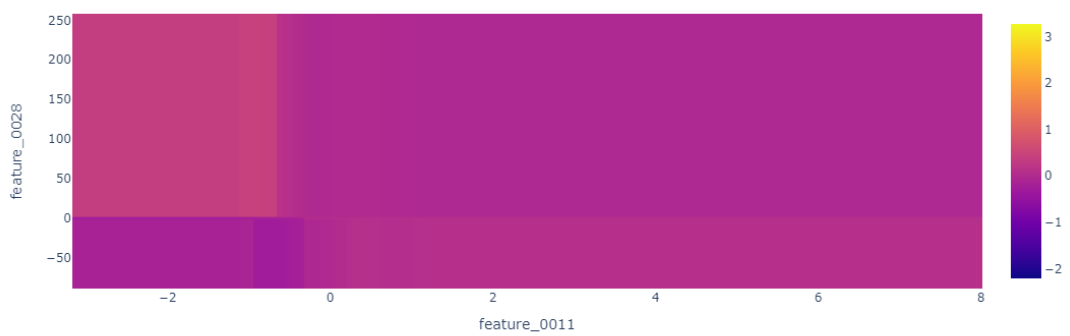
Term: feature\_0011 & feature\_0014 (interaction)



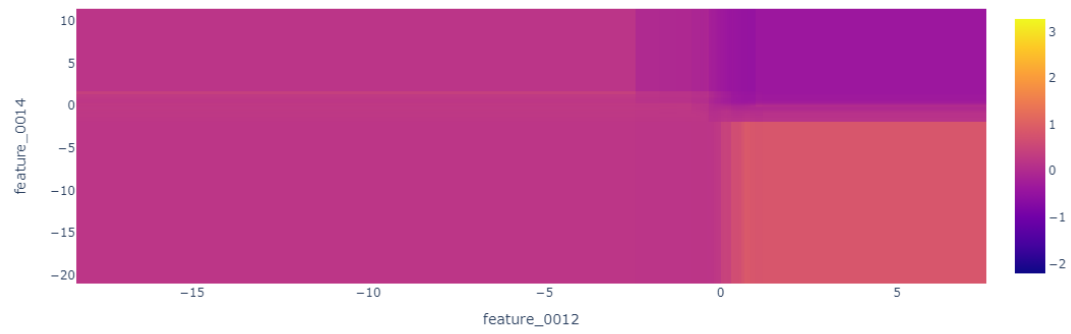
Term: feature\_0011 & feature\_0026 (interaction)



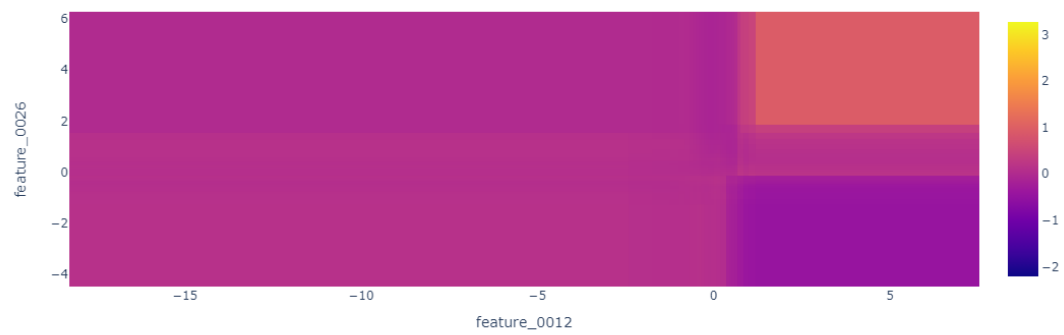
Term: feature\_0011 & feature\_0028 (interaction)



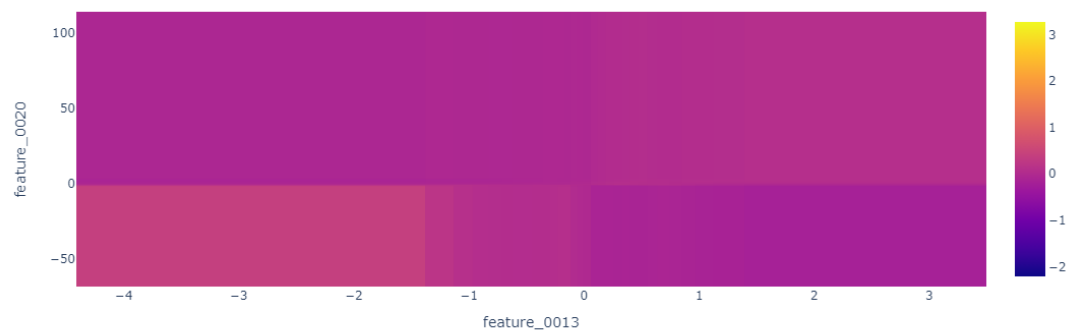
Term: feature\_0012 & feature\_0014 (interaction)



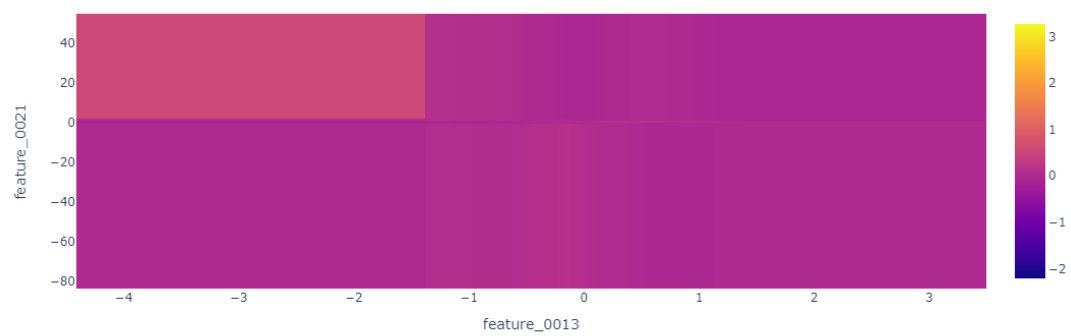
Term: feature\_0012 & feature\_0026 (interaction)



