RapidMiner Automated Model Ops, Model Deployment and Management.

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Introduction

Although enormous datasets are increasingly generated, not only in the formal health care setting, but also emanating from data streams from medical and consumer devices, wearables, patient-reported outcomes, as well as environmental, community and public health sources, explainability and interpretability continue to be a significant barrier for implementing AI/ML tools in particular when physicians need to be convinced the investment in new technology leads to a higher standard of care.

However, the tools for automated model development, model deployment and management have recently become more accessible using intuitive technology enabling collaboration on models, monitor for governance, drift and bias issues, inclusive set up alerts and integration strategy options.

This document illustrates how predictive modeling can be developed using a code-free intuitive visual approach increasing explainability and interpretability without black boxes. Next the developed models are deployed and the tools available for monitoring are visualized.

Methods

The data used in this document is based on a recent PLOSONE publication by Pengcheng Yang et al. The first dataset (https://doi.org/10.1371/journal.pone.0226962.s002) was used for model development (inclusive validation) using RapidMiner AutoModel tool (more information can be found here: https://docs.rapidminer.com/latest/studio/guided/auto-model/). The second dataset (https://doi.org/10.1371/journal.pone.0226962.s003) was injected for model deployment monitoring taking into account that full deployment monitoring requires more additional datasets (as explained here: https://docs.rapidminer.com/latest/studio/guided/deployments/)

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RESEARCH ARTICLE

A new method for identifying the acute respiratory distress syndrome disease based on noninvasive physiological parameters

Pengcheng Yang, Taihu Wu, Ming Yu, Feng Chen, Chunchen Wang, Jing Yuan, Jiameng Xu, Guang Zhang

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Results

Figure 1: features (n=44) used for predictive modeling

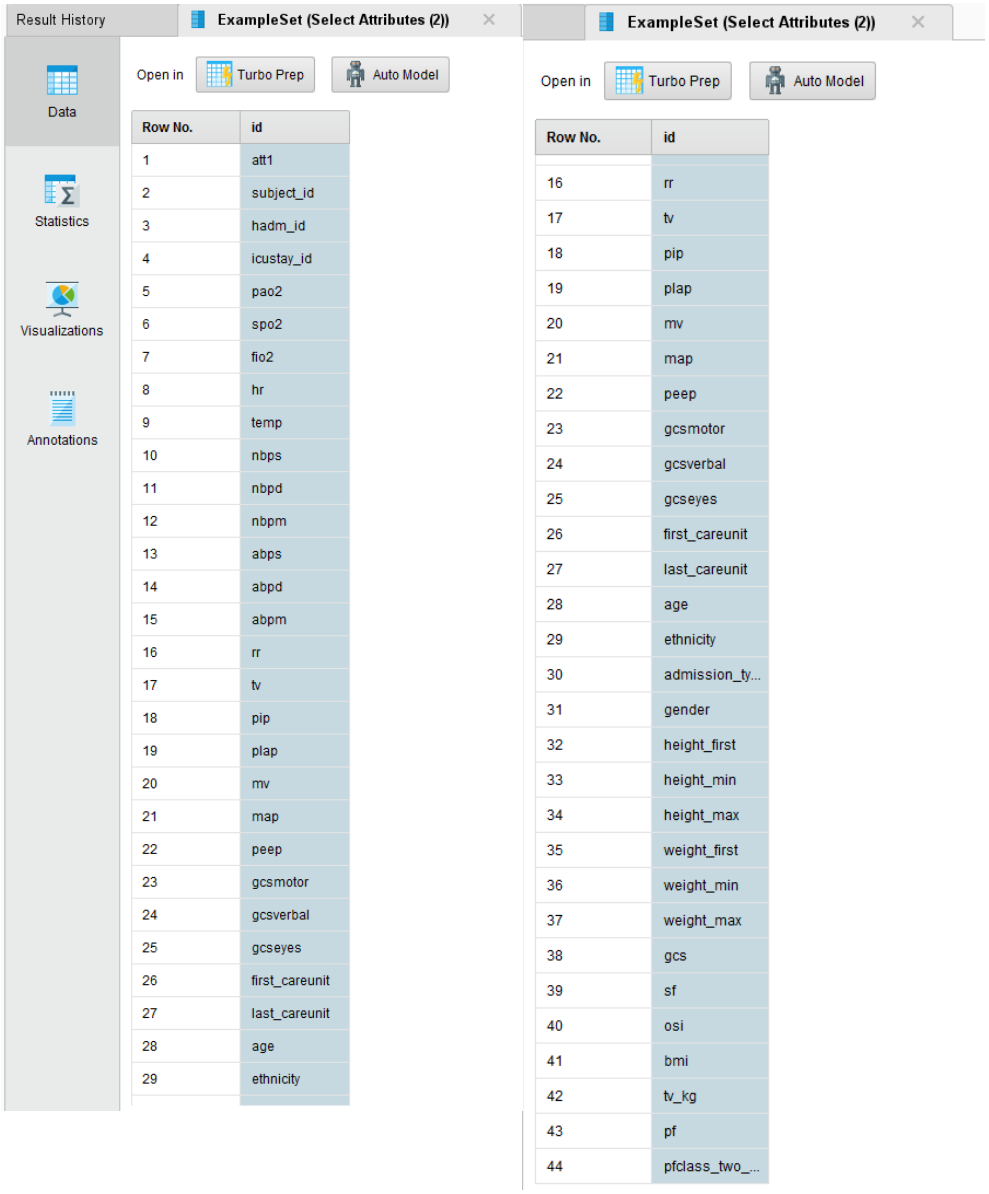


Figure 2: Results of modeling with standard Naive Bayes parameters.

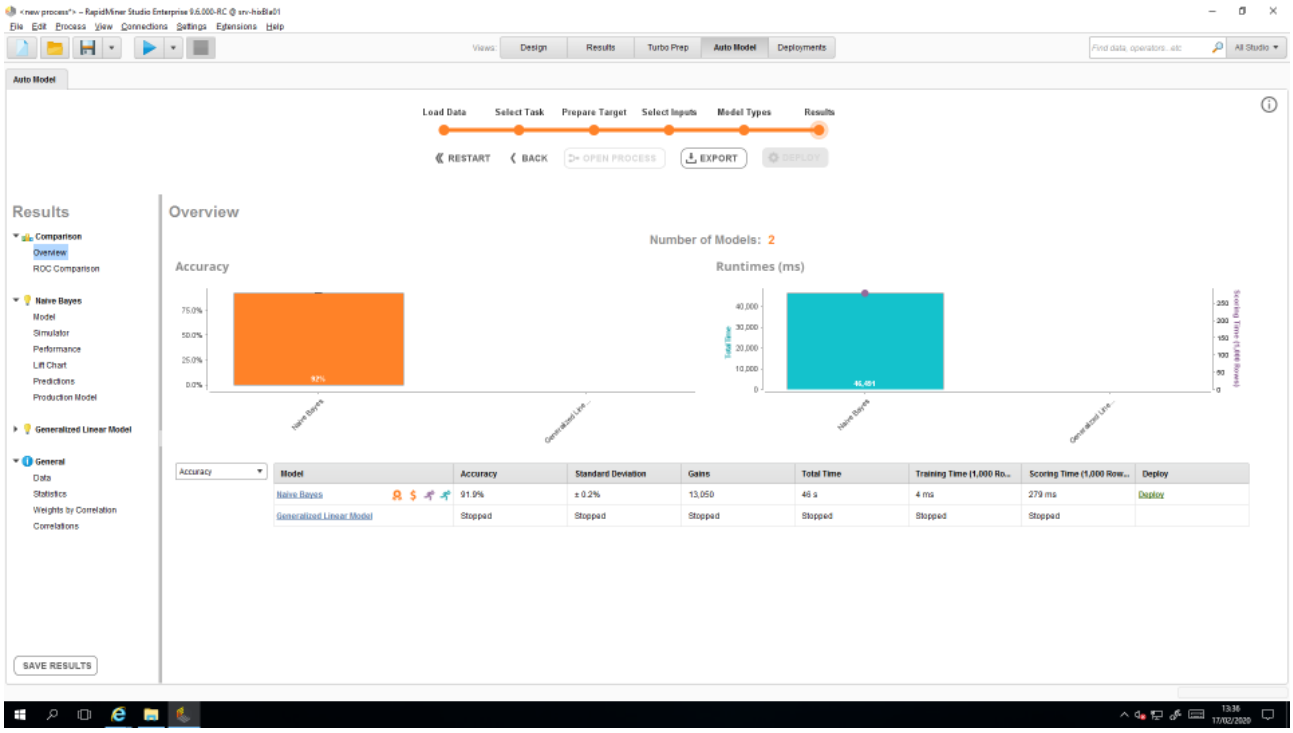


Figure 3: ROC curve of Naive Bayes.

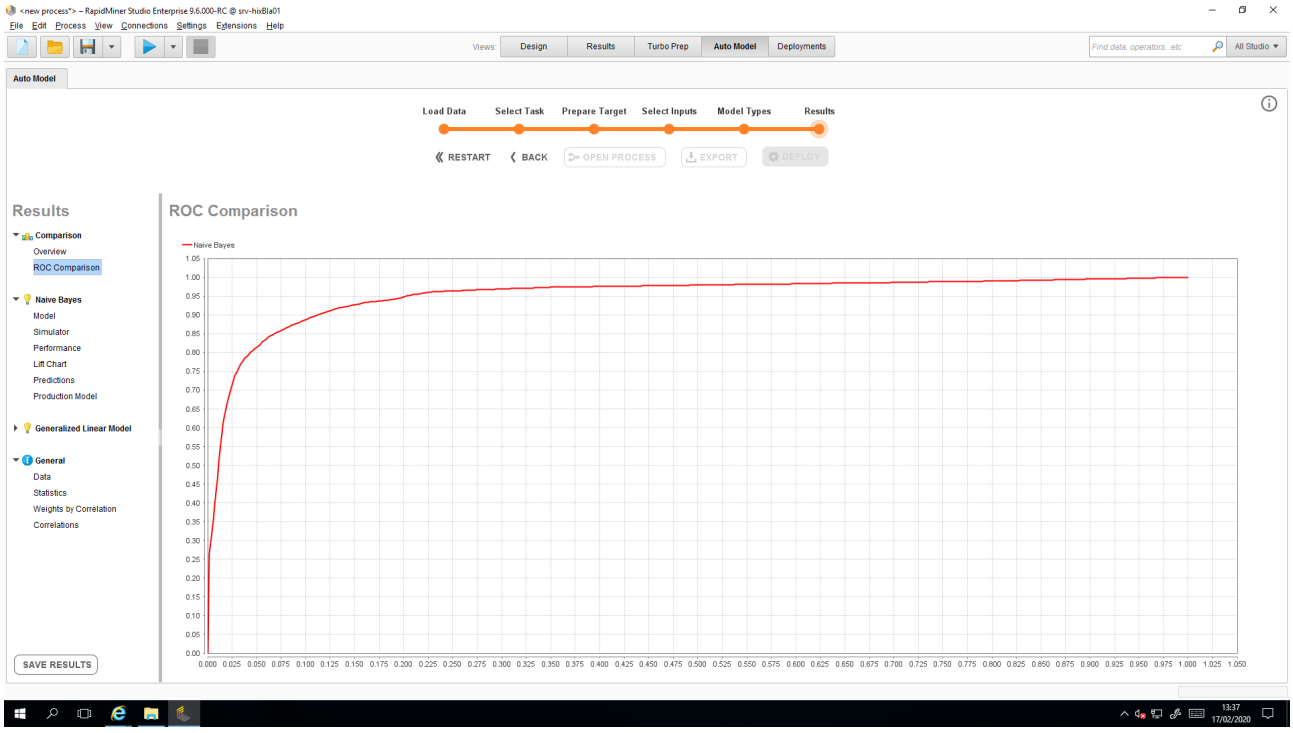


Figure 4: Weight by correlation of Naive Bayes.

