Université IBM i 2018 16 et 17 mai IBM Client Center Paris

thirty years

Session S12 IBM i & Data Science: Introduction à Watson Studio & IBM Datascience Experience (DSX Local)

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Session S12

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IBM Systems

Plan de la présentation



- Introduction: Pourquoi l'intelligence artificielle? Quelle bénéfices?
- Solutions AI d'entreprise: IBM Watson, Watson Studio, Data Science Experience
- AI & IBM i
 - Exemple d'intégration dans un environnement IBM i avec démonstration
- Comment démarrer sur un projet AI Questions / Réponses

IBM i & Artificial Intelligence

Approximate (AI) & precise (Transactional) computing together



- Data is the key in all AI projects: your business data resides on IBM i and can be integrated with AI
- Use pre-trained & customizable models with IBM Watson (Developer Cloud) services in IBM Cloud
- Build your own use case & business specifics models with IBM Watson Studio IBM Cloud / on premises (DSX Local w/ Cloud Private)

AC922

Artificial Intelligence Introduction

Machine learning is everywhere – influencing nearly everything we do

VARCOS

Trending Now

HOUSE





NETFLIX

ORANGE

BLAC



IBM Cloud / Watson and Cloud Platform / © 2018 IBM Corporation



data

From raw data to AI & Cognitive





A full pipeline to leverage machine learning techniques to solve daily issues

What is Machine Learning?



R2 D3

A Visual Introduction to Machine Learning

In machine learning, computers apply statistical learning techniques to automatically identify patterns in data. These techniques can be used to make highly accurate predictions.

Keep scrolling. Using a data set about homes, we will create a machine learning model to distinguish homes in New York from homes in San Francisco.



Read the speaker notes, Appendix, and check out "A Visual Introduction to Machine Learning" – <u>http://bit.ly/1LRTISi</u>

Deep Learning = Training Artificial Neural Networks

Based on biological neurons. Artificial neurons learn by recognizing patterns in data.



A human brain has:

- 200 billion neurons
- 32 trillion connections between them
- → Artificial neural networks have far fewer



Impact of Machine Learning: A simple example



Direct marketing — 1% response rate			yea
Send marketing mail to 1,000,000 customers at cost of \$2 per mailing to sell a \$220 service.	\$2 x 1,000,000	\$2,000,000	Traditional
One percent response rate means 10,000 customer will buy service.	\$220 x 10,000	\$2,200,000	
	Profit*	\$200,000	
Predictive direct marketing — 3% response rate			
Send marketing mail to 250,000 customers <i>predicted most likely to buy</i> at cost of \$2 per mailing to sell a \$220 service.	\$2 x 250,000	\$500,000	Machine
Three percent response rate means 7,500 customer will buy service.	\$220 x 7,500	\$1,650,000	learning
Profit when	\$1,150,000		

*Profit calculation does not include other expenses.

Every industry is changing & can benefit

Leaders everywhere are monetizing data & developing strategies to embed AI in business



Retail Market Basket Analysis, Next Best Offer, Customer Churn, propensity to buy



Marketing Discount targeting, email optimization, lifetime client value



Healthcare Medicare fraud, AI-assisted diagnosis, drug demand forecast



Manufacturing Predictive maintenance, process optimization, demand forecast



Energy and Utilities Power usage prediction, smart grid management



Banking Customer segmentation, credit risk, credit card fraud detection



Con Security tion Malicious activity detection, logs analysis



Travel & transportation Dynamic pricing, call center assistants, tourism forecasting, Self-driving cars

Big Data: Machine Learning techniques

- Classification: predict class from observations
 - E.g. Spam Email Detection
- Clustering: group observations into "meaningful" groups
 - - E.g. Amazon Recommendations
- Regression (prediction): predict value from observations
 - E.g. Energy consumption



and many different technologies and libraries are available:





Example: Predictive Maintenance



DSX Demo available https://ibm.ent.box.com/v/power-iot-dsx-video-mp4

Historical Data from NASA <u>https://ti.arc.nasa.gov/tech/dash/groups/pcoe/prognostic-data-repository/</u>





Why are enterprises struggling to capture the value of AI?

- Data
- Data resides in silos & difficult to access
- Unstructured and external data wasn't considered

- Governance
- If the data isn't secure, self-service isn't a reality
- Challenge understanding data lineage and getting to a system of truth

- Skills
- Data Science skills are in low supply and high demand
- Nurturing new data professionals is challenging

- Tools & Infrastructure
- Need an environment that enables a "fail fast" approach
- Discrete tools present barriers to productivity

Artificial Intelligence: IBM Solutions

Watson Studio: accelerating value from AI for enterprises

Watson Studio accelerates the machine and deep learning workflows required to infuse AI into your business to drive innovation. It provides a suite of tools for data scientists, application developers and subject matter experts to collaboratively and easily work with data and use that data to build, train and deploy models at scale.