Term: feature\_0013 & feature\_0020 (interaction)

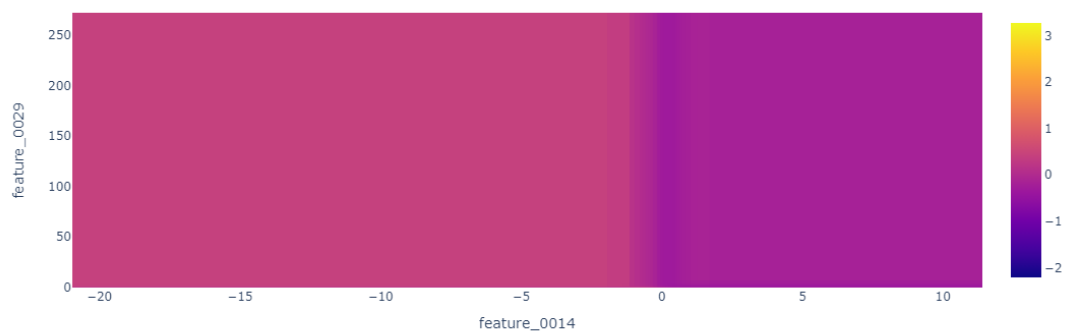


Term: feature\_0013 & feature\_0021 (interaction)

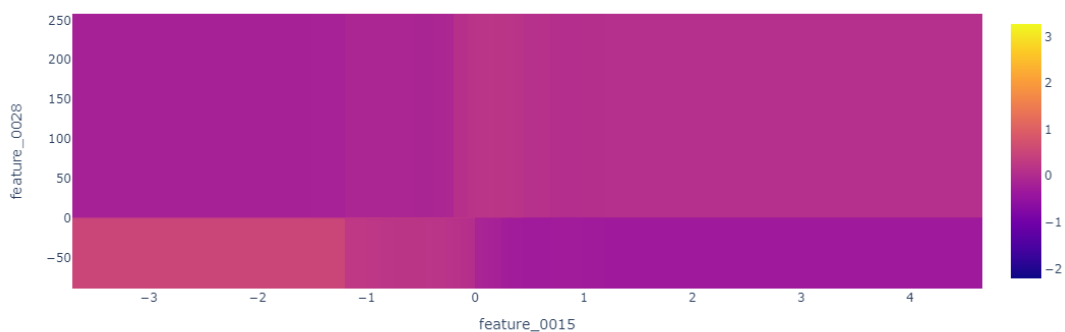




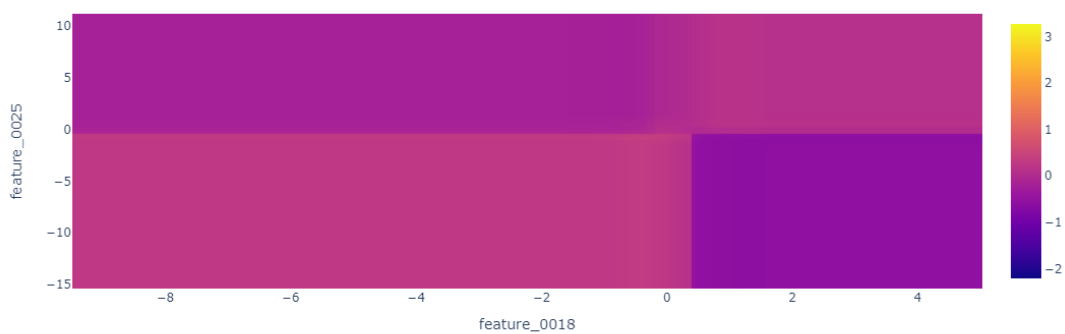
Term: feature\_0014 & feature\_0029 (interaction)



Term: feature\_0015 & feature\_0028 (interaction)



Term: feature\_0018 & feature\_0025 (interaction)



Term: feature\_0019 & feature\_0024 (interaction)



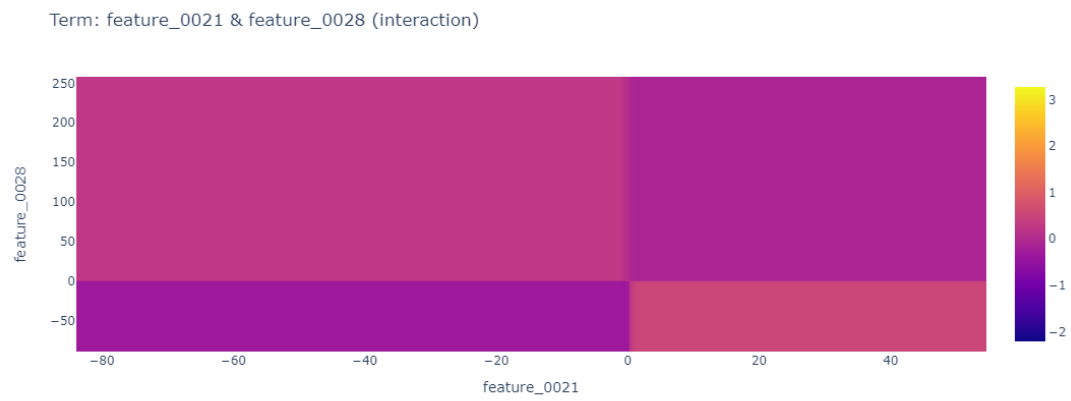
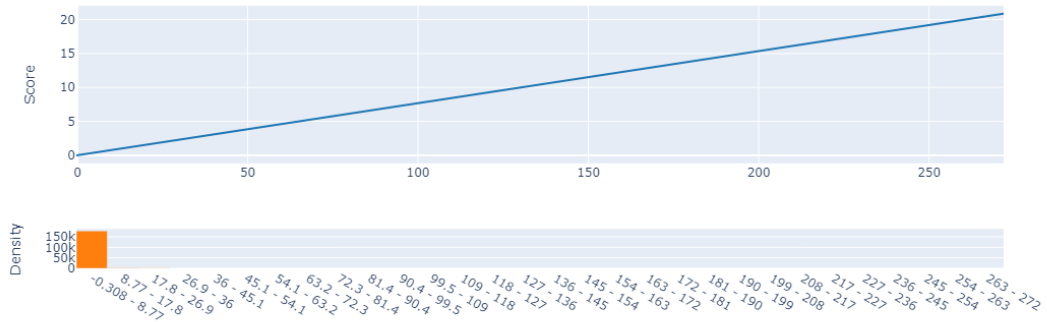
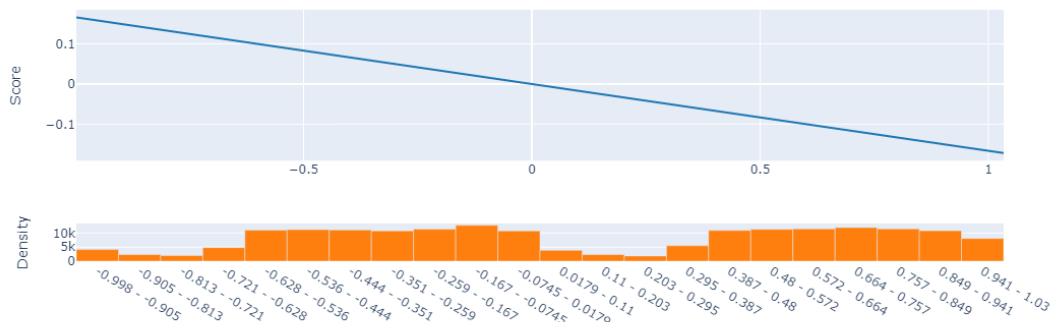