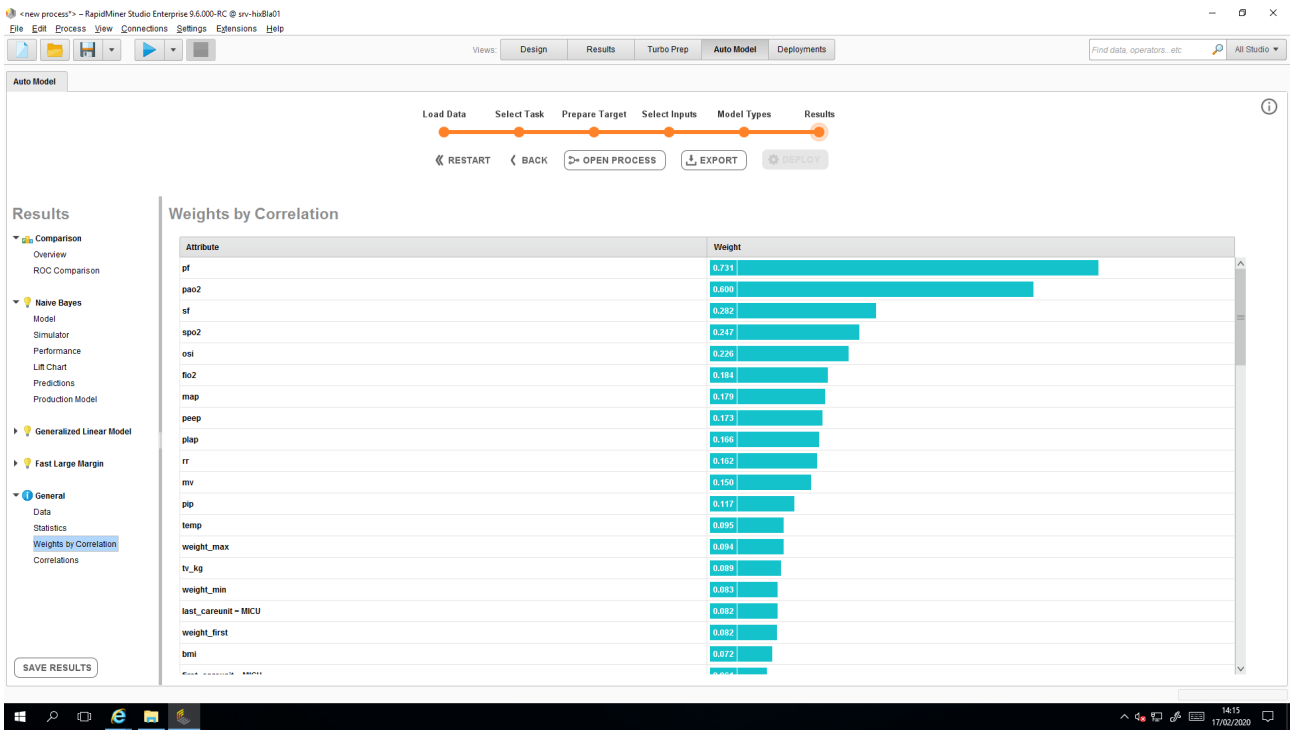


Figure 5: Performance of Naive Bayes.

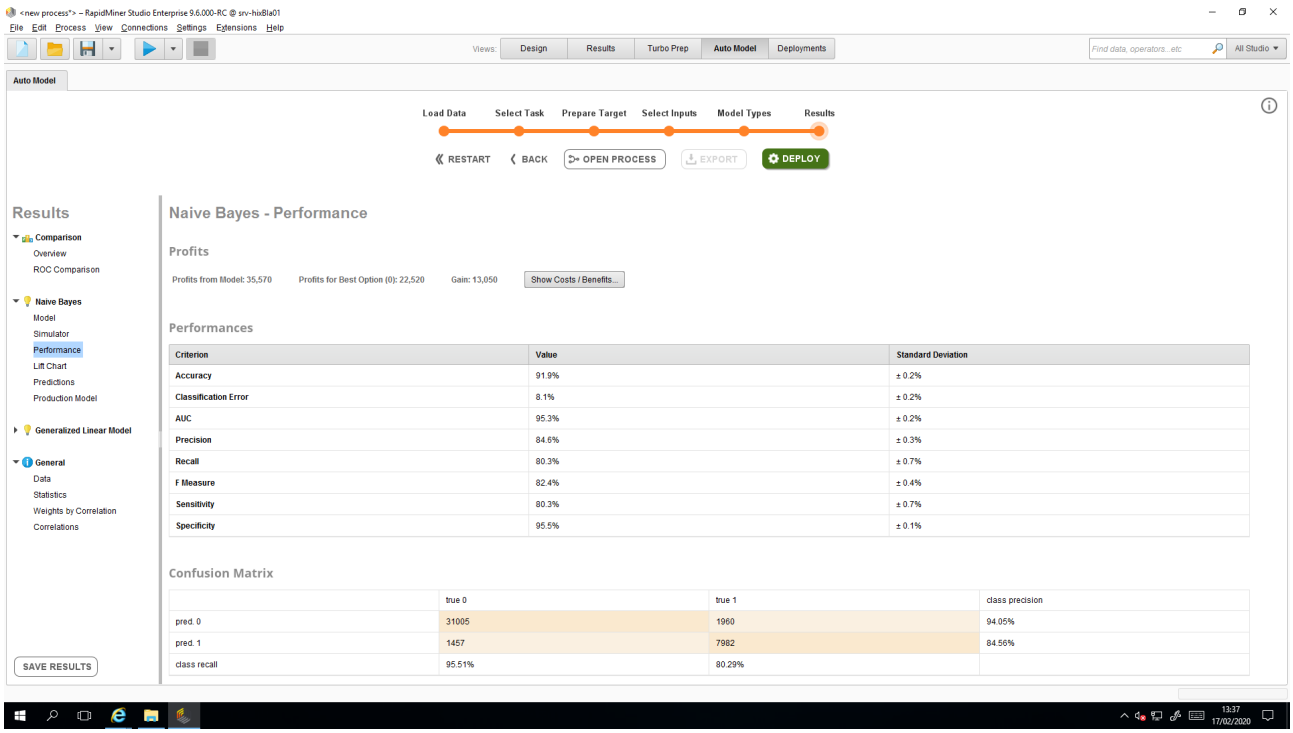


Figure 6: Data modeling by Naive Bayes, GLM, Fast Large Margin.

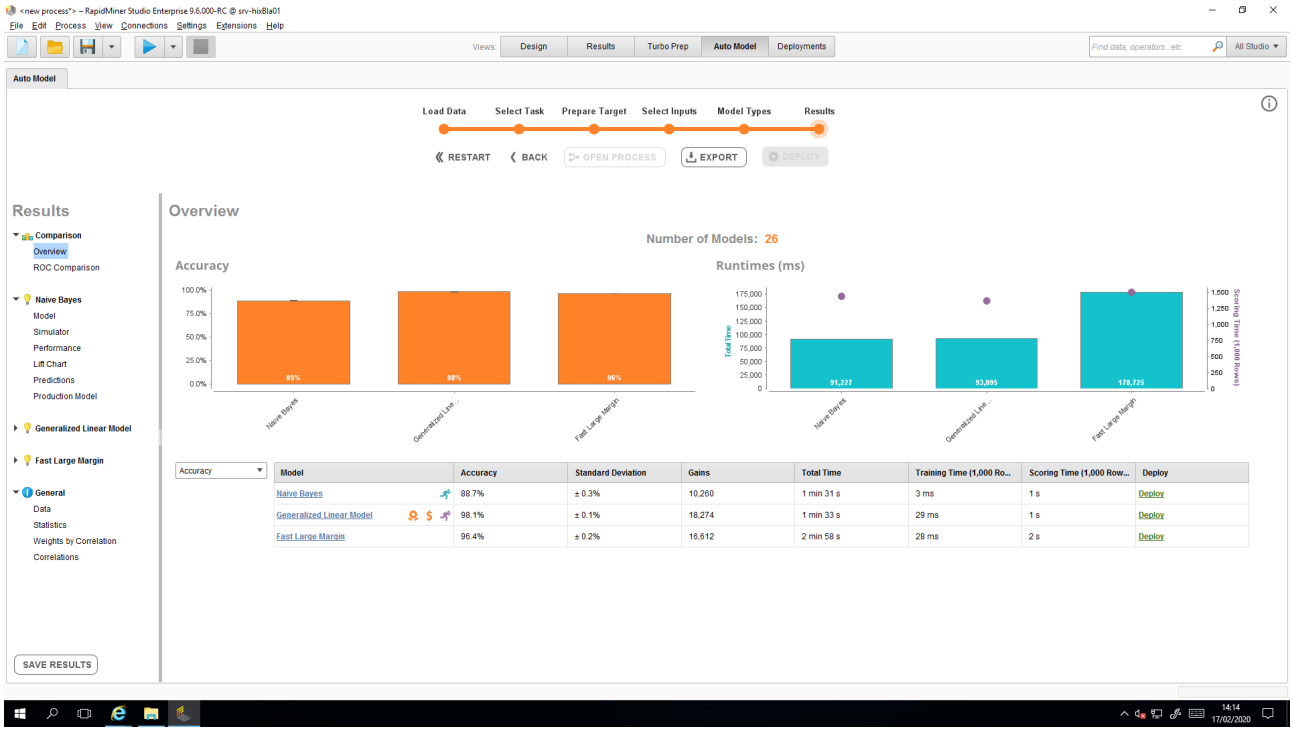


Figure 7: ROC comparison of NB, GLM, Fast Large Margin.

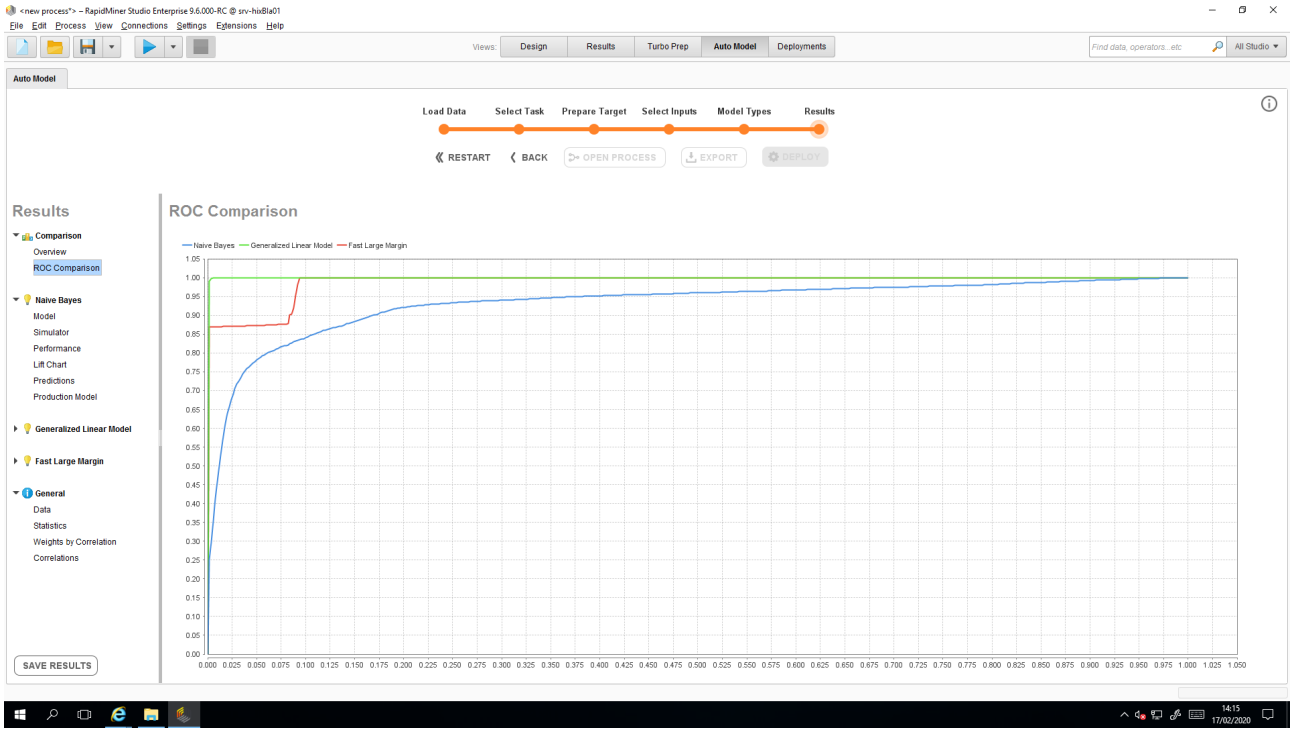


Figure 8: Correlations.

