Platform overview: Analytics

Machine learning, governance and deployment with SAS Viya

Antti Heino, Cloud Advisor on ML&AI

3.3.2021





Antti Heino Cloud Advisor on ML&AI, SAS Finland

- 3 years of analytics advisory at SAS
 - Predictive analytics
 - Fraud detection
 - Predictive maintenance
 - Industrial process analysis
 - Text Analytics
 - Customer feedback analysis
 - Maintenance log understanding
 - Internal document classification & search
 - Healthcare document classification
 - Computer vision
 - Object detection
 - Video analytics



 3 seasons of AI podcast "Tekoäly Nyt"



 5 years prior experience on analytics consulting

- Free time
 - Travel
 - Diving
 - Sports

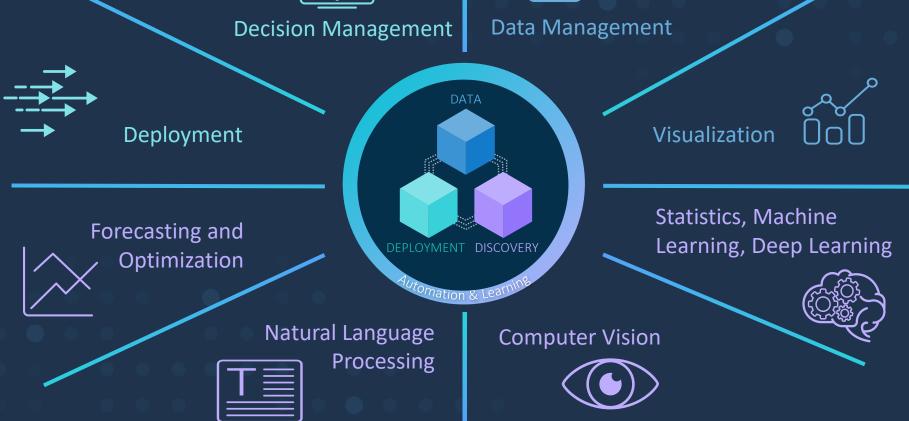




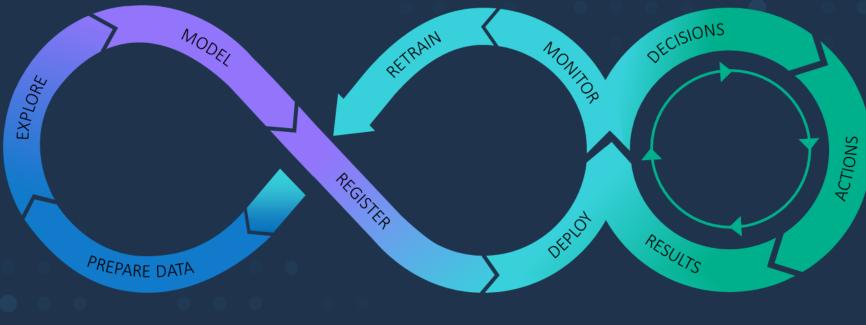








Operationalizing Analytics



ANALYTICS	- п	BUSINESS
-----------	-----	----------



Georgia Pacific

one of the world's leading makers of tissue, pulp, packaging, building products and related chemicals 30k employees, 180+ locations world-wide

"I think we have about **1,900 models that run multiple times a second**. **Each one of them is deployed in the SAS platform** to help us in each of those three buckets [process, asset and safety] we talked about. We constantly need to do more with those models or make better models."



Roshan Shah VP of Collaboration & Support Center and Advanced Analytics

<u>Article:</u> <u>https://diginomica.com/georgia-pacific-cuts-complex-data-modelling-times-half-sas</u>

Video: <u>https://vshow.on24.com/vshow/Global_Forum/exhibits/Industry_Connection</u> Manufacturing -> Digital Transformation at Georgia-Pacific



Copyright © SAS Institute Inc. All rights reserved.

"You can have multiple folks going into the platform and being able to build and deploy those models, really, really quickly. Something that we used to struggle with in the past is we would build a model, but then we would hand that off to IT. Not that there's anything wrong with that, it's just we didn't know how to add all the additional things - such as error handling - that need to go with it.

What we've been able to do with SAS is we can enable a citizen data scientist, or an engineer, to build those models. And what really matters, they can go from taking a complex time series data and building a neural net within minutes and hours. They can go and deploy it."



"It used to take us on average about twelve weeks to take a complex model, get it built, and deploy that, and then put it in production. I think we could easily say that that's gone, on average, about three to six weeks, sometimes even shorter. That's pretty unprecedented.

We don't care so much about it being perfectly accurate. We look for time to value of money. These folks are able to do that, which in turn, frees up the data scientists to solve the much more complex problems. If you look at it from IT's perspective, it really frees them up to focus more on, how do you make data available."