- Al is not magic
- Al is algorithms + data + team



Data Science Ecosystem



We've been recognized for our vision

Gartner Magic Quadrant 2017 Data Science Platforms RapidMiner IBM MathWorks Quest Alteryx Angoss Microsoft SAP FICO H20.a Dataiku Teradata 🔵 Domino Data Lab ABILITY TO EXECUTE Alpine Data As of February 2017 COMPLETENESS OF VISION \longrightarrow

DeveloperWeek 2017

Devie



Forrester Wave 2017 Predictive Analytics & Machine Learning



Source: <u>https://www.gartner.com/doc/reprints?id=1-3TKD8OH&ct=170215&st=sb</u> http://www.developerweek.com/awards/2017-devies-award-winners/

Watson: Al for Smarter Business

										`
	Watson Business Solutions		Wa	Watson Applications		ISV &	ISV & Third Party Applications			
Co	mpliance Assist	Customer Care	Expert Assist	Voice of the Customer	Watson Assistant	Watson Cybersecurity	Compare & Comply			
	Watson Studio									
	Watson APIs									
Å	Conne	ect & Access Data	Search & Relevant	Find Data >	Prepare Data (Ingest, Curate, & Enrich)	> Build A	& Train odels	Deploy AI Models	> Monitor, Man	Analyze, > age
	Continuous Learning									
	Watson Machine Learning and Deep Learning as a Service									
	Watson Knowledge Catalog									
	Watson I Anal	Enriched Data & ytical Assets	Watson Socia	Powered Searce I Collaboratior	ch & A D Ei	ctive Policy nforcement	M Tra	odel Governance, ceability & Lineage	Data	Kits

Data Science is a Team Sport

- Building ML-infused apps requires multiple skillsets:
 - Define an ML model
 - Store, manage, update training data
 - Manage lifecycle of the trained model
 - Ability to do inferencing on the trained model(s)

Driving the Success of Data Science Solutions: Skills, Roles and Responsibilities ...

Business

Skills

"Analytics Leader'

Ask good questions

Latency at Execution? -

Build, Buy, Outsource

Gauge political

friction

Deployment

Data





Know the constraints

(e.g., legal, ethics, market)

Transparent Versus "black box"

Performance Criteria That Matter

(ROI, accuracy, profitability

versus market gain)

Feature Engineering

Recalibration With

Decision Making

Watson Studio Built for AI teams – enabling team productivity and collaboration



Tanya Domain Expert

Her Job:

To transfer knowledge to Watson for a successful user experience.

What she does:

- Range of domain knowledge and uses that to teach Watson and develop a custom models
- As Tanya gains more experience she optimizes her knowledge to teach Watson to design better end-user experiences.

Sometimes known as:

Subject matter expert, content strategist.



Mike Data Scientist

His Job:

Transform data into knowledge for solving business problems.

What he does:

- Runs experiments to build custom models that solve business problems.
- Use techniques such as Machine Learning or Deep Learning and works with Tanya to validate success of trained models.

Sometimes known as: ML/DL engineer, Modeler, Data Miner



Ed Data Engineer

His Job: Architects how data is organized and ensures operability

What he does:

- Builds data infrastructure and ETL pipelines. Works with Spark, Hadoop, and HDFS.
- Works with data scientist to transform research models into production quality systems.

Sometimes known as: Data infrastructure engineer



Deb The Developer

Her Job:

Builds AI application that meet the requirements of the business.

What she does:

- Starts PoCs which includes gathering content, dialog building and model training
- Focus is on app building for the team or company to use. Will handle ML Ops as needed

Sometimes known as: Front-end, back-end, full stack, mobile or low-code developer

Watson Studio Supporting the end-to-end AI workflow

Connect &	Search and Find	Prepare Data	Build and Train	Deploy Models	Monitor, Analyze
Access Data	Relevant Data	for Analysis	ML/DL Models		and Manage
Connect and discover content from multiple data sources in the cloud or on premises. Bring structured and unstructured data to one toolkit.	Find data (structured, unstructured) and AI assets (e.g., ML/DL models, notebooks, Watson Data Kits) in the Knowledge Catalog with intelligent search and giving the right access to the right users.	Clean and prepare your data with Data Refinery , a tool to create data preparation pipelines visually. Use popular open source libraries to prepare unstructured data.	Democratize the creation of ML and DL models. Design your AI models programmatically or visually with the most popular open source and IBM ML/DL frameworks or leverage transfer learning on pre- trained models using Watson tools to adapt to your business domain. Train at scale on GPUs and distributed compute	Deploy your models easily and have them scale automatically for online, batch or streaming use cases	Monitor the performance of the models in production and trigger automatic retraining and redeployment of models. Build Enterprise Trust with Bias Detection, Mitigation Model Robustness and Testing Service Model Security .