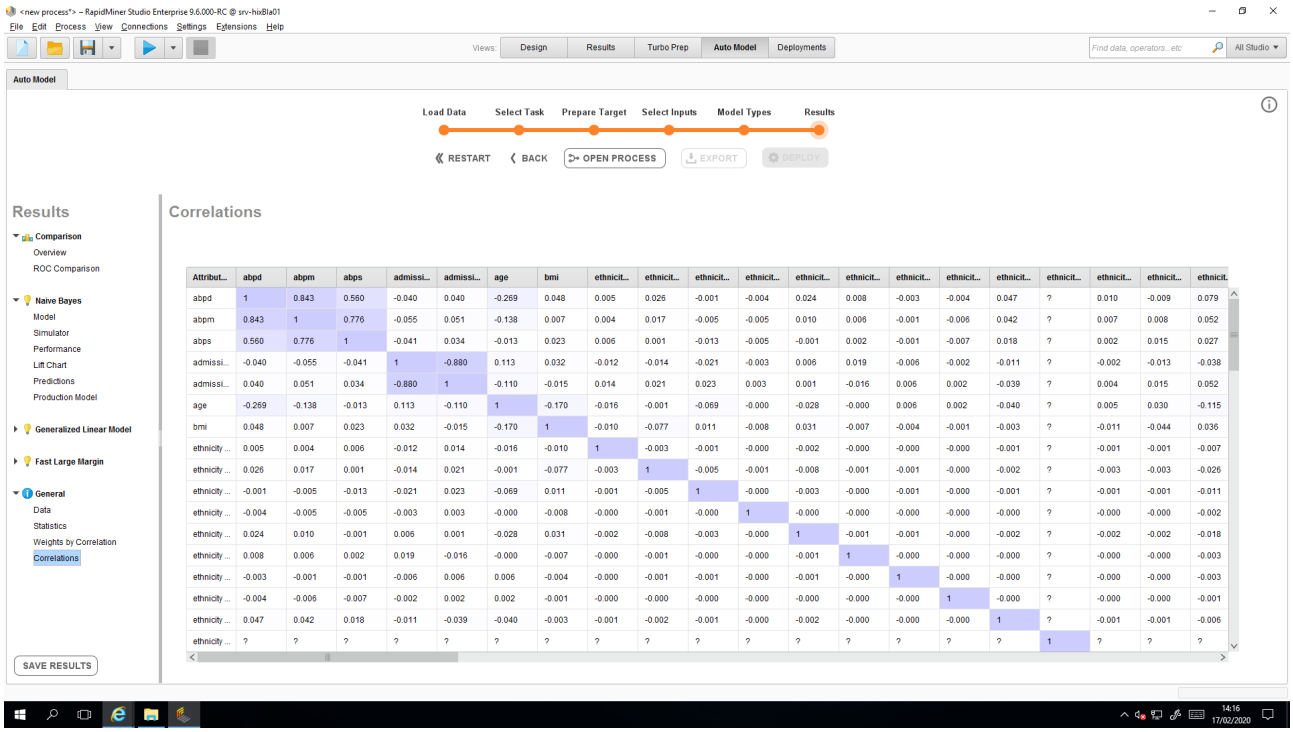


Figure 9: Deployment of NB model as use case.

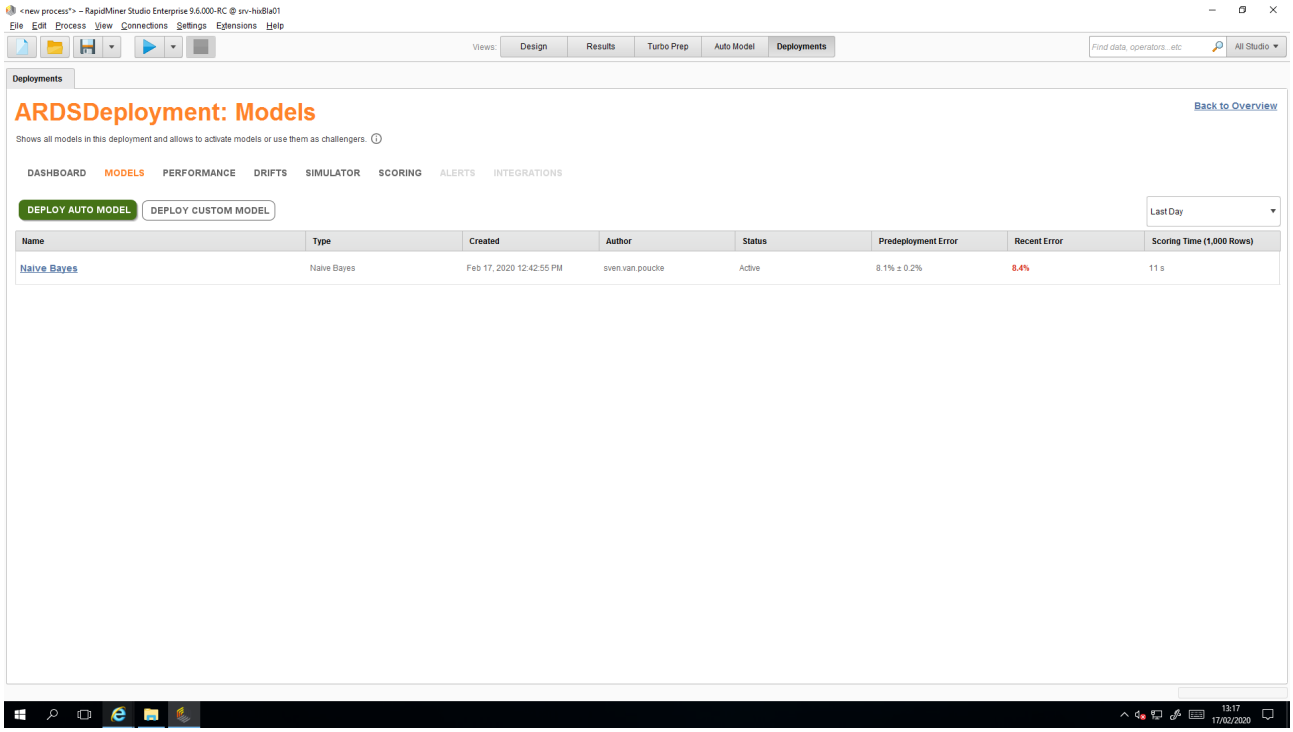


Figure 10: Deployment Dashboard.

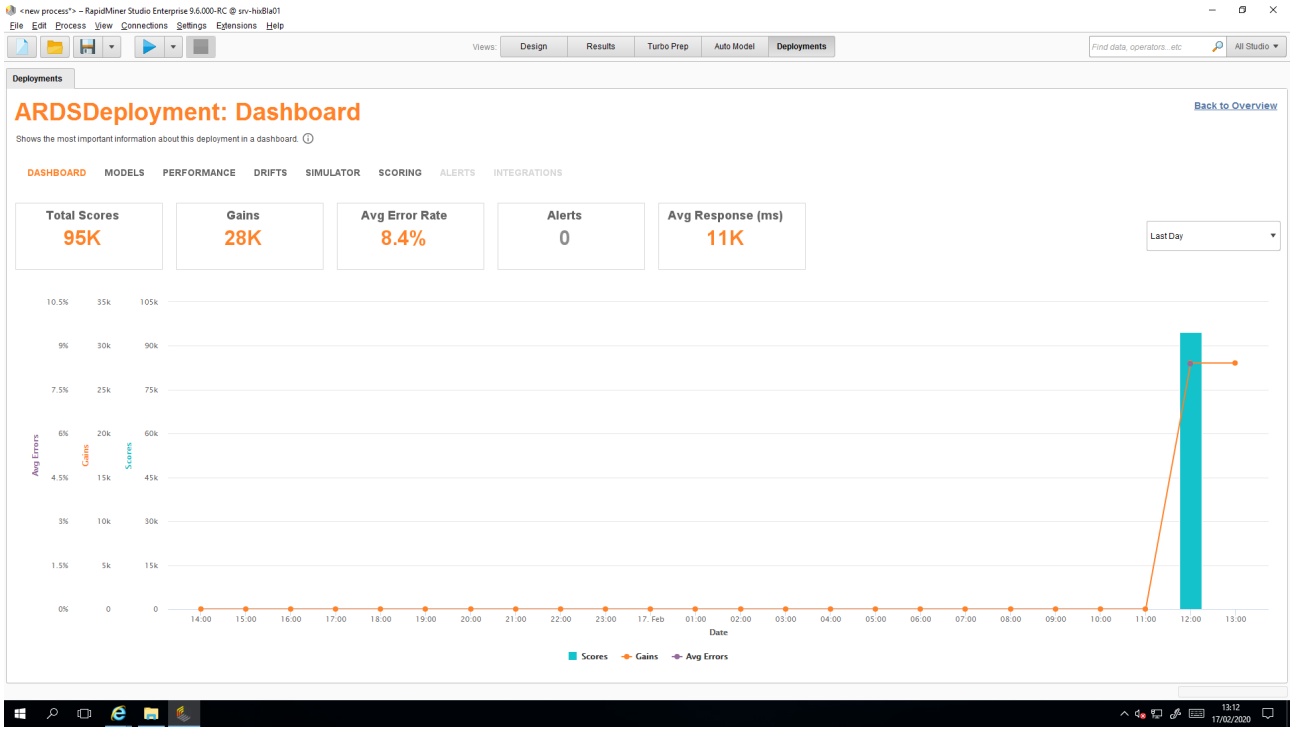


Figure 11: Performance of deployed model(s).

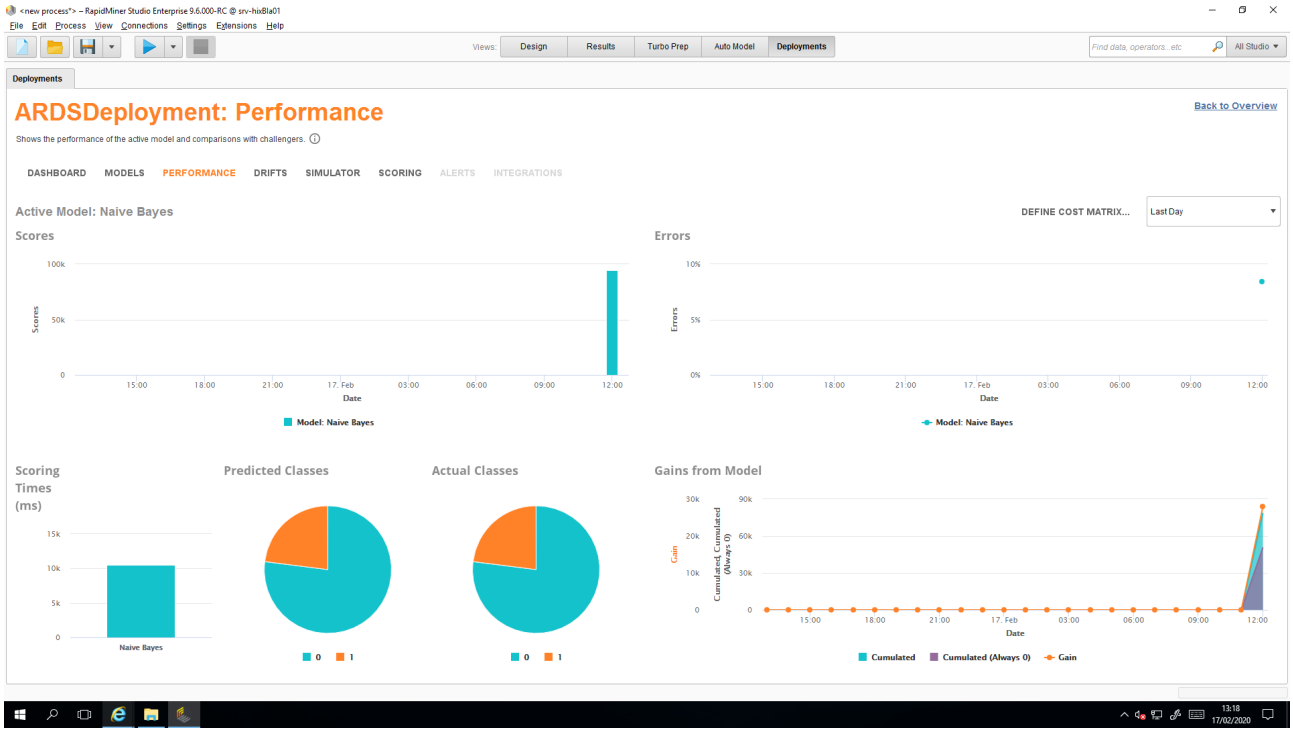


Figure 12: Drifts: highlights the columns where the data lately deviates from the training data.