Data Preparation

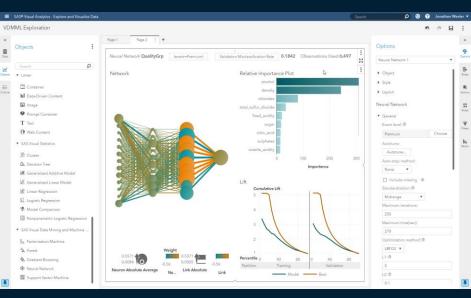
\$/	AS® Data Studio - Prepare Data											Sei	arch	Q	۲	Sasder
y D	Data prep plan 🗙 +															
	Transforms	Split - Step 2 o	é 2										ŝ	Run	Save	1
	Add Transform	1 Join -	— 💿 Sp	olit												8
		Source column:		Split	data:	(Delimiter: N	lame of new colum	in 1:	Name of re	w column 2:					
	▼ Column Transforms	& Develope	er Location	* On	a delimiter	•	Comma +	New Latitude		New Lon	gitude	¢				ł
	Change case															
	Convert column	Options for no	w columns													
	Rename															
	Remove															
	Split															
	Trim whitespace															
	▼ Custom Transforms															
	Calculated column															
	Calculated column Code															
	Code • Data Quality Transforms	0.015.0175.0														
	Code	GAME DATA (session)				E	Table Profile	Metadata							
	Code • Data Quality Transforms Casing	GAME DATA (session)				E	Table Profile	Metadata					Result rows:	100	Ø
	Code • Data Quality Transforms Casing Persing	GAME DATA (Release Date	Since Launch	Cenre	A Franchise			D Longitude	& Develope	l Platform	د Timed Pla			
	Code • Data Quality Transforms Casing Parsing Field extraction			Release Date 22AUG	Since Launch 2,	& Genre Racing				D Longitude -12	Ĉ: Develope T00004	D Platform PC	الله Timed Pla No			Class #
	Cade Cata Qually Transforms Caring Field extraction Gender analysis	د New Latit	& New Long					e 🖒 Develope	G Latitude					& Distribu	ni 🕭 (Class #
	Code Code Julio Transforms Caring Paring Field exerction Generar analysis Identification analysis	🖒 New Latit 47.6041	& New Long	22AUG	2,	Racing		 Develope 47.6041 	Catitude	12	T00004	PC	No	& Distribu	nti de e	Class II
	Cade Cade Quality Transforms Caring Paning Find actraction Generar analysis Identification analysis Identification analysis	& New Latit 47.6041 30.2697	New Long -122.32	22AUG 19DEC	2,	Racing Action		 A Develope 47.6041 30.2697 	Latitude 47 30	·12	T00004 T2012	PC Mobile	No No	& Distribut Online Online	nti 🕹 (AA AA	Class II
	Cole • Das Quality Transforms Caring Paning Felide execution Gender analysis Identification analysis Match coles Sandurdize • Muki seput Transforms	b New Latit 47.6041 30.2697 34.0366	New Long -122.32 -97.741 -118.23	22AUG 19DEC 19MAY	2, 1, 1,	Racing Action Action		 Develope 47.6041 30.2697 34.0366 	Latitude 47 30 34	-12 -97 -11	T00004 T2012 T2875	PC Mobile Mobile	Na Na Yes	& Distribut Online Online Online	nti de c AA AA AA	Class II
	Code • Data Cuality Yandoma Carag Parting Pada dematión Gender analysis Macho code Sondrafez Macho code Sondrafez	New Latit 47.6041 30.2697 34.0366 37.7629	New Long -122.32 -97.741 -118.23 -122.43	22AUG 19DEC 19MAY 30AUG	2, 1, 1, 1,	Racing Action Action Racing		 Develope 47.6041 30.2697 34.0366 37.7629 	Latitude 47 30 34 37	-12 -97 -11 -12	T00004 T2012 T2875 T00006	PC Mobile Mobile Multi-PI	No No Yes No	& Distribut Online Online Online Online	AA	Class II
	Cole • Das Quality Transforms Caring Paning Felide execution Gender analysis Identification analysis Match coles Sandurdize • Muki seput Transforms	& New Latt 47.6041 30.2697 34.0365 37.7629 40.7768	New Long -122.32 -97.741 -118.23 -122.43 -73.978	22AUG 19DEC 19MAY 30AUG 10APR2	2, 1, 1, 1, 3,	Racing Action Action Racing Strategy	A Franchise	 & Develope 47.6041 30.2697 34.0366 37.7629 40.7768 	Latitude 47 30 34 37 40	-12 -97 -11 -12 -73	T00004 T2012 T2875 T00006 T3596	PC Mobile Mobile Multi-PI Corsole	No No Yes No No	& Distribut Online Online Online Online	nti do ti AA AA AA AA B	Class
	Code • Data Cuality Yandoma Carag Parting Pada dematión Gender analysis Macho code Sondrafez Macho code Sondrafez	& New Latt 47.6041 30.2697 34.0365 37.7629 40.7768 44.9992	New Long -122.32 -97.741 -118.23 -122.43 -73.978 -93.241	22AUG 19DEC 19MAY 30AUG 10APR2 13JAN2	2, 1, 1, 1, 3, 4,	Racing Action Action Racing Strategy Puzzle	A Franchise	 Develope 47.6041 30.2697 34.0366 37.7629 40.7768 44.9692 	Latitude 47 30 34 37 40 44	-12 -97 -11 -12 -73 -93	T00004 T2012 T2875 T00006 T3596 T1010	PC Mobile Mobile Multi-PI Console Mobile	No No Yes No No	& Distribut Online Online Online Online Online	nte de s AA AA AA AA AA AA AA AA	Class
	Code • Das Quality Transforms Paring	 New Lett 47.6041 30.2697 34.0365 37.7629 40.7768 44.9692 34.0365 	New Long -122.32 -97.741 -118.23 -122.43 -73.978 -93.241 -118.23	22AUG 19DEC 19MAY 30AUG 10APR2 13JAN2 11DEC	2, 1, 1, 1, 2, 4, 1,	Racing Action Action Racing Strategy Strategy	A Franchise	 & Develope 47.6041 30.2697 34.0366 37.7629 40.7768 44.9692 34.0366 	Latitude 47 30 34 37 40 44 34	-12 -97 -11 -12 -73 -93 -11	T00004 T2012 T2875 T00006 T3596 T1010 T2875	PC Mobile Mobile Multi-PI Console Mobile Multi-PI	No No Yes No No No	& Distribut Online Online Online Online Online Online	nte 46 0 AA AA AA AA B AA A A	Class