Figure 32: Global Explanation from explanation boosting on pairwise interaction

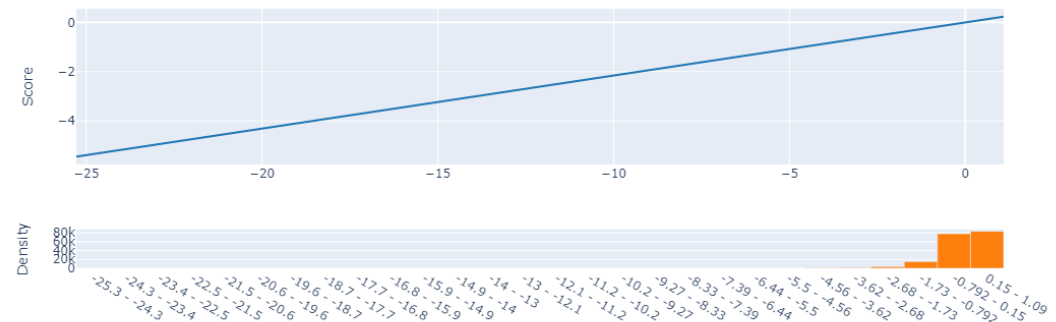
feature\_0029



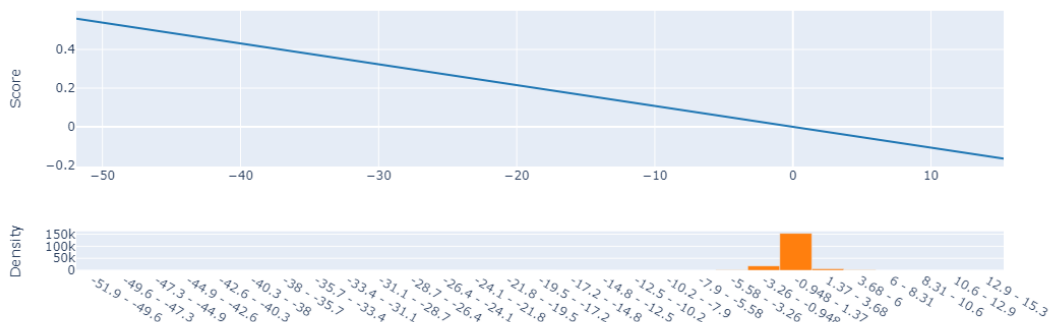
feature\_0000

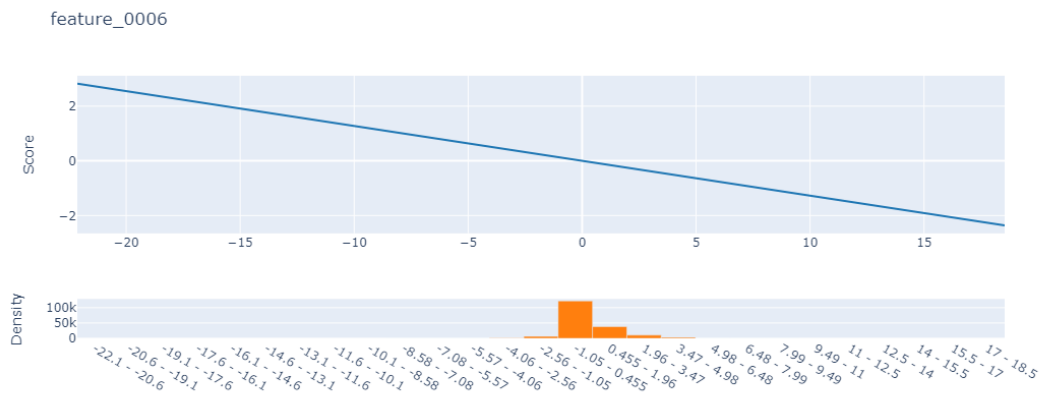
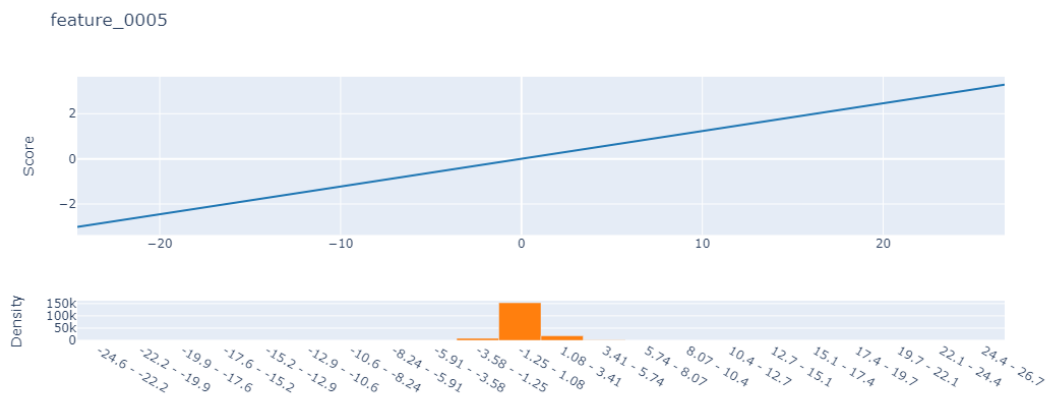
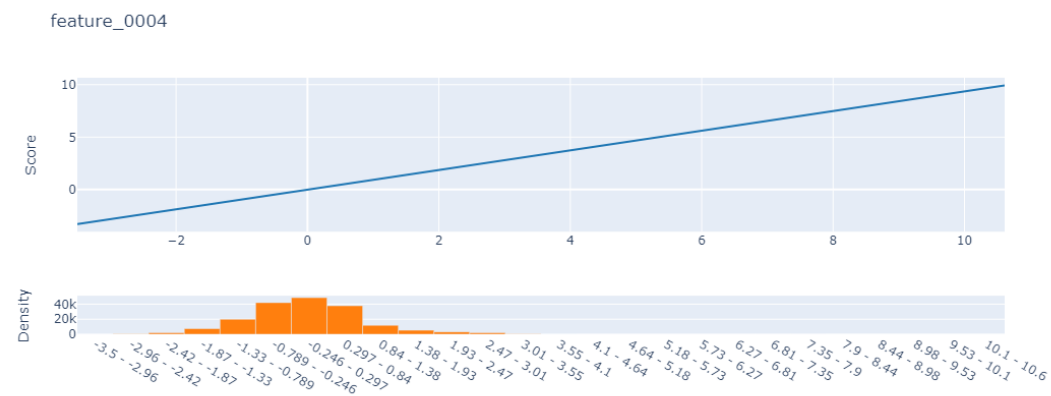
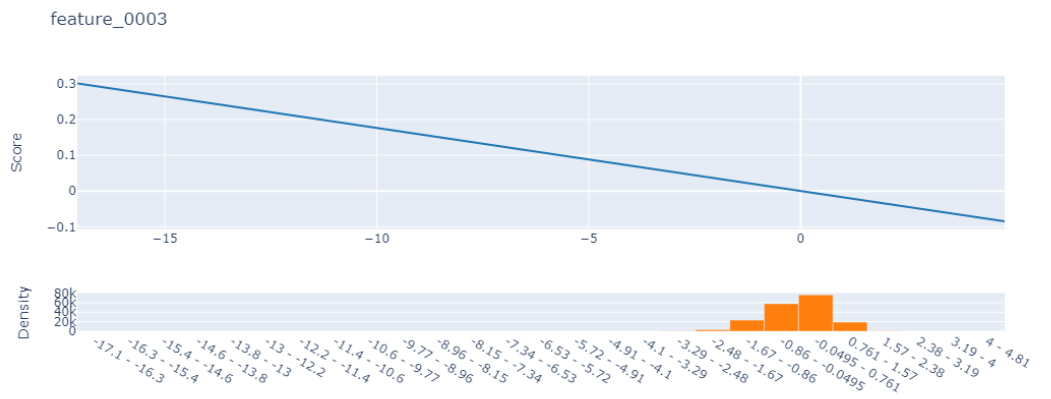