Watson Studio Comprehensive set of tools for the end-to-end AI workflow

- Create, collaborate, deploy, and monitor
- Best of breed open source & IBM tools
- Code (R, Python or Scala) and no-code/visual modeling tools
- Most popular open source frameworks
- IBM best-in-class frameworks
- Fully managed service
- Container-based resource management
- Elastic pay as you go CPU/GPU power



Watson Studio Differentiating Capabilities

Integrated Collaboration Environment	Choice of Tools for the full AI lifecycle	Support for all levels of expertise
 Data Scientists, Subject Matter experts, Business Analysts & Developers all in one environment to accelerate innovation, collaboration and productivity Built-in learning to get started or go the distance with advanced tutorials 	 Best in-breed open source and IBM tools that support the end-to-end AI lifecycle Choice of code or no-code tools to build and train your own ML/DL models or easily train and customize pre-trained Watson APIs 	 Use Watson smarts and recommendations for the best algorithms to use given your data, OR Use the rich capabilities and controls to fine tune your models
Experiment centric DL workflow	Model lifecycle & management	Integrated with Knowledge Catalog
 Monitor batch training experiments then compare cross-model performance without worrying about log transfers and scripts to visualize results. You focus on designing your neural networks. We'll manage and track your assets. 	 Deploy models into production then monitor them to evaluate performance. Capture new data for continuous learning and retrain models so they continually adapt to changing conditions. 	 Intelligent discovery of data and AI assets that enables reuse & improves productivity Seamlessly integrated for productive use with Machine Learning and Data science Powerful governance tools to control and protect access to data

ExistingCustomer



Link to Case Study

Geo: Nordics (Europe) **Sector:** Commercial – Media & Entertainment Background

- GroupM is the world's
 largest media
 investment group with
 more than \$102bn
 billings (RECMA, 2016)
 and 24,000 employees
 across 81 countries
- They are a broker of digital advertisement, specialised in banner placing in digital media (web, cell phones...)
- Their Nordics team has ~8 data scientists

Business Problem

- GroupM needs to know
 when and where to
 place advertisements
 most effectively and
 how much to charge for
 it.
- To do so, they were using manual forecasting (based on R) and they were encountering difficulties to scale out the process.
- They were looking for a way to effectively automate their analysis.

Solution

- With Watson Studio, Group M was empowered to:
- To feed data into one single platform, in a structured way.
- To develop models with
 common tooling and
 reuse existing assets to
 accelerate the
 development of new use
 cases.
- To consume their models as micro-services through rest APIs.



Human & Technological Gallery



Geo: Japan Sector: Human Resource Management/ IT Professional Services

Background

Forum Engineering (FE) is a leading human resource management company specialized in engineering in Japan. They provide engineer staffing services to their clients across different sectors. including Automotive, Industrial Machinery, Electricity, **Electronics**, **Precision** Equipment, and Information and Communications sectors. Their clients are leading manufacturers in Japan, and they introduce human resources to their clients and job opportunities to engineers. They conduct thorough research on client's technical needs. corporate culture and requirement then pair them with

engineers' technical capabilities,

personal preferences and

parties.

personality to ensure the best

match and experience for both

Business Problem

.

- The organization spent a majority of their time and resources dispatching sales people to conduct lengthy interviews and evaluations with their clients and engineer candidates.
- With such a wide range of clients' technical demands, and large variation in engineers' skills and specialties, the manual background research, ensuing analyses, and matching performed were extremely time-consuming. They find the limitation of growth because of their labor-intensive process.
- Forum Engineering needed help to increase growth rate by automating manual process and shifting to knowledge-based business, and provide their quality engineer staffing services and accurate matching program.