- Access to different data sources
- Training-Validation Data
 Partitioning
- Feature Engineering (e.g. parameters, interactions)
- Variable selection and missing values



Visual exploration & Machine Learning

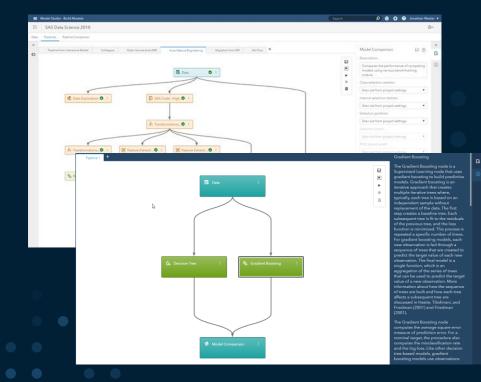
- Interactively discover relationships, trends, outliers
- Smart autocharting
- Analytics driven visualizations
- Explore predicted outputs
- Variable Transformation



- Decision Forests
- Neural Networks (Deep Learning and Computer Vision)
- Gradient Boosting
- Support Vector Machines
- Factorization Machines
- Bayesian Networks
- Dirichlet Gaussian Mixture Models
- Semi-supervised learning
- T-SNE



Model Studio



• Pipeline of activities

- Best practices templates
- Automated feature engineering
- Drag and drop and access to code
- Nodes are run asynchronously
- Algorithm annotations
- R and Python support



Coding interfaces



Getting Started with SAS Viya Programming

Access the capabilities of the SAS Viva through Cloud Analytic Services (CAS) actions for data access and analytics, run directly from SAS applications.



REST APIs for any client language to access SAS analytics, data and services. The REST APIs are written to make it easy to integrate the capabilities of SAS Viya to help build applications or create scripts.

Python

SAS integrates with Python through various code libraries and tools that allow open source developers to unite the Python language with the analytic power of SAS.



Getting Started with SAS Viya for R

Combine R language functions with SAS through various code libraries.