feature\_0001

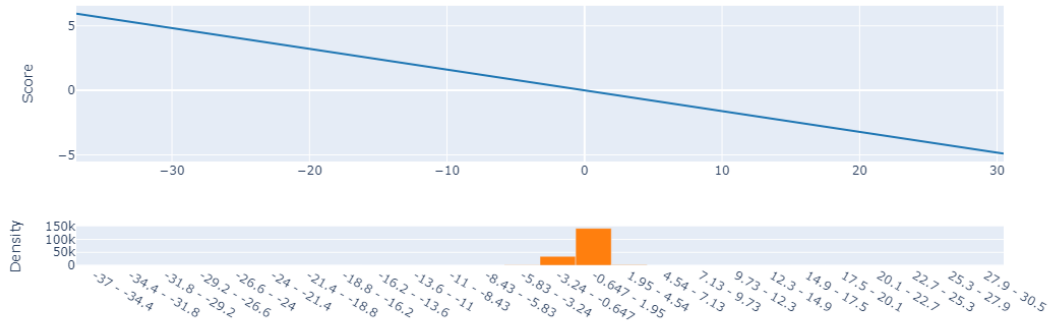


feature\_0002

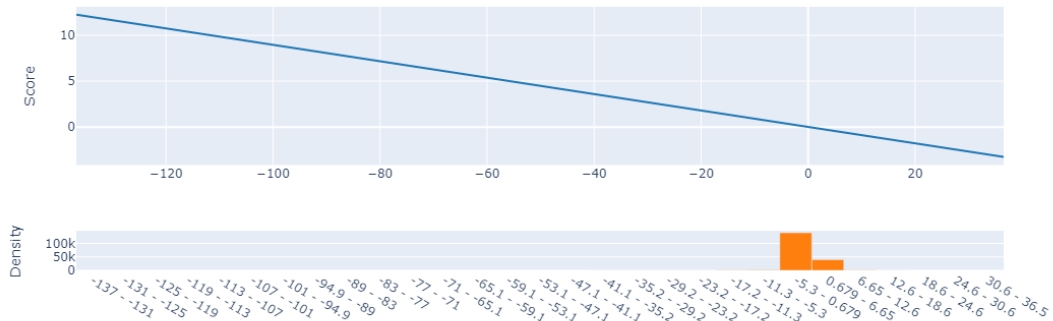




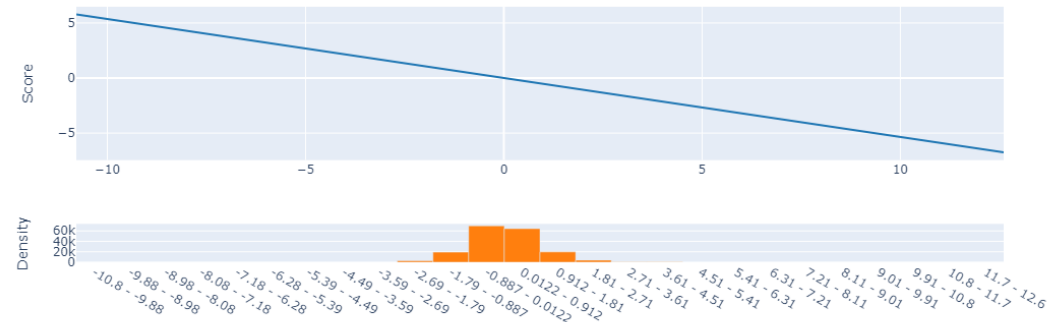
feature\_0007



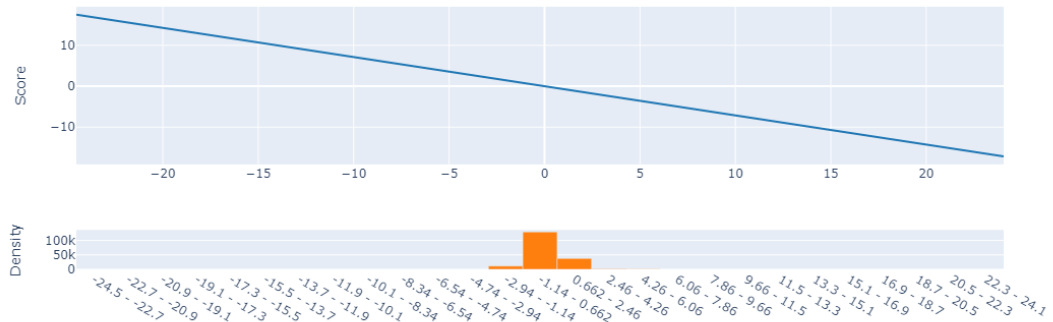
feature\_0008



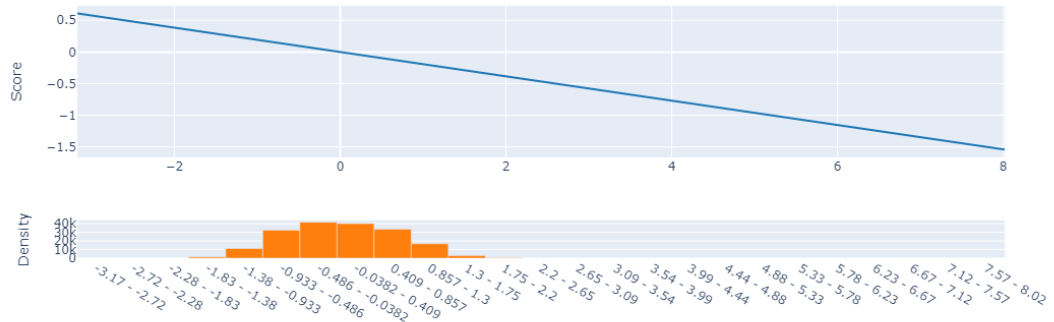