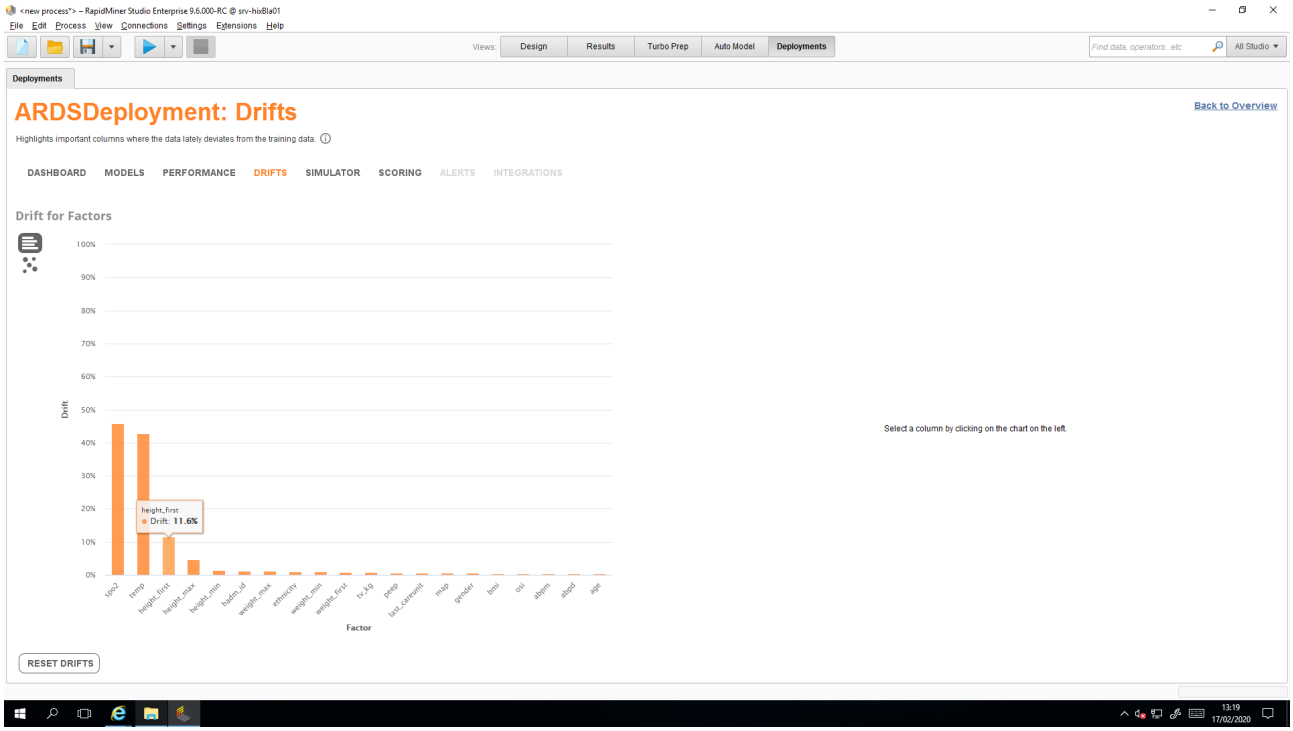
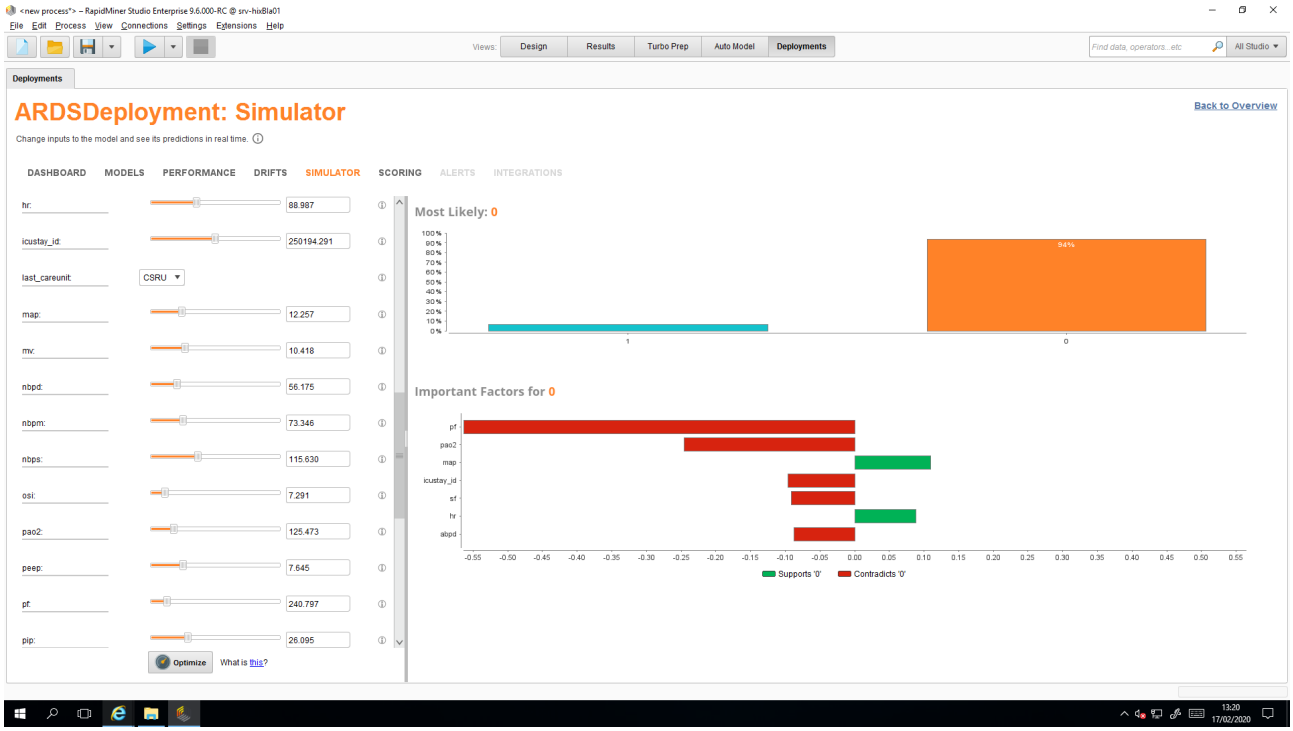


Figure 13: Deployment Simulator.



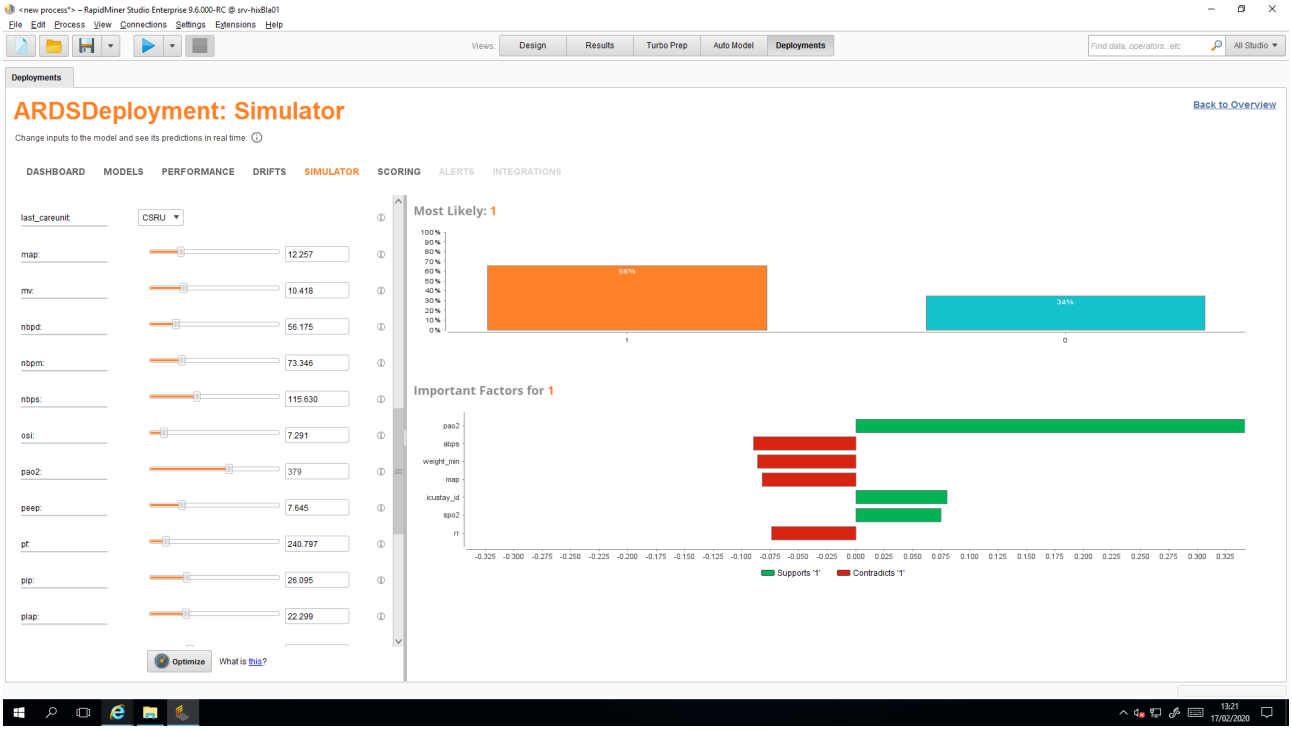


Figure 14: Input Data of Deployment Model.

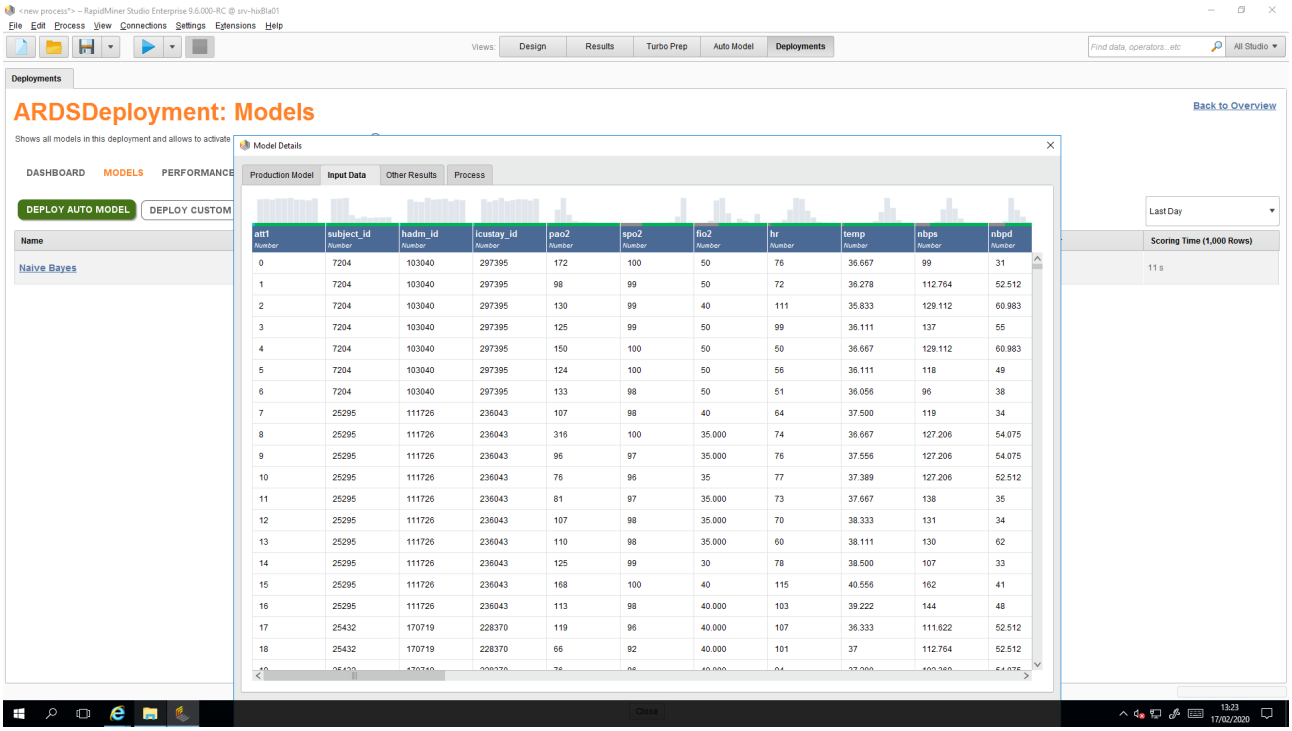


Figure 15: Production Model: Feature Details:

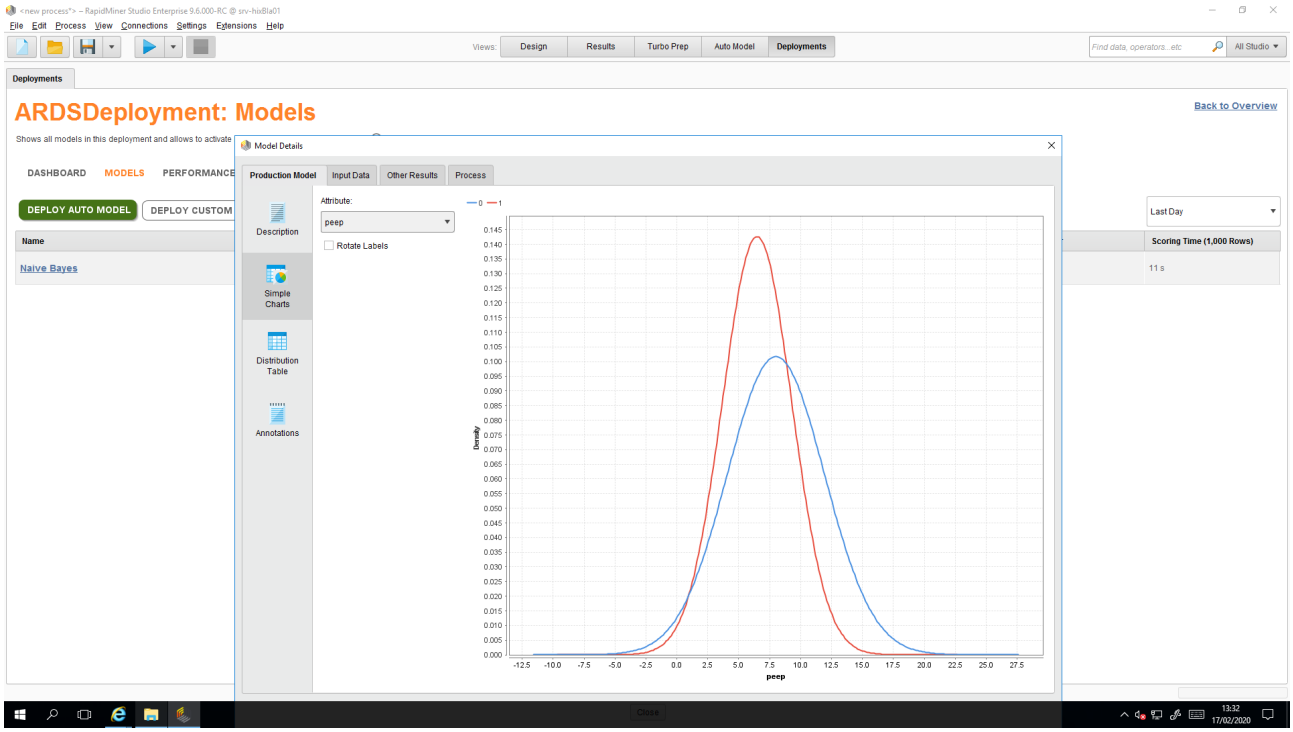


Figure 16: Lift Chart.

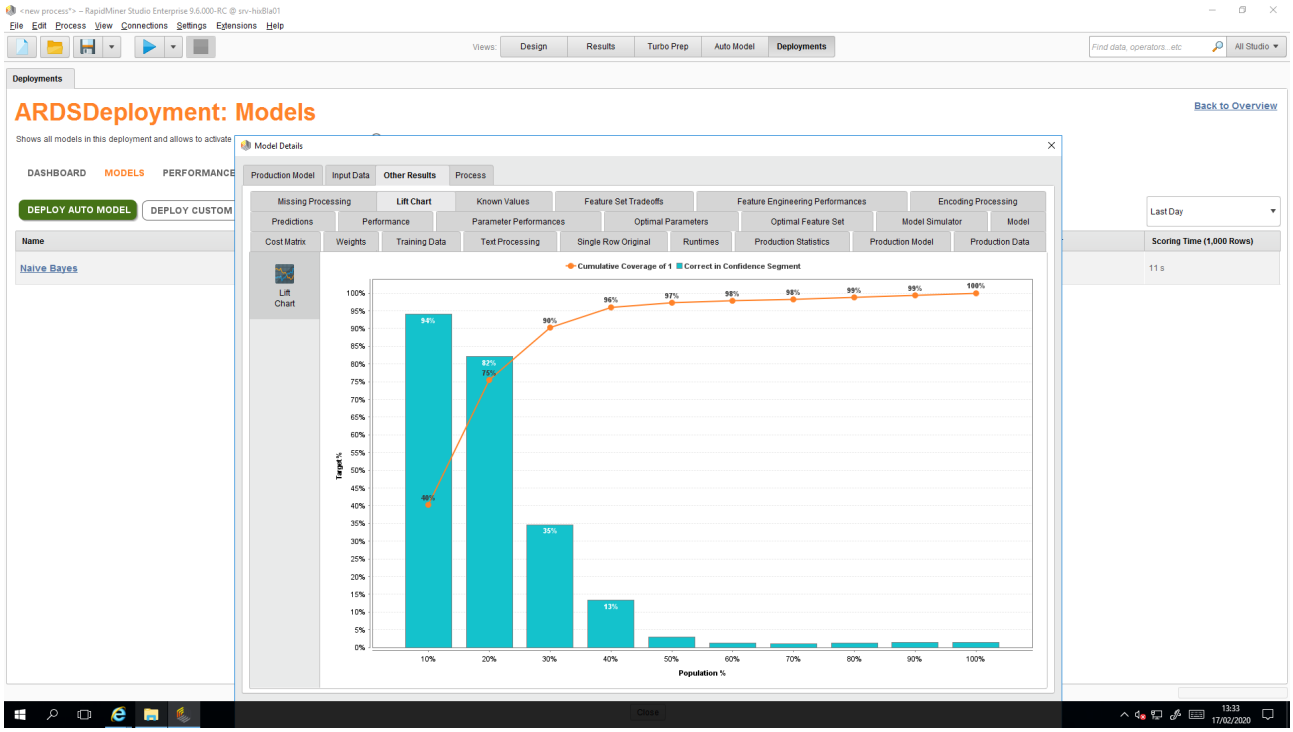


Figure 17: Predictions with confidence (0,1) and cost.

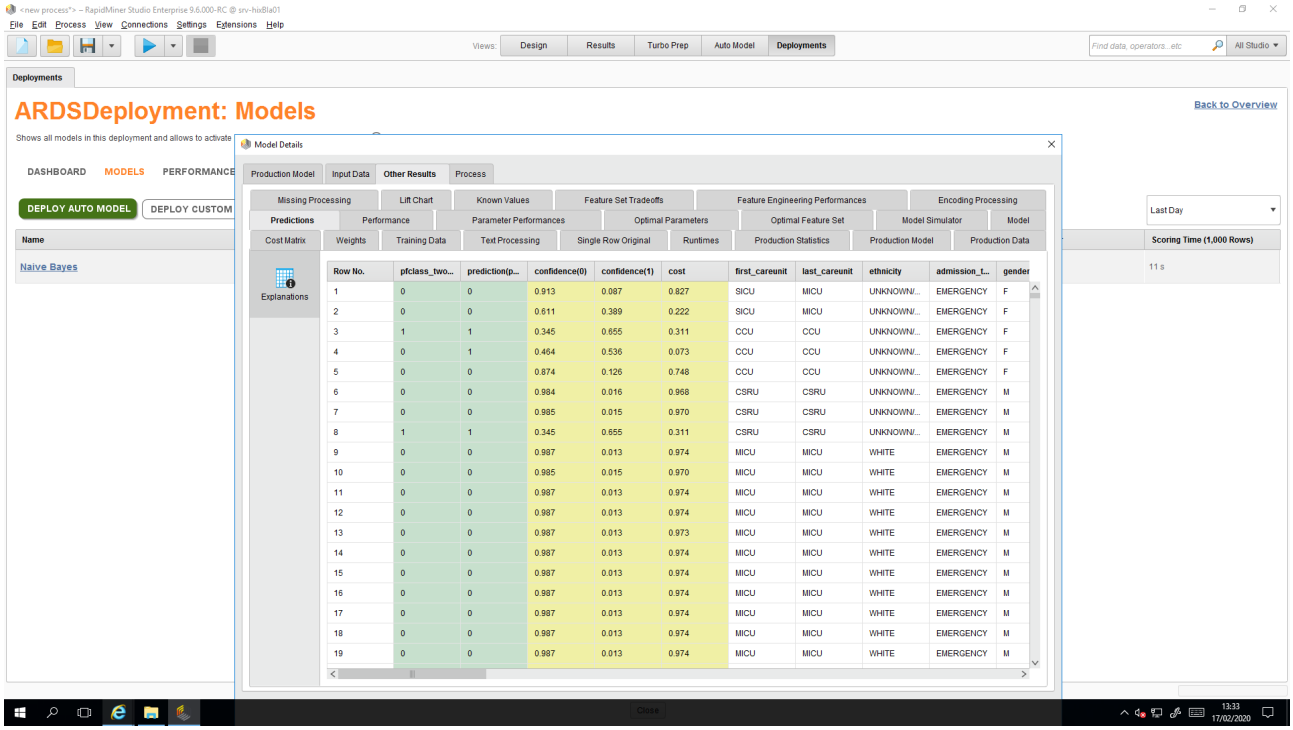


Figure 18: Performance of Production Model.