Getting Started with SAS Viya for Java™

Java APIs for using SAS Viya CAS actions



Getting Started with SAS Viya for Lua

Lua APIs for using SAS Viya CAS actions

Developer.sas.com

Register



Organize & Manage Analytic Assets

Central, searchable repository for *all* models/pipelines

Compare models side-by-side

Version control and track project history

					SAS* M	odel Manager - Manage Models			۹ 🔳 ۱
N	Nodels	s							≎ Hide Dashboard 🛛 🗭
					Мо	dels per Score Code Typ	•	Published Models p	er Destination
		84 Total Number of Models				34 otal	DATA mpp DG3 embedded process GG3 embedded process GG3 multi-type Nos specified Tython SAS program	33 Total	AWSDemo AUNSTeat Aurum Tento Aurum Tento CASDest HarborTett PrivetBocker Indebocker Indebocker Indebocker
	Sear	ch name	↑ I	Role	Project (Version)	Model Attributes	Model Function	Modified By	Add models •
		Auto m rYpl5ePP77FgmwE6Bnz3			Auto p ero7yyXflDwf7dN0sOD7_Version 1 ((DATA step)	Classification	(E) edmdev	Jun 3, 2020 10:14 PM
		COV					analytics	(5) servic	May 29, 2020 03:44 AM
		Decision Tree			Fleet Management, Version 1/1.0)	(Published) (DATA step)	Classification	(E) edmdev	Jun 4, 2020 08:47 AM
		Decision Tree		0	Fleet Management Selection Version 1 (1.0)	(DATA step)	Classification	(E) edmdev	Jun 4, 2020 08:31 AM
		DecisionTree		-		DATA step	Classification	(D) dishaw	Jun 3, 2020 05:32 PM
		Fleet SKLearn DTree			Fleet Management Selection, Version 1 (1.0)	Python	Classification	(E) edmdev	Jun 4, 2020 08:06 AM
		Fleet SKLearn DTree			Fleet Management Version 1/1.0)	Python	Classification	(E) edmdev	Jun 4, 2020 08:40 AM
		Fleet SKLearn Logistic			Fleet Management Selection Version 1 (1.0)	Python	Classification	(E) edmdev	Jun 4, 2020 08:06 AM
		Fleet SKLearn Logistic		•	Fleet Management, Version 1 (1.0)	Published Python	Classification	(E) edmdev	Jun 4, 2020 08:48 AM
		Fleet XGBoost			Fleet Management Selection, Version 1 (1.0)	Python	Classification	(E) edmdev	Jun 4, 2020 08:07 AM
		Fleet XGBoost		•	Fleet Management, Version 1 (1.0)	Published Python	Classification	(E) edmdev	Jun 4, 2020 08:48 AM
					Fleet Management. Version 1 (1.0)	DS2 multi-type	Classification	(D) dishaw	Jun 3, 2020 06:03 PM
		Forest							
		Forest			Fleet Management Selection, Version 1 (1.0)	DS2 multi-type	Classification	(E) edmdev	Jun 4, 2020 08:07 AM





Deploy



Deployment and Scoring

Quick and easy access to different production environments

Deploy in-batch, streaming, cloud or edge device

Azure Container Publishing Destination for Open Source models

Supported publishing destinations include SAS Cloud Analytic Services (CAS), Apache Hadoop, SAS Micro Analytic Service (MAS), Teradata, as well as container destinations such as Amazon Web Services, Azure, and Private Docker

-							SAS® Model Manager - Manage Mode				
	:= 0	Fleet Management									Ø 🚺 Close
0		Variables Properties Sco	ring Perfor	mance Workflow	History						
ß					×					Add models * Compare	
		Name	÷	Role	Model Function	Pro	ject Version	Algorithm	Date Modified	Modified By	
		Fleet SKLearn DTree			Classification	Ver		Decision Tree	Jun 3, 2020 12:58 PM		
		Fleet SKLearn Logistic		~	Classification	Ver		Logistic regression	Jun 3, 2020 05:12 PM	dishaw	
		Fleet XGBoost		0	Classification			×	Jun 3, 2020 05:12 PM	dishaw	
							Publish Models				
						Items to publish:					
						Name	Published Name	Replace			
						Fleet_SKLearn_Logistic (3.	0) Fleet_SKLearn_Logistic				
						Fleet_XGBoost (3.0)	Fleet_XGBoost				
						Destination: ©					
						Amazon Web Services (AW Amazon Web Services (AW		clails			
						Amazon Web Services (AW	STest)				
						Azure (AzureDemo)		Publish Cancel			
						Azure (AzureTest) Azure (AzureTest2)		.8			
						Azure (AzureTestWithValida	tion)				
						CAS (CASDest)					
						Hadoop (HadoopDest)					
						Private Docker (HarborTest)					
						Private Docker (PrivateDock					
						SAS Micro Analytic Service SAS Micro Analytic Service					
						Teradata (TeradataDest)	(masiocal)				
						reresers (reredatablest)					



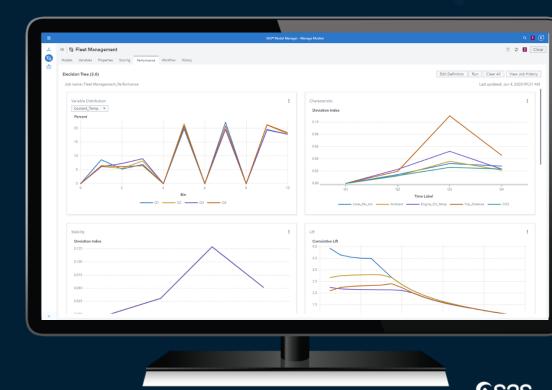


Monitor

Monitor Model Drift and Performance

- Wizard to simply generation of out of the box performance reports
- Performance-monitoring tasks including data source changes, score value changes, model accuracy over multiple time periods, and input/output variable feature contribution plot
- Users can access the data to generate their own reports