feature\_0009



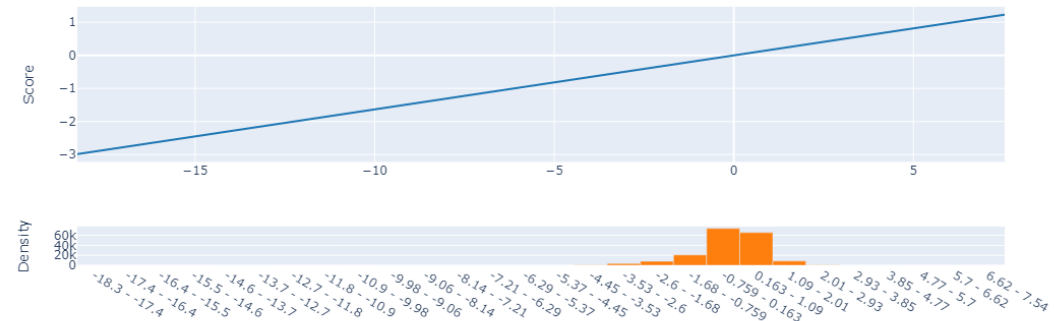
feature\_0010



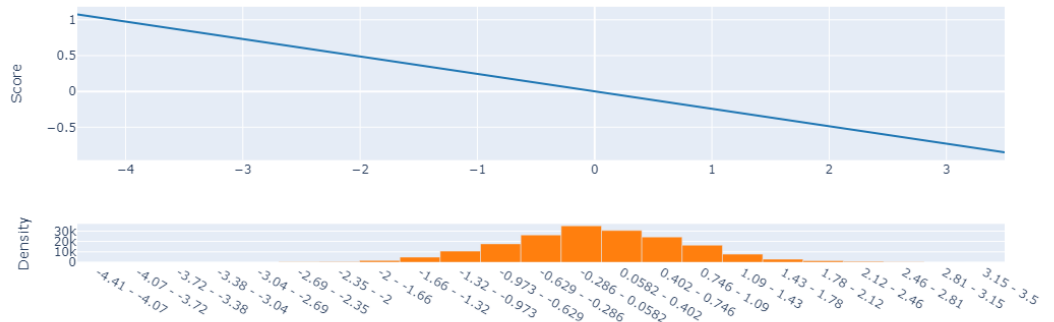
feature\_0011



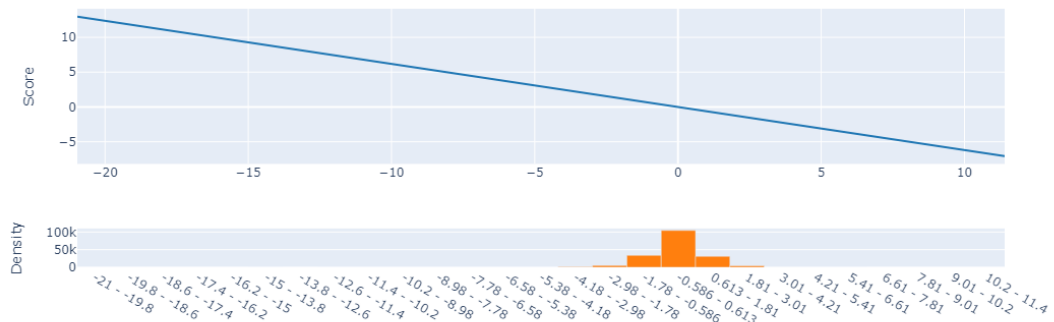
feature\_0012



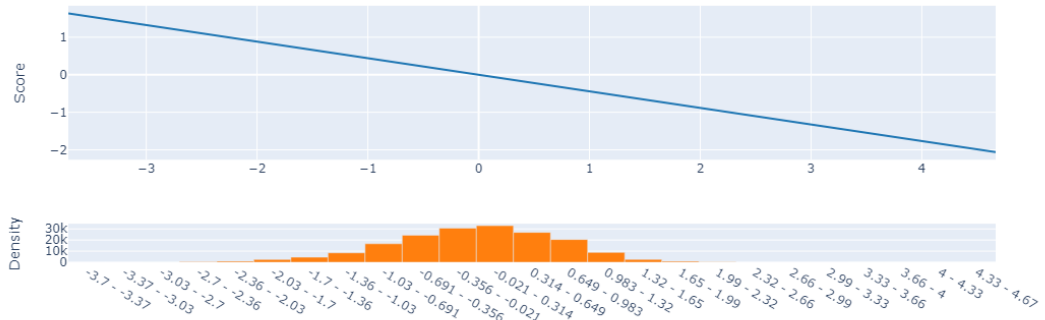
feature\_0013