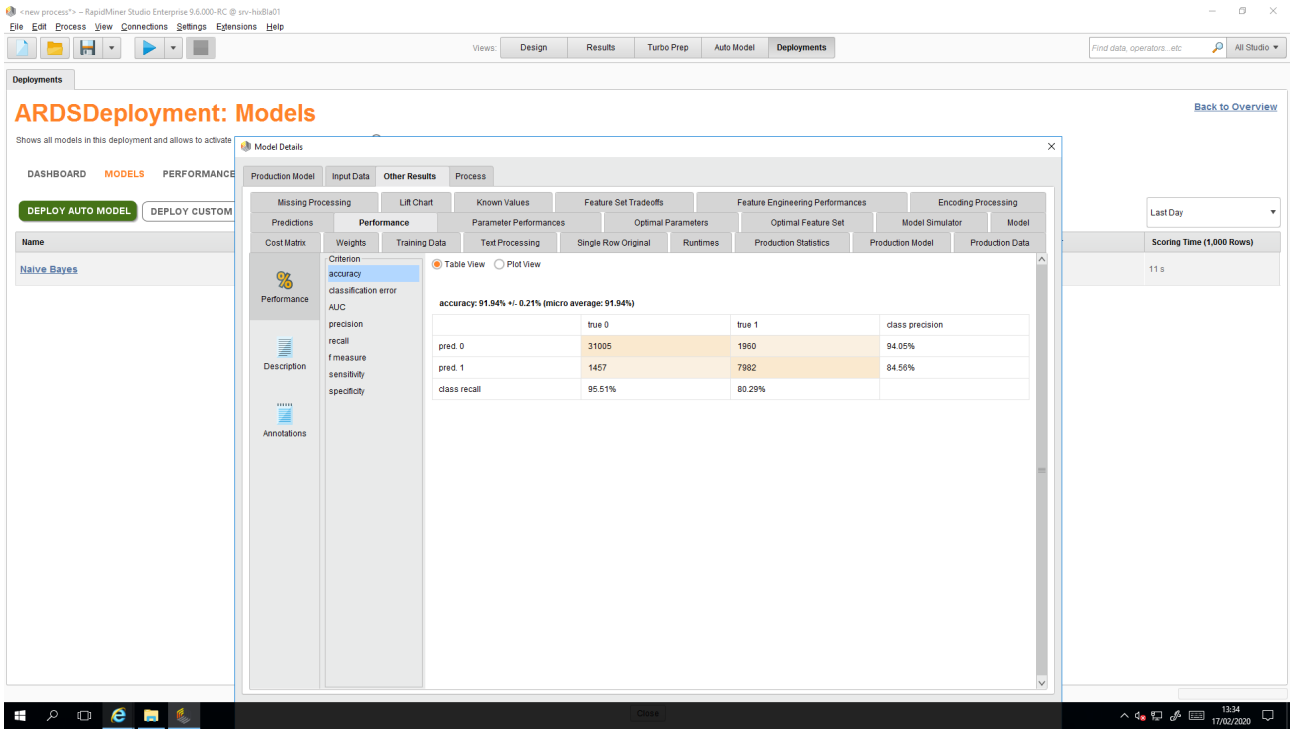


Figure 19: Production Statistics Features.

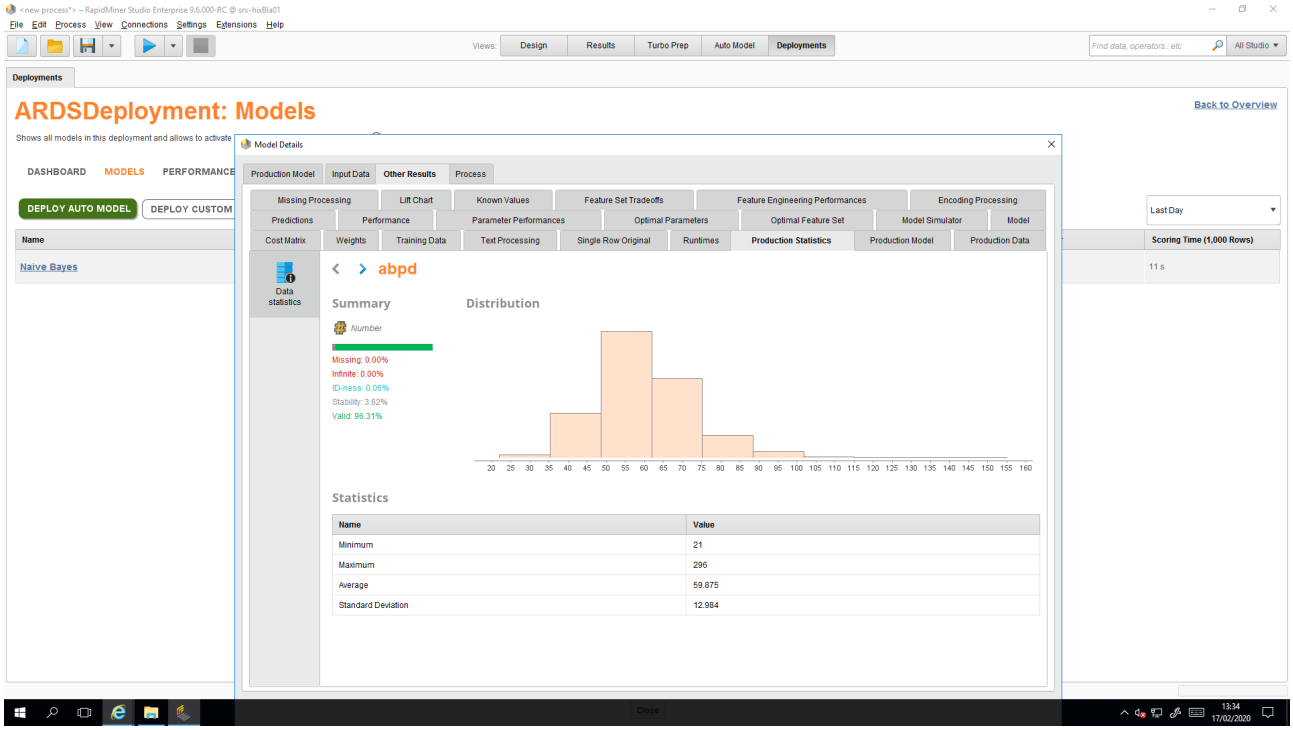


Figure 20: XML Code Process.

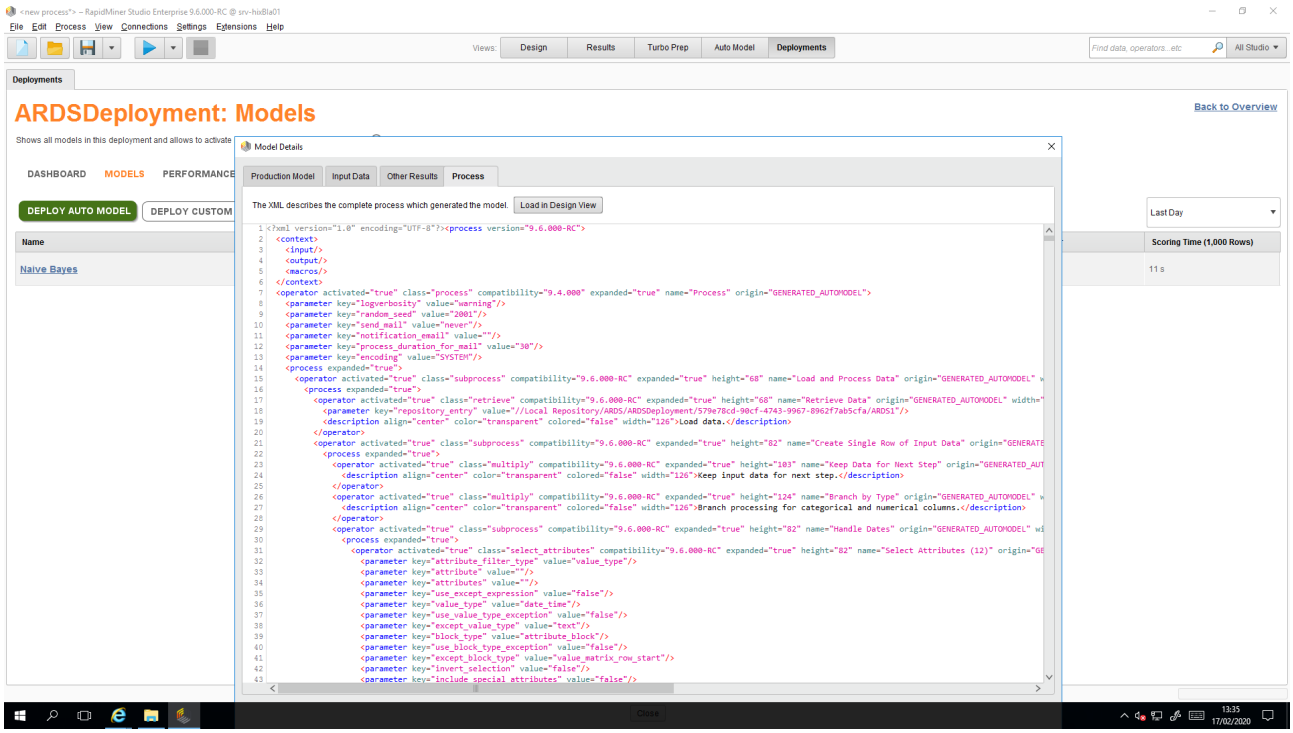


Figure 21: GLM with Feature Generation Model.

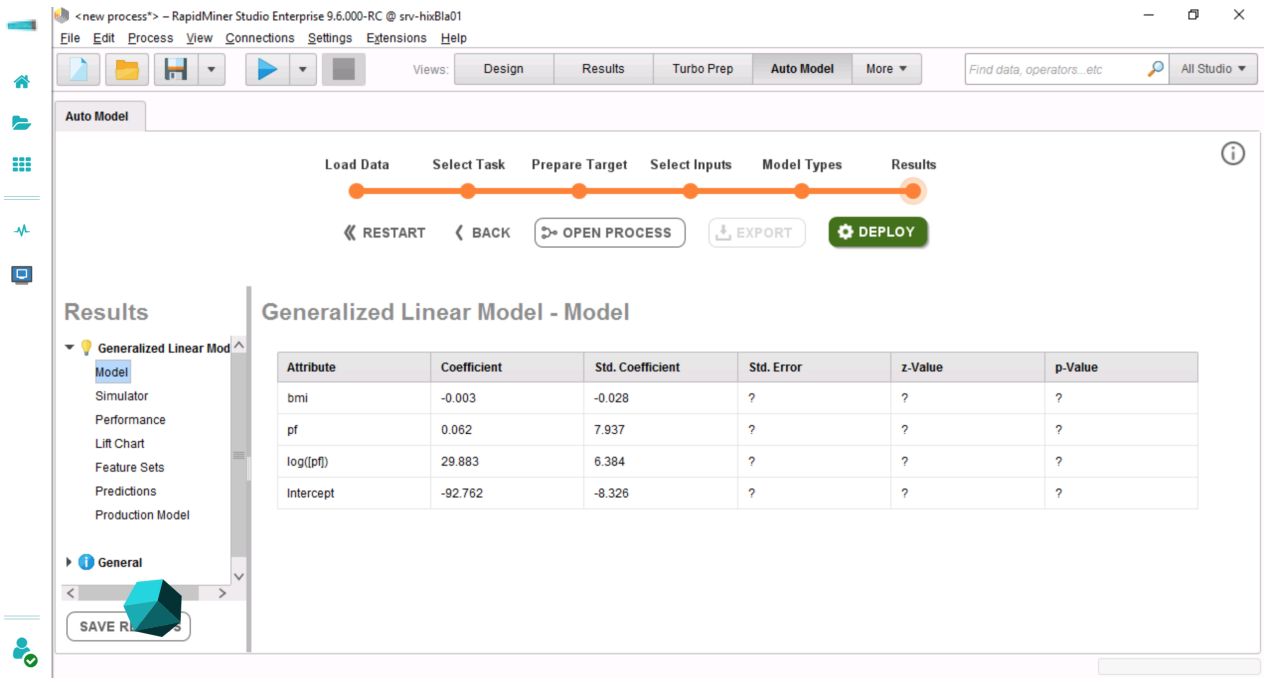


Figure 22: GLM with Feature Generation Production Model.