Designing Decisions

Decision Flow

						🗉 🎼 Personalization Rules (1.1)	Publish Import Exp
						Rule Set Properties Variables Scoring Versions History	
			Q P (Lookup tables		t
t_Conference (1.2)			Publish : 🗘 1 Clo	se	E Treatment groups	✓ Presentation Code Calculation	
roperties Variables Scoring	Versions History	>>					Record :
	ର ର	Output Variables				IF • ageParsed • 18	
	Start	Score rows in this dat	a grid			AND ageParsed • 36	
		Select an item	- -				
	Retrieve Full Conterner	Output Variable	Maps To			THEN ASSIGN presentationCode MILLEN	
	Ļ	presentationCode	ta presentatio ▼			ELSE • ageParsed • >= • 36	
	A Is_Existing_Customer =	numberOfRedemptio	點 numberOfR *				
	YESNO	ageParsed	👪 ageParsed 🔹			AND ageParsed • < • 60	
	BB Analyst Marketing Seg [] BB Personalization Pulses (1					THEN ASSIGN	
	🕒 Lookup inventory availa : 🍞 ProparaitytePurchase 👔						
						ELSE • ageParsed • >= • 60	
	PhopensitytoPurchase :					THEN ASSIGN	
	YES NO				**		
	間 Analyst, HighValueOffen () 間 HighValueOffen () 間 Consumer Staple Offers	1					
	Ag Record_Contacts	1					
	Le Track Customers Contact						
	End i				Busin	ess Rules Mana	gement
				_			6000
							<u>(</u> Sas

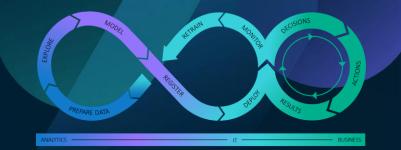
SAS* Intelligent Decisioning - Manage Decisions



Modeling gas turbine measurements to reduce emissions

SAS Viya demo steps

- Exploration
- Modeling
- Model tuning and registration (Model Studio & Open source)
- Model deployment (single OS model & decision flow)





Case description

CASE DESCRIPTION

The dataset contains 11 sensor measures aggregated over one hour (by means of average or sum) from a gas turbine power plant for the purpose of studying flue gas emissions, namely CO and NOx. CO emission is removed from inputs as it may not be available at prediction time.

Nitrogen oxides are produced in combustion processes, partly from nitrogen compounds in the fuel, but mostly by direct combination of atmospheric oxygen and nitrogen in flames.

Elevated levels of nitrogen dioxide can cause damage to the human respiratory tract and increase a person's vulnerability to, and the severity of, respiratory infections and asthma. High levels of nitrogen dioxide are also harmful to vegetation-damaging foliage, decreasing growth or reducing crop yields.

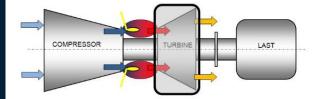
Source: http://archive.ics.uci.edu/ml/datasets/Gas+Turbine+CO+and+NOx+Emission+Data+Set

OBJECTIVE

Model Nitrogen oxide (NOx) emissions to understand when they are highest and can we reduce them using that information



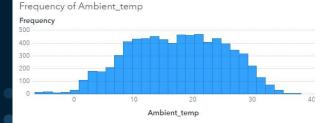
Frequency



Frequency of Nitrogen_oxides

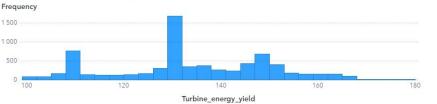






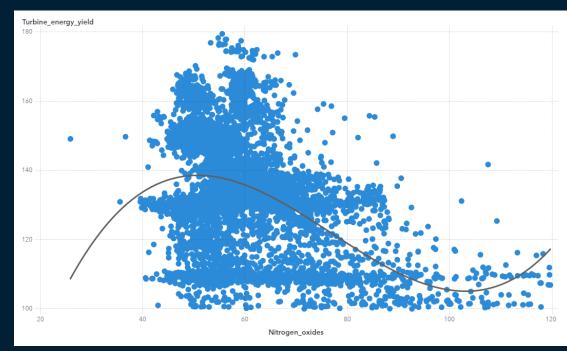


Copyright © SAS Institute Inc. All rights reserved.