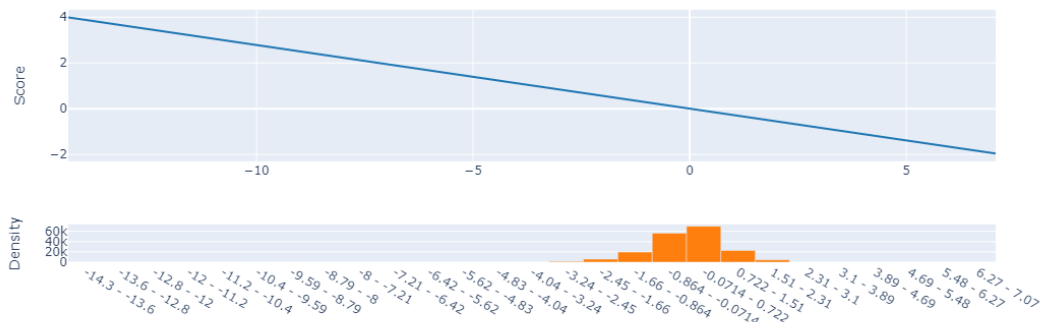
feature\_0014



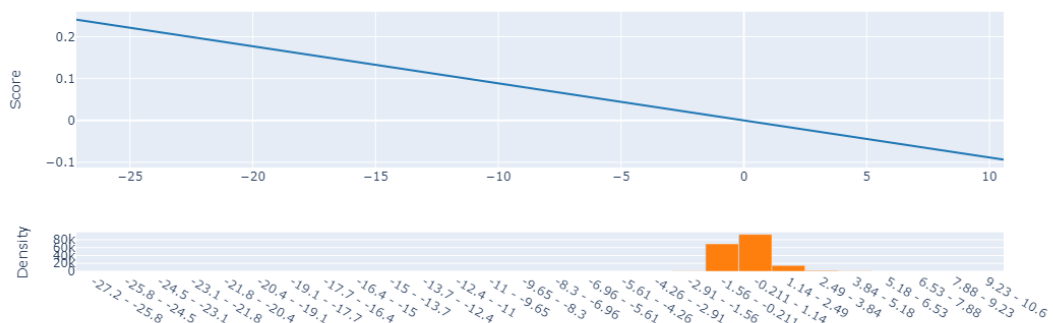
feature\_0015



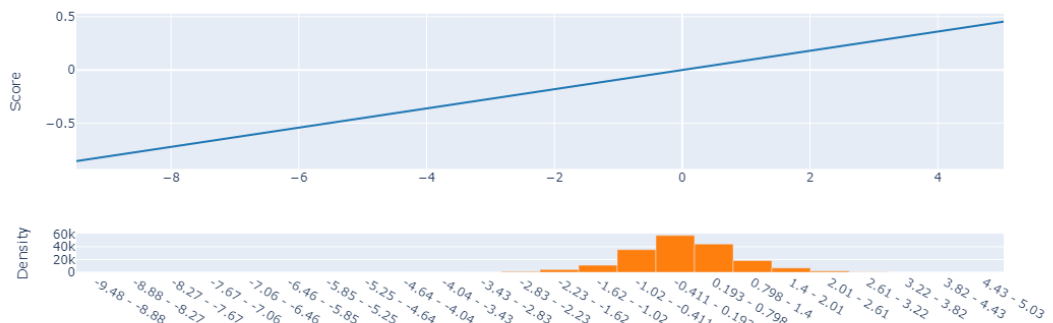
feature\_0016



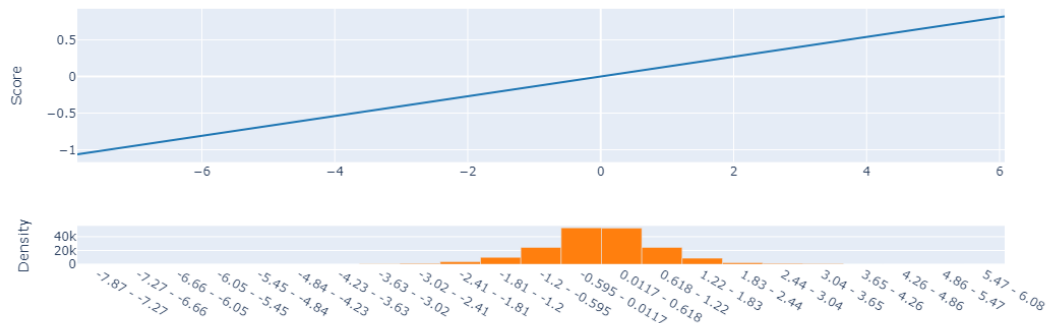
feature\_0017



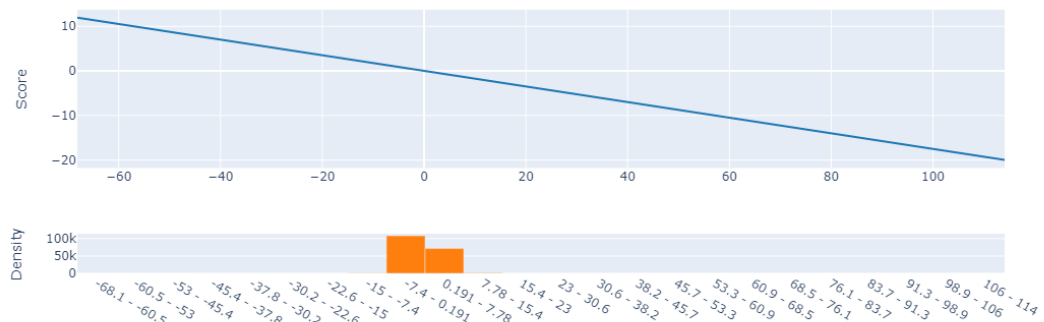