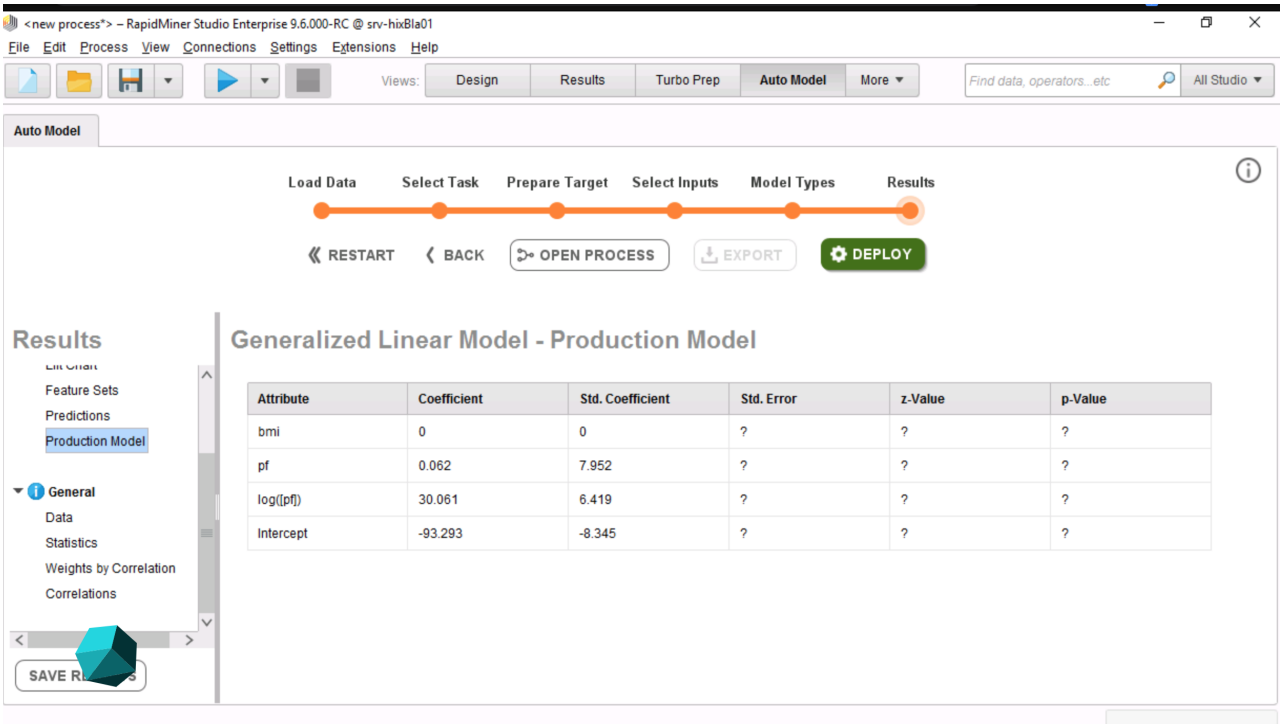
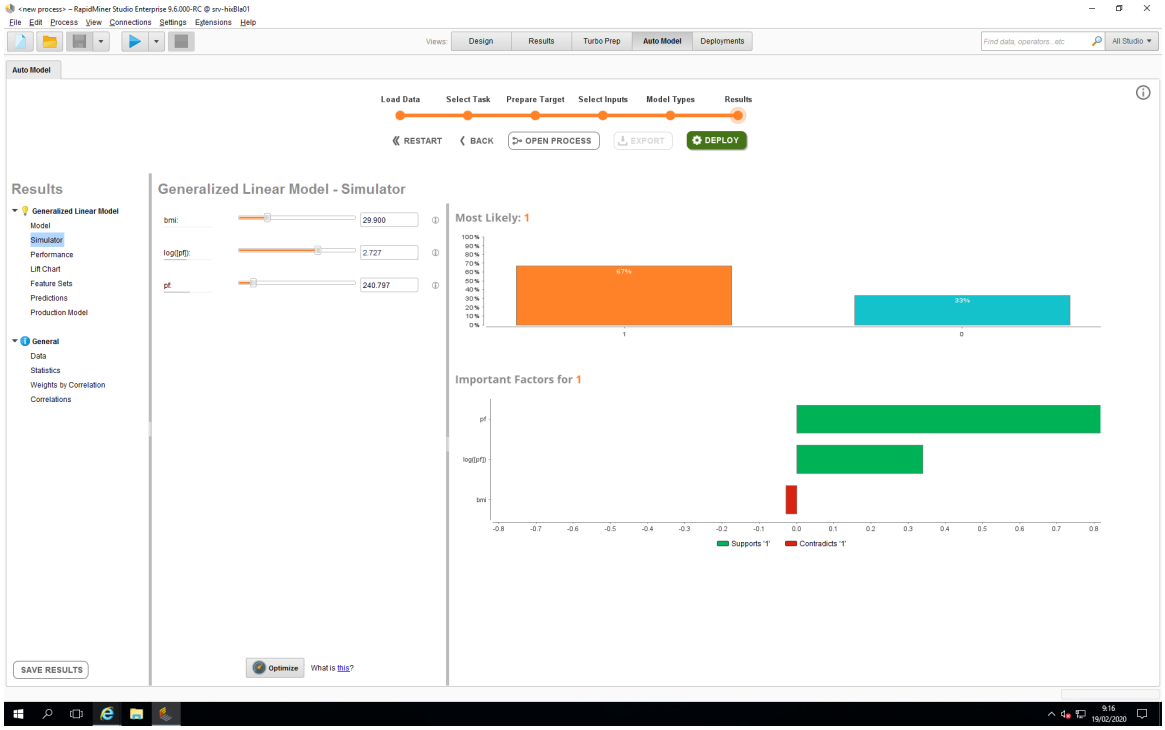


Figure 23: Simulator GLM Model with Feature Generation.



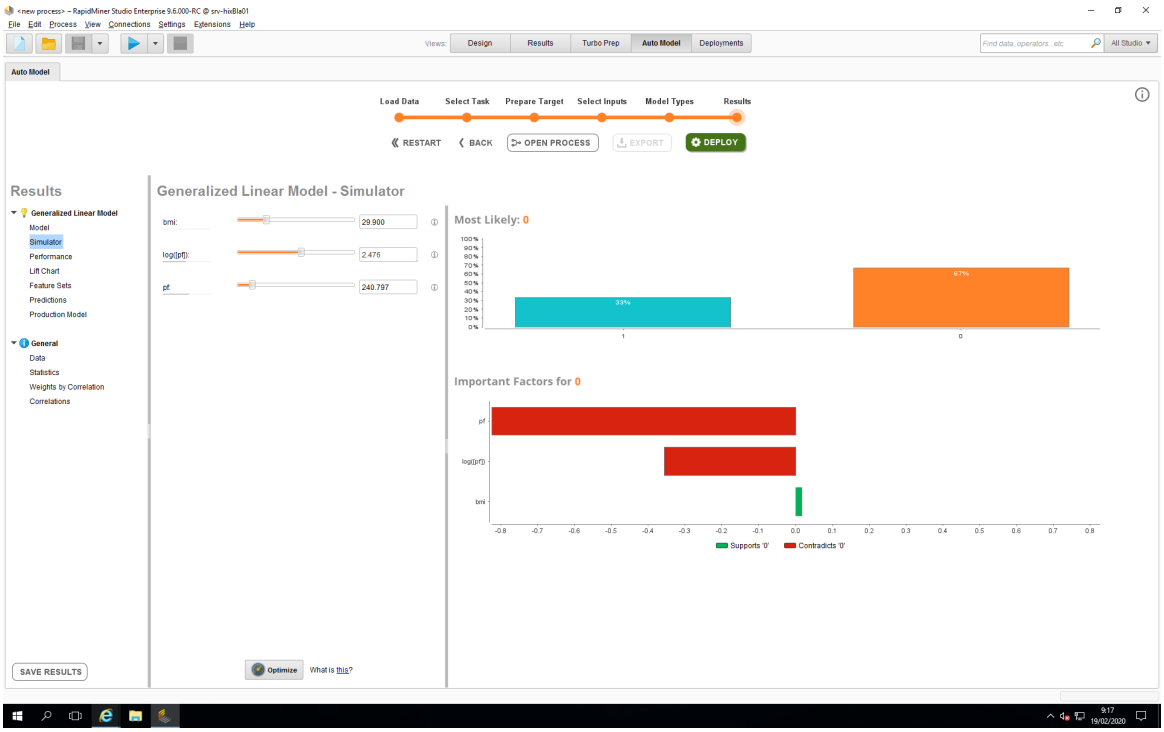


Figure 24: GLM with Feature Generation Performance.

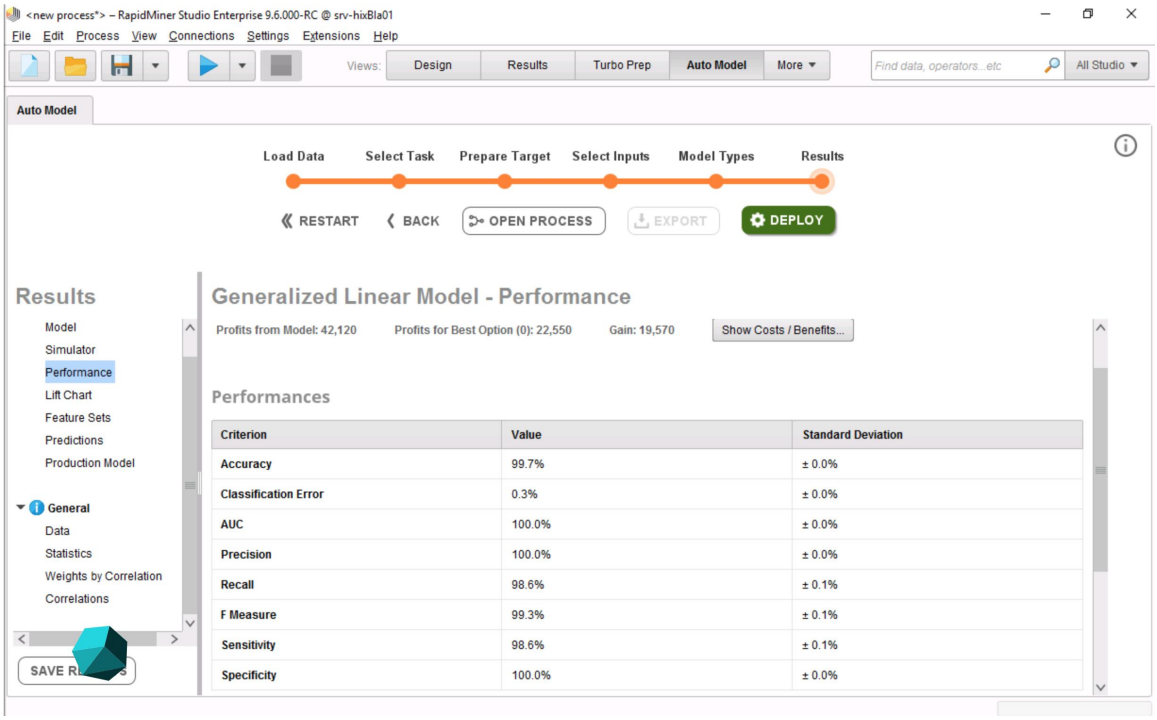


Figure 25: GLM Feature Generation, Feature Set.