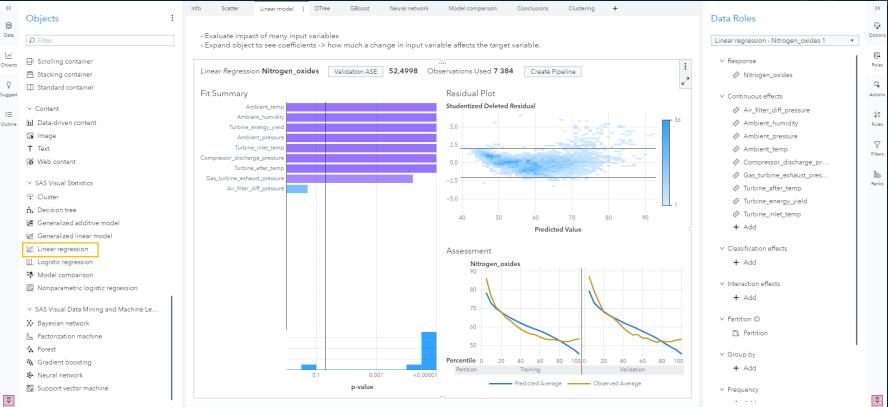
Understanding the data by modeling simple relationships

- Using fit lines on scatter plot we can see that we are able to achieve high energy yields also with lower NOx levels
- With this method we are only able to study relationship between two variables





Linear models with multiple inputs can be built just as easily

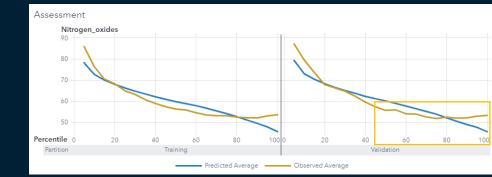


Ssas

Parameter estimates and assessment statistics tell us that linear model might not be the best choice

- Parameter estimates show how each input affects the target (NOx level)
- The assessment plots indicate that the model is still far from perfect. Probably because of non-linear relationships we are not taking into account
- Explained variance is 58%
- Let's try other algorithms

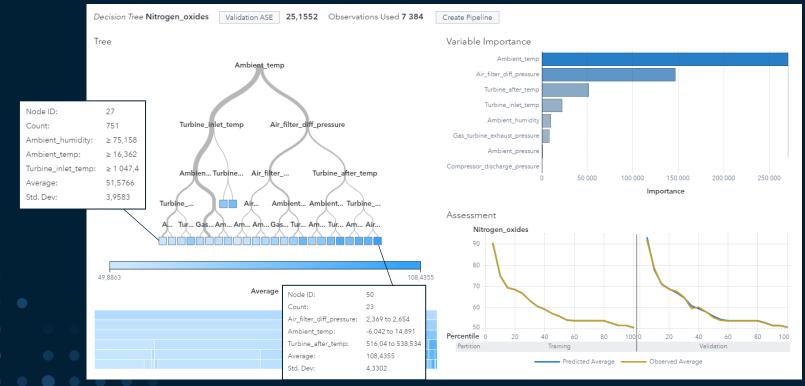
Dimensions Overall ANOVA Parameter Estimates Tvpe III Test Assessment Assessment Statistics Standard Error Parameter Estimate t Value Compressor_discharge_pressure 12.28666 2.094132 5.867187 Turbine after temp -0.957270,181769 -5.26638 Gas_turbine_exhaust_pressure 0.290256 0.072239 4.018009 Air filter_diff_pressure 0.951382 0.727478 1.307781



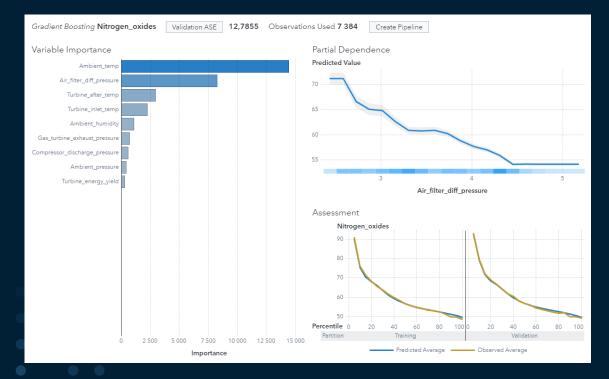
Dimensions	Overall ANOVA	Fit Statistics	Parameter Estimates Ty	pe III Test Assessment	Assessment Statis	itics	
Source		Deg Freedom	Sum of Squares	Mean Square	F Value	Pr > F	R-Square
Model		9	366875,5	40763,94	811,1802	<0,00001	0,585942
Error		5159	259253,3	50,25263			



Decision tree is more accurate & we learn what kind of situations produce high/low NOx levels and should be avoided/favored



Increasing accuracy at the cost of explainability

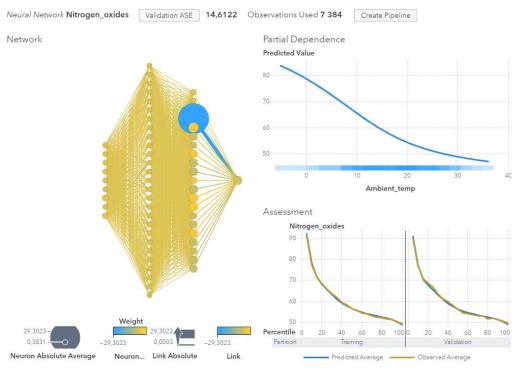


- Gradient boosting algorithm (multiple decision trees) cuts the error in half
- Model interpretability methods are needed to understand the predictions
- Partial dependence describes the average effect an input has on the target
- This information can be used to find parameter ranges that result in acceptable NOx levels