feature\_0018



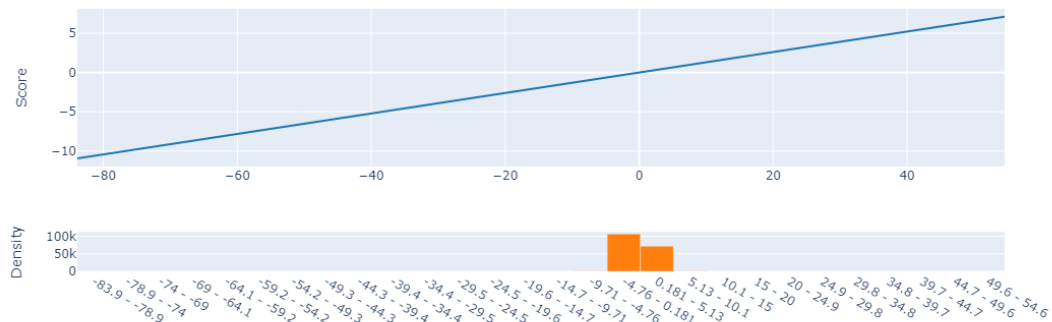
feature\_0019



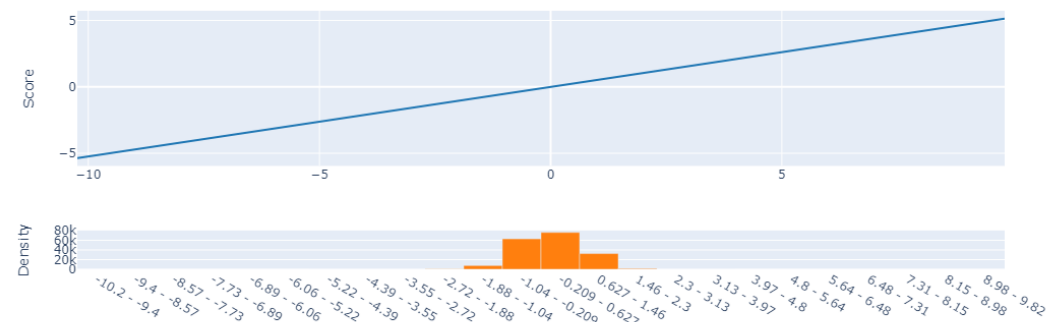
feature\_0020



feature\_0021

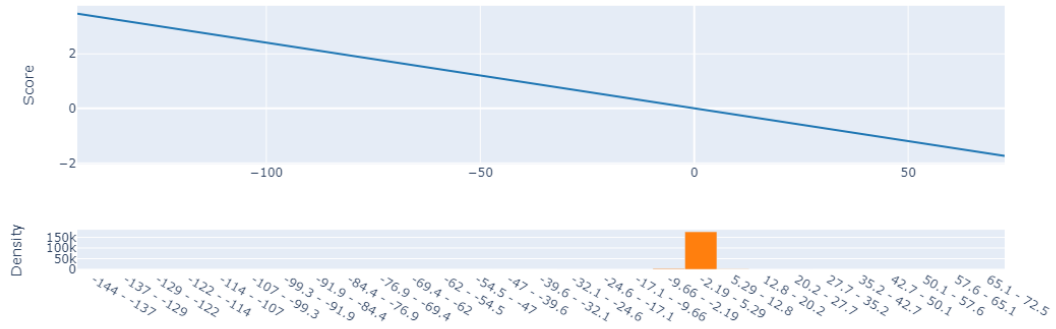


feature\_0022

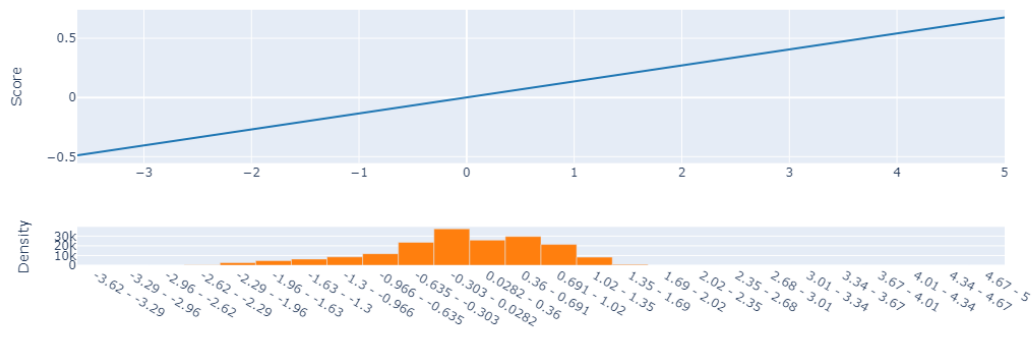