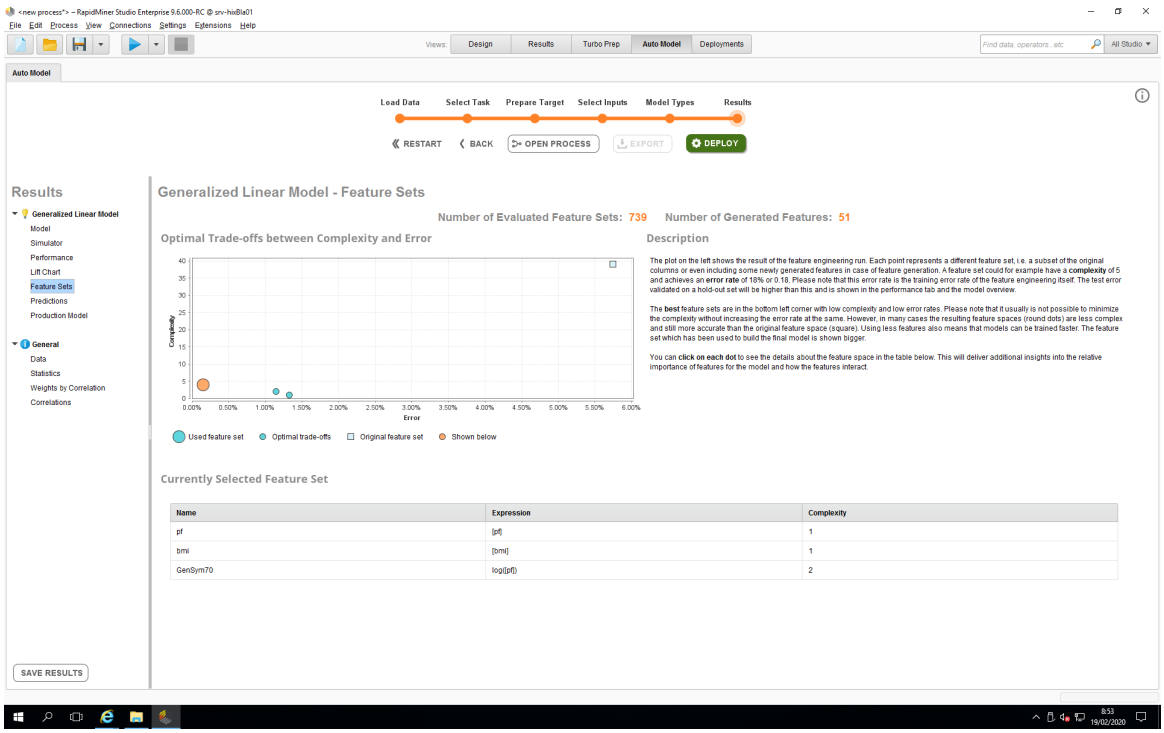
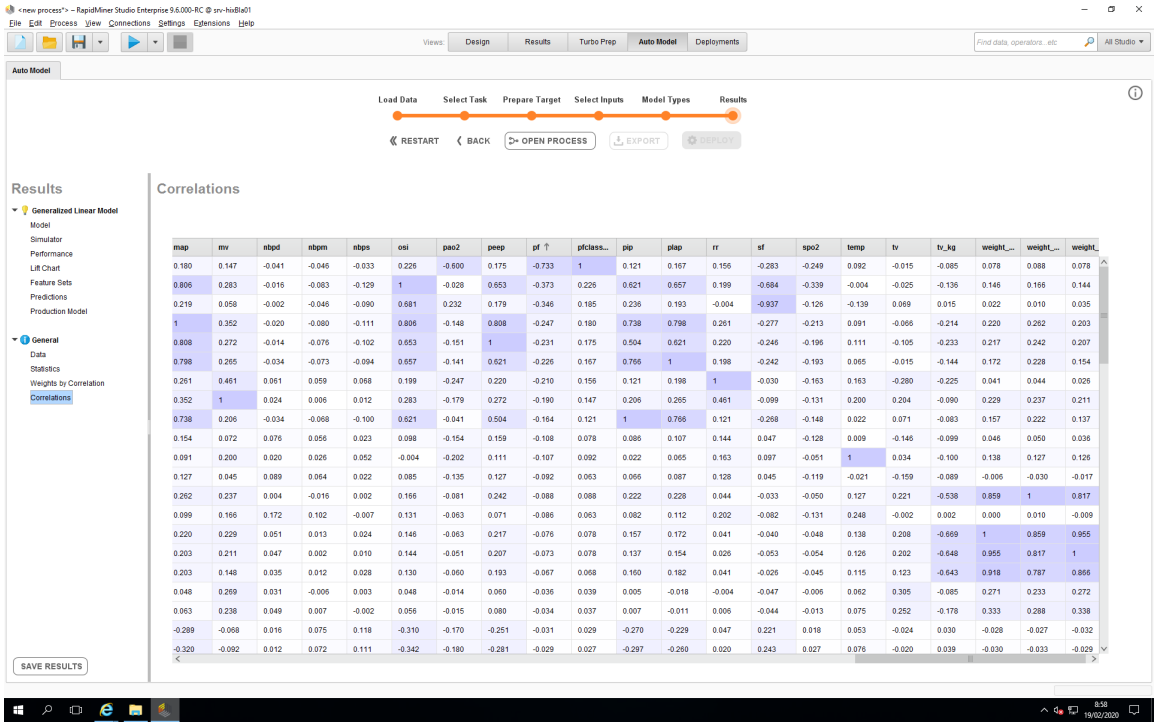
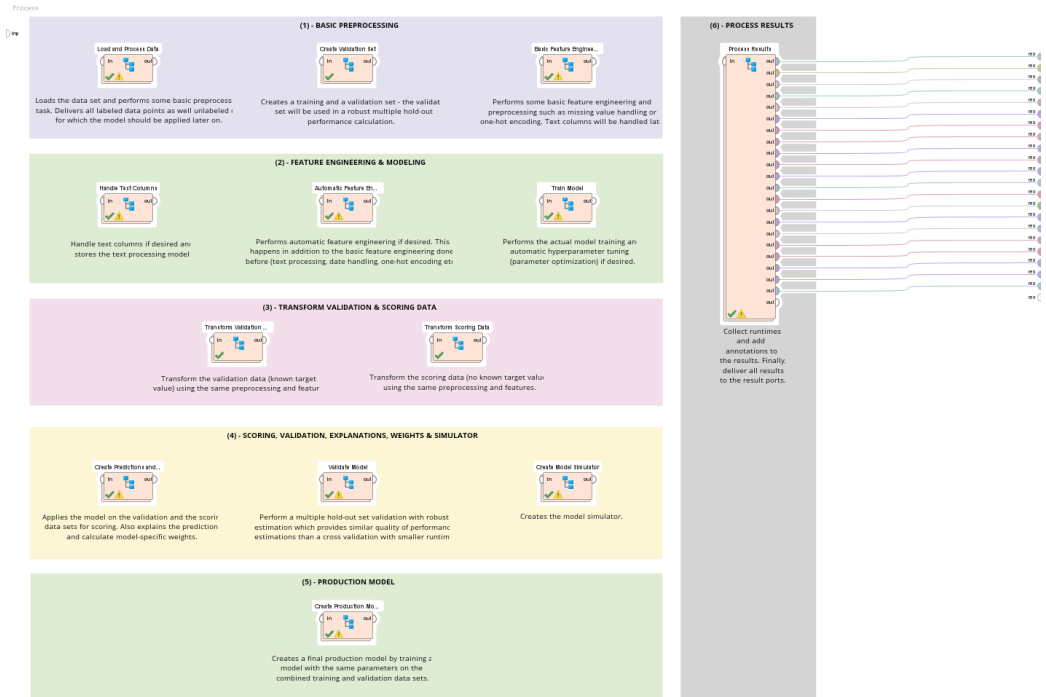


Figure 26: Correlations based on GLM Model.



map	mv	nbpd	nbpm	nbps	osi	pao2	peep	pf	pfclass...	pip	plap	rr	sf	spo2	temp	tv	tv_kg	weight_...	weight_...	weight_
0.180	0.147	-0.041	-0.046	-0.033	0.226	-0.600	0.175	-0.733	1	0.121	0.167	0.156	-0.283	-0.249	0.092	-0.015	-0.085	0.078	0.088	0.078
0.806	0.283	-0.016	-0.083	-0.129	1	-0.028	0.653	-0.373	0.226	0.621	0.657	0.199	-0.684	-0.339	-0.004	-0.025	-0.136	0.146	0.166	0.144
0.219	0.058	-0.002	-0.046	-0.090	0.681	0.232	0.179	-0.346	0.185	0.236	0.193	-0.004	-0.937	-0.126	-0.139	0.069	0.015	0.022	0.010	0.035
1	0.352	-0.020	-0.080	-0.111	0.806	-0.148	0.808	-0.247	0.180	0.738	0.798	0.261	-0.277	-0.213	0.091	-0.066	-0.214	0.220	0.262	0.203
0.808	0.272	-0.014	-0.076	-0.102	0.653	-0.151	1	-0.231	0.175	0.504	0.621	0.220	-0.246	-0.196	0.111	-0.105	-0.233	0.217	0.242	0.207
0.798	0.265	-0.034	-0.073	-0.094	0.657	-0.141	0.621	-0.226	0.167	0.766	1	0.198	-0.242	-0.193	0.065	-0.015	-0.144	0.172	0.228	0.154
0.261	0.461	0.061	0.059	0.068	0.199	-0.247	0.220	-0.210	0.156	0.121	0.198	1	-0.030	-0.163	0.163	-0.280	-0.225	0.041	0.044	0.026
0.352	1	0.024	0.006	0.012	0.283	-0.179	0.272	-0.190	0.147	0.206	0.265	0.461	-0.099	-0.131	0.200	0.204	-0.090	0.229	0.237	0.211
0.738	0.206	-0.034	-0.068	-0.100	0.621	-0.041	0.504	-0.164	0.121	1	0.766	0.121	-0.268	-0.148	0.022	0.071	-0.083	0.157	0.222	0.137
0.154	0.072	0.076	0.056	0.023	0.098	-0.154	0.159	-0.108	0.078	0.086	0.107	0.144	0.047	-0.128	0.009	-0.146	-0.099	0.046	0.050	0.036
0.091	0.200	0.020	0.026	0.052	-0.004	-0.202	0.111	-0.107	0.092	0.022	0.065	0.163	0.097	-0.051	1	0.034	-0.100	0.138	0.127	0.126
0.127	0.045	0.089	0.064	0.022	0.085	-0.135	0.127	-0.092	0.063	0.066	0.087	0.128	0.045	-0.119	-0.021	-0.159	-0.089	-0.006	-0.030	-0.017
0.262	0.237	0.004	-0.016	0.002	0.166	-0.081	0.242	-0.088	0.088	0.222	0.228	0.044	-0.033	-0.050	0.127	0.221	-0.538	0.859	1	0.817
0.099	0.166	0.172	0.102	-0.007	0.131	-0.063	0.071	-0.086	0.063	0.082	0.112	0.202	-0.082	-0.131	0.248	-0.002	0.002	0.000	0.010	-0.009
0.220	0.229	0.051	0.013	0.024	0.146	-0.063	0.217	-0.076	0.078	0.157	0.172	0.041	-0.040	-0.048	0.138	0.208	-0.669	1	0.859	0.955
0.203	0.211	0.047	0.002	0.010	0.144	-0.051	0.207	-0.073	0.078	0.137	0.154	0.026	-0.053	-0.054	0.126	0.202	-0.648	0.955	0.817	1
0.203	0.148	0.035	0.012	0.028	0.130	-0.060	0.193	-0.067	0.068	0.160	0.182	0.041	-0.026	-0.045	0.115	0.123	-0.643	0.918	0.787	0.866
0.048	0.269	0.031	-0.006	0.003	0.048	-0.014	0.060	-0.036	0.039	0.005	-0.018	-0.004	-0.047	-0.006	0.062	0.305	-0.085	0.271	0.233	0.272
0.063	0.238	0.049	0.007	-0.002	0.056	-0.015	0.080	-0.034	0.037	0.007	-0.011	0.006	-0.044	-0.013	0.075	0.252	-0.178	0.333	0.288	0.338
-0.289	-0.068	0.016	0.075	0.118	-0.310	-0.170	-0.251	-0.031	0.029	-0.270	-0.229	0.047	0.221	0.018	0.053	-0.024	0.030	-0.028	-0.027	-0.032
-0.320	-0.092	0.012	0.072	0.111	-0.342	-0.180	-0.281	-0.029	0.027	-0.297	-0.260	0.020	0.243	0.027	0.076	-0.020	0.039	-0.030	-0.033	-0.029

Figure 27: Visual Representation of the Process from Preprocessing to Production Model.



Discussion

The approach presented in this document never intended questioning the results of the paper as published by Pengcheng Yang et al. However the technology available from RapidMiner enabling automated predictive modeling, model deployment and monitoring are illustrated. In particular the presented tools should stimulate a feasible implementation in any medical setting or environment. The most relevant arguments for a more widespread use of this approach are:

1. Code free deployment
2. Deploy models without the need for technical skills
3. Manage multiple deployment locations and share deployed models with other users
4. Drive collaboration on models, monitor for governance, drift and bias issues and even set up alerts and integrations
5. See how models work in the wild and adjust your strategy accordingly
6. Deploy multiple models together where one model is active and others are ‘challengers’, where predictions and error rates are also stored for challengers
7. Review performance of active and challenger models over time on the leaderboard
8. Setup alerts to notify you when a challenger outperforms the active model
9. Swap the active model with a single click so you’ve always got the best model deployed into your workflow
10. Go beyond ‘accuracy’ stats to understand and demonstrate medical outcome and or financial impact of your models
11. Show cumulative gains and impact produced by your active model
12. Analyze scoring times to pick models fast enough for your needs
13. Compare distribution differences between predictions and actual values
14. Instantly understand problematic trends and address them proactively
15. Understand models and see how they behave with weights, model visualizations, interactive simulators and full prediction explanations
16. Compare models’ latest performance with expected error rates to detect concept drift or shift
17. Calculate input factor drift and compare drift with factor importance as early indicators for problematic concept shift or drift
18. Observe suspicious changes between training and scoring data and detect bias in training data