Autotuning can help get the final improvements to accuracy

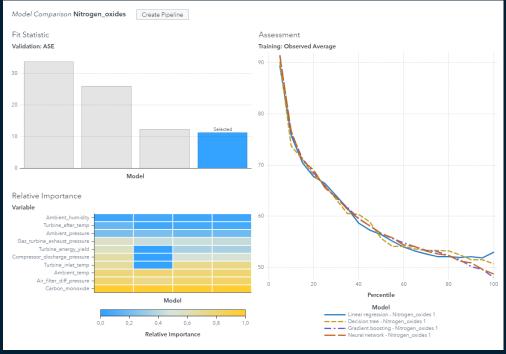
- Neural networks typically need tuning to get best possible performance
- You can use autotuning to find better hyperparameters for your model
- Neural network slightly outperforms gradient boosting in this case





Model comparison

- Model comparison object shows which of the models was best in terms of ASE (averaged squared error)
- It also shows which variables were most important across models

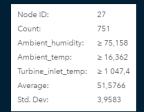


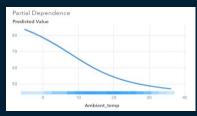


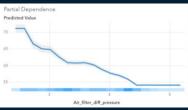
Copyright © SAS Institute Inc. All rights reserved

What we have found out so far

- The relationships in the data may be non-linear
- Decision trees showed how there are certain situations when NOx emissions are low
 - Those settings should be favored when running the turbines
- Partial dependence showed for example how ambient temperature and Air filter difference pressure affect the emissions
 - The information can be used do decide how and when to run the turbines and where they should be located



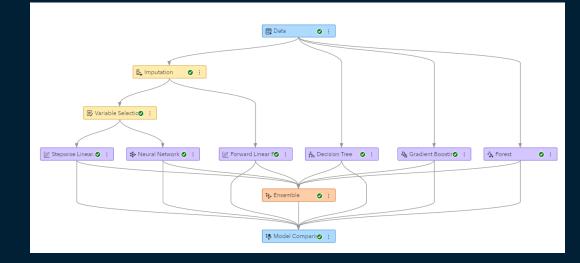






Tuning the accuracy further to get the best possible model

- Pipeline view in Model Studio is aimed for data scientists
- There different modeling strategies can be attempted
 - Imputation
 - Variable selection
 - Transformations
 - PCA etc.
- Different algorithms and modeling strategies can be automatically competed to find the best combination

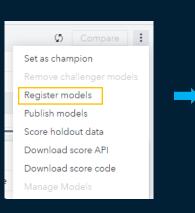




Registering the best possible model to Model Manager

Data	Data Pipelines Pipeline Comparison Insights										
Q Fi	D Filter Data: Test V										
	Champion \downarrow	Registered	Name	Algorithm Name	Pipeline Name	Average Squared Error					
	*		Gradient Boosting	Gradient Boosting	Adv Template	9,061					
			Forest (2)	Forest	∋ Pipeline 2	10,144					

- After running the pipelines with autotuning, the best possible model turned out to be Gradient boosting with ASE of 9,061
- We should now register the model centralized Model Manager
- It was important to get the most accurate model as next we will publish the model to run simulations on situations that produce lowest emissions

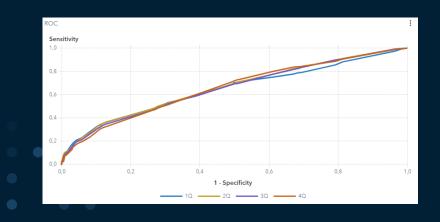


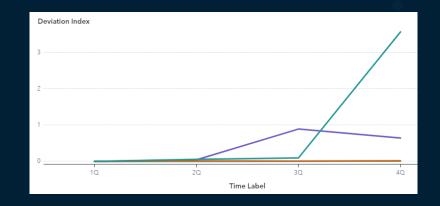
:= G) Gas_emi	ssions_MS	5					
Models	Variables	Properties	Scoring	Perfo	rmance	Work	flow	History
Q S	earch name		Ver	sion: [Version	n 1 (1.0)	•
	Name			\uparrow	Rol	e	Mode	l Function
	Gradient Bo	osting (Adv	<u>Template)</u>		*		Predic	tion



Model Manager helps with monitoring performance of the models that are in production

 Variable distribution shows show there has been a significant change in 4th quarter with one of the inputs





- Different accuracy measurements can be used to track the model performance in production
- When performance deteriorates too low, the model needs to be retrained



Open-source models can be trained with python and registered to the same centralized Model Manager