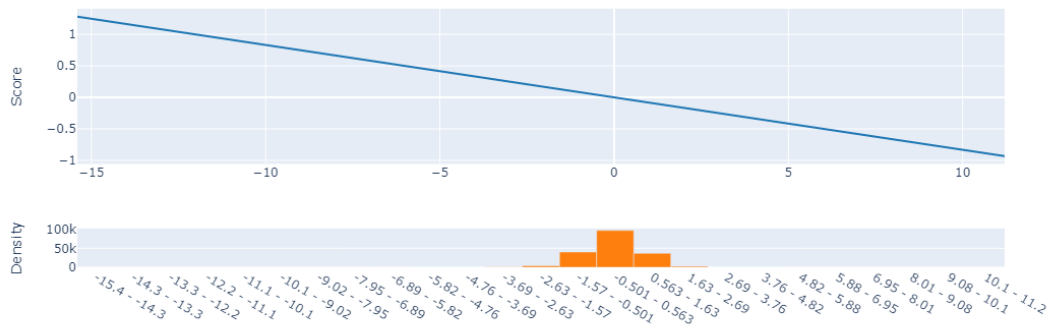
feature\_0023



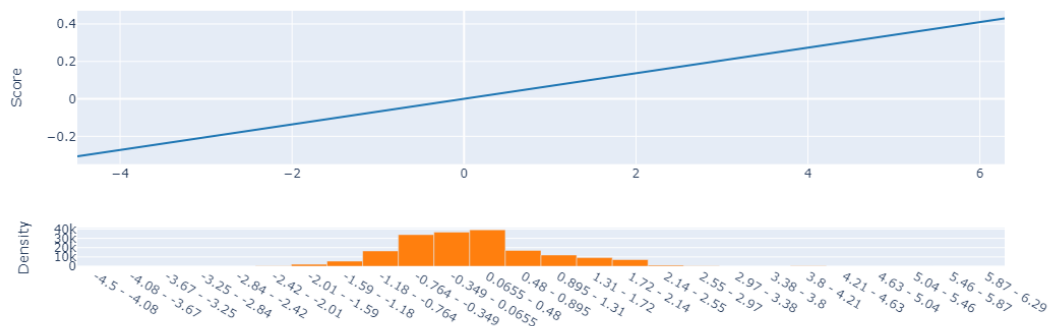
feature\_0024



feature\_0025



feature\_0026



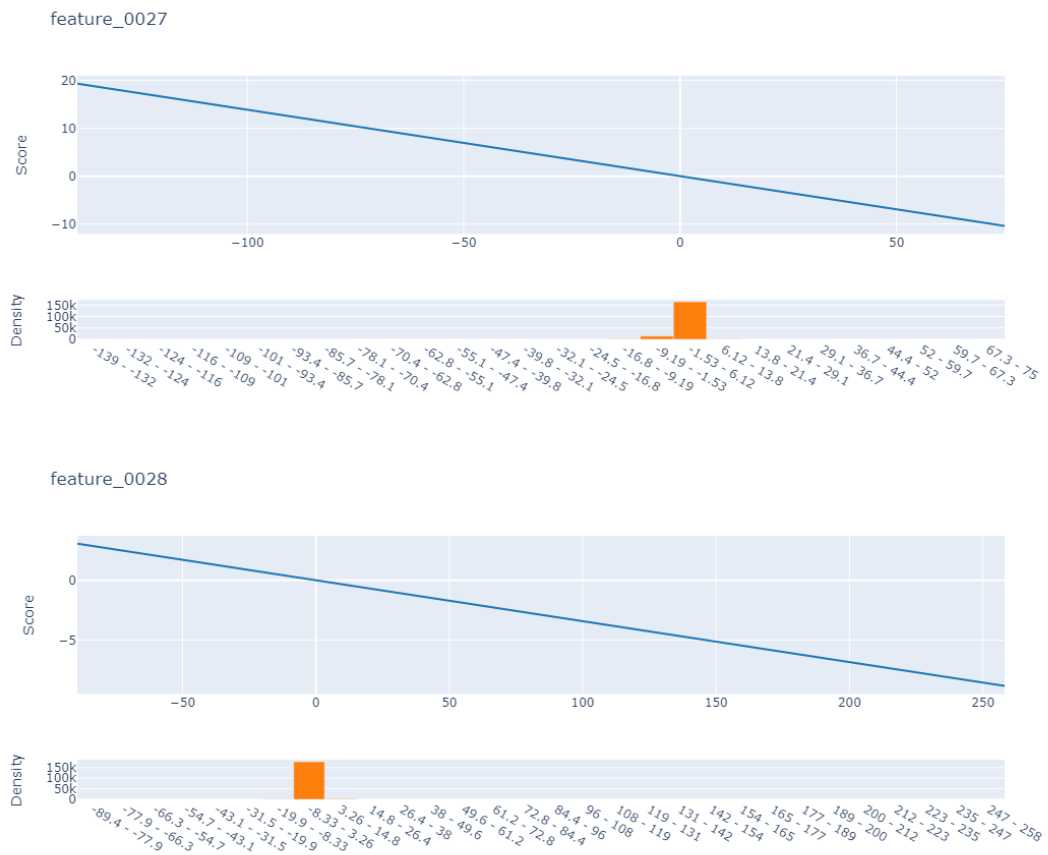


Figure 33: Global Explanation from Logistic Regression on each variables