In [17]:		<pre>import xgboost from sklearn.md</pre>	s np port Session, re as xg pdel_selection i	mport train_tes	t_split	/SASSecurityCertificateFr	amework/cacerts/	'trustedcerts.pem	e.
In [18]:	н	df = pd.read_cs	w('GAS_EM_SMPL.	csv')					
In [19]:		df2 = df.iloc[: X = df2.iloc[:, y = df2.iloc[:,	.:-1]						
In [20]:	н	X.head()							
Out[20]:	Ambient_temp	Ambient_pressure	Ambient_humidity	Air_filter_diff_pressure	Gas_turbine_exhaust_pressure	Turbine_inlet_temp	Turbine_after_temp	Turl
		0 1.95320	1020.1	84.985	2.5304	20.116	1048.7	544.92	_
		1 1.21910	1020.1	87.523	2.3937	18.584	1045.5	548.50	_
		2 0.94915	1022.2	78.335	2.7789	22.264	1068.8	549.95	
		3 1.00750	1021.7	76.942	2.8170	23.358	1075.2	549.63	
		4 1.28580	1021.6	76.732	2.8377	23.483	1076.2	549.68	
		4							•
In [21]:	н	y.head()							
Out[1 112.020 2 88.147 3 87.078 4 82.515	oxides, dtype:	float64					
In [22]:	H	xTrain, xTest,	yTrain, yTest -	train_test_spl	it(X, y, test_size=	0.3, random_state=42)			
In [24]:	H	xgb_r = xg.XGBF	Regressor(object n_estimators	ive ='reg:squar = 10, seed = 1					
In [25]:	н	xgb_r.fit(xTrai	in, yTrain)						
_									

- XGBoost model is trained in jupyter with the same data
- Data can be also pulled for Viya's in-memory tables
- The model can be registered to Model Manager
- The model can be easily deployed

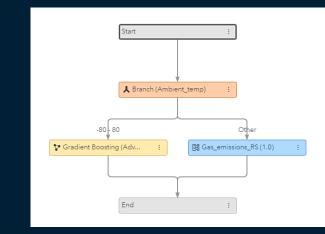
In [27]: M with Session('localhost', 'user', 'pw'): model_name = 'GE_XGB' project_name = 'Gas_emission_XGB'

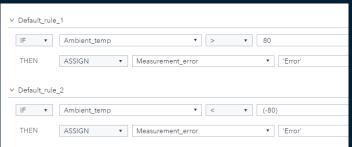
> # Register the model in SAS Model Manager register_model(xgb_r, model_name, project_name, input=xTrain, force=True)



Models usually need logic around them before they can be used in production processes

- Decision flows are a great way to add surrounding business logic to a model
- It is much more manageable than hard coding that logic somewhere
- You can add
 - Data base / API calls for more data
 - Business rules / data quality checks
 - Multiple models
 - Decision branches etc.







Publishing models or decisions to production

- Models and decision flows can be published on the realtime engine MAS or the batch engine CAS
- After publishing the model is ready to return predictions based on inputs
- Other publishing destinations can be configured, such as containers

and the set of the base					
ms to publish: Name	Published Name	Ŷ	Replace	Rule-Fired	Path Tracking
Gas_emissions_DF (1.0)	Gas_emissions_DF				
estination: @					
AS Micro Analytic Serv	vice (maslocal)		▼ Details		



Sending scoring requests to the model via REST to simulate different scenarios and the resulting NOx emission

air_filter_diff_pressure_	
4	
ambient_humidity_	
80	
ambient_pressure_	
1010	
ambient_temp_	
20	
carbon_monoxide_	
carbon_monoxide_ (decimal)	
compressor_discharge_pressure_	
13	
gas_turbine_exhaust_pressure_	
30	
turbine_after_temp_	
510	
turbine_energy_yield_	
150	
turbine_inlet_temp_	
1100	
	Submit
	Results:
	EM_PREDICTION: 57.4333

air_filter_diff_pressure_
5
ambient_humidity_
100
ambient_pressure_
1100
ambient_temp_
25
carbon_monoxide_
carbon_monoxide_ (decimal)
compressor_discharge_pressure_
15
gas_turbine_exhaust_pressure_
20
turbine_after_temp_
510
turbine_energy_yield_
150
turbine_inlet_temp_
1300
Submit
Results:
EM_PREDICTION: 50.4715



Copyright © SAS Institute Inc. All rights reserved.

Resources

- Data set
 - <u>http://archive.ics.uci.edu/ml/datasets/Gas+Turbine+CO+and+NOx+Emission+Da</u> <u>ta+Set</u>
- SAS VDMML
 - <u>https://www.sas.com/en_us/software/visual-data-mining-machine-learning.html</u>
- ModelOps
- <u>https://www.sas.com/en_us/solutions/operationalizing-analytics/modelops-approach.html</u>