Solution

- Powered by IBM Watson and Watson Studio, Forum Engineering released 2 new initiatives- "Insight Matching" and "Cognitive Staffing" to fundamentally change the way they run their business. The IBM-powered solution allows FE to gather & analyze a massive amount of internal and external data, and quickly calculate matching ratios based on its analysis and reasoning. They also use the solution to build matching dictionaries (seeding keywords/content to look for), and to run matching accuracy tests. In particular, Watson Studio provides not only the data analysis, but Spark data processing and Machine Learning capabilities that FE was seeking.
- The solution is expected to dramatically improve their matching accuracy, eliminate human bias from the process, and increase their sales/staffing efficiency. They expect further growth by shifting surplus resources to growth area and new business development. 29





Kubernetes & Docker based infrastructure (IBM Cloud / IBM Cloud Private)



• Data Science as a Team Sport

Lets *data scientists/engineers*, *analysts*, stakeholders *collaborate* to collect, share, explore, *analyze data* in order to *derive insights and train models*, *and share or deploy resulting assets*

- Projects collaborate as team or work individually
- Jupyter Notebooks + IBM value add
 - Integrated in Projects with access control
 - Spark integration with R/Python/Scala kernels
 - Versions, comments, share link, publish to GitHub
 - PixieDust, Brunel, ...
- Machine Learning integrated in Projects: Use ML Wizard and Flows to train Models
- **RStudio** integrated with Spark
- DSX Integrates with Data in many places
 - Object Storage (SWIFT now, new Cloud Object Storage soon)
 - Watson Data Platform Services and WDP Catalog
 - Message Hub and IBM Streaming Analytics
 - Can call any IBM service, e.g. Watson, Quantum, etc
 - Third party data services on premise or on other clouds
- Built on the IBM Cloud platform



Coming Soon! Watson Machine Learning Machine Learning lets you create and train predictive analytics models. Learn More





Collaborate Work smarter using community, work faster with your team.

Try it yourself at <u>https://datascience.ibm.com</u>

IBM Watson Studio (aka DSX) is available

- As a cloud offering aka Watson Studio
- As a desktop application
 - Free, disconnected mode
- As an on-premises solution
 - DSX Local on x86/Power
 - Power: Scale-out LC Systems with PowerAI + GPU / Nvlink acceleration
 - Possible private cloud deployment with IBM Cloud Private







Deployment Example: IBM Private Cloud & DSX Local





IBM Data Connect **IBM Machine Learning** "Data Refinery" IBM Cloud Object Storage for Busine for Busines Data Science Experience MySQL Validate model IMS Teradata Area Under ROC Curve Service amazon webservices[™] S3 SQL Server IEM DB2 Microsoft Azure

Data Access:

- Easily connect to Behindthe-Firewall and Public Cloud Data
- Catalogued and Governed Controls through Watson Data Platform

Creating Models:

- Single UI and API for creating ML Models on various Runtimes
- Auto-Modelling and Hyperparameter Optimization

Web Service:

- Real-time, Streaming, and Batch Deployment
- Continuous
 Monitoring and
 Feedback Loop

Intelligent Apps:

- Integrate ML models with apps, websites, etc.
- Continuously Improve and Adapt with Self-Learning

IBM i & Watson Studio / DSX + Demonstration

IBM i , AI & Data Science

- □ AI = Algorithms + Data (including Data in Db2 for i)
- □ Native (RPG) & New Db2 features & Languages available on i facilitates the IBM i ← → Watson / AI Integration
- □ Work & prepare directly your data using SQL, Python, Java, etc. directly on IBM i
- Build intelligence & predictive capabilities using Watson Data Platform (including Studio & Data Refinery) & Machine learning techniques




Data Science tools & technologies

Kaggle 2017 Data Science Tools Survey



Ready for AI: Connecting your business to the future



The art of fine seating

How does luxury manufacturer JORI help customers find their perfect furniture?



Offers 100+ seating frames, fabrics and finishes



Wanted to help customers visualize possible combinations



Created a 3D configurator with open source software on IBM[®] i



Inspires customers to create their ideal designs



50% faster deliveries, as configurator accelerates manufacturing



Will use IBM Watson[®] cognitive technology to help consumers find their preferred fabric



Ready for AI: Connecting your business to the future





IBM i & Artificial Intelligence



AC922



- Data is the key in all AI projects: your business data resides on IBM i and need to be integrated with AI
- Use pre-trained & customizable models with IBM Watson (Developer Cloud) services in IBM Cloud
- Build your own use case & business specifics models with IBM Watson Studio IBM Cloud / on premises (DSX Local w/ Cloud Private)

Demo



	atson Projects T	ools Community Servic	es			US South		A	MG
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	Watson Data Plu	IBM Wa Try out o	Ome Manish! tson Studio is part of IBM Wat ther IBM Watson apps.	son.					
	Get started with key tasks	5							
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Machine Learning & IBM i Demo:

Predict outdoor equipment purchase





Machine Learning & IBM i Demo:

Predict outdoor equipment purchase

- 1. Export or connect your data on IBM i
 - Use Access Client Solutions (ACS) for CSV Export or create a jdbc Connector to your Db2 for i database
 - In that demonstration, one table (GOSALES/SALES) containing historical data outdoor equipment purchases -- Alternative: Direct connection to your IBM i with a DSX "Connection" !
- 2. Work on your Data with Watson Studio / DSX Local
 - Data visualization, cleaning, Data Refinery, feature engineering Complement Watson Explorer
 - Jupyter (R, Scala, Python) or R Studio Data science & ML/DL Libraries (Spark ML, Tensorflow, Panda, etc)
- 3. Create & Evaluate your Machine Learning Models
 - Demo: Machine learning with IBM Machine Learning with Automatic Model Builder or Jupyter (PySpark)
 - Machine Learning techniques: Classification Purchase prediction based on client features
- 4. Deploy your predictive models & publish it as a REST API
- 5. Augment your IBM i applications
 - REST API Calls for any programs. In our case, Node-RED & Node.js (5733OPS)
- 6. Monitor & re-evaluate your models

Original Tutorial : here



AI = Data, Data, and Data

□ AI usually requires quantity & quality

- Depends on your business objectives & required precision
- ML (including DL) techniques choice impact the result
- □ AI = Data, Data, Data & skills (Data Science)
- □ Watson Studio / DSX can assist you in that modeling & training phases – demo
- □ In our simple case, we choose a classification algorithm for predicting the next purchase (label = PREDICT_LINE column) of a customer based on his characteristics (features = GENDER, AGE, MARITAL_STATUS, PROFESSION)
- □ Training the model ⇔ executing the classification algorithm against our historical Db2 data and compare it to the real PRODUCT_LINE value (supervised training). The training framework will adjust parameters to make it more accurate. At the end, the model is trained based on this data.
- □ It doesn't mean that the predictive function is precise enough. This relevance has to be determined by the Line of business.

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)	PRODUCT LINE	GENDER	AGE	MARITAL STATUS	PROFESSION		
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60250	Meuntaincoring Equipment	E		Married	Other		
60259	Personal Accessories	-	52	- Homocified	Hernitality		
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60264	Camping Equipment	-		9 Married	Other		
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60272	Mountaineering Equipment	M	20) Single	Sales		
60273	Personal Association		20	7 Single	Other		
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60275	Camping Equipment	2	24	2 Married	Dotail		
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60270	Comping Equipment	M	2:	9 Single 9 Single	Retail		
60229	Camping Equipment	M	43	7 Single 8 Married	Trades		
60260	Camping Equipment	M	43	2 Married	Trades		
60201	Camping Equipment	-		2 Uppposified	Hamitality		
60262	Camping Equipment	-	43	o Unspecified	Hospitality		
60263	Camping Equipment	-	40	S Unspecified	Hospitality		
60204	Camping Equipment	-	40	o Unspecified	Hospitality		
60265	Camping Equipment	5	10	o Onspecified	Other		
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60290	Personal Accessories	-	18	s single	Student		
60291	Camping Equipment	F	31	1 Married	Executive		
60292	Camping Equipment	M	28	s single 4 Gianla	Trades		
60293	Mountaineering Equipment	F	24	+ Single	Student		
60294	Camping Equipment	F	29	9 Single	Other		

File Edi

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ID

Watson Studio / DSX Dashboard

Projects

Data Assets

from import or Direct datasource connection

Code	(Notebooks)
Maul. a.	the date

Work on the data programmatically

Models (Machine Learning)

Data Flows
(Data Refinery)
from CSV
or direct Connections

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Extract Data

File Edit View Run VisualExplain Monitor Options Connection Tools Help

2 SELECT * from GOSALES.SALES;

1

ID	PRODUCT_LINE	GENDER	AGE	MARITAL_STATUS	PROFESSION
60257	Personal Accessories	M	27	7 Single	Professional
60258	Personal Accessories	F	39	Married	Other
60259	Mountaineering Equipment	F	39	Married	Other
60260	Personal Accessories	F	56	5 Unspecified	Hospitality
60261	Golf Equipment	M	45	5 Married	Retired
60262	Golf Equipment	М	45	5 Married	Retired
60263	Camping Equipment	F	39	Married	Other
60264	Camping Equipment	F	49	Married	Other
60265	Outdoor Protection	F	49	Married	Other
60266	Golf Equipment	М	47	7 Married	Retired
60267	Golf Equipment	M	47	7 Married	Retired
60268	Mountaineering Equipment	М	21	L Single	Retail
60269	Personal Accessories	F	66	Married	Other
60270	Camping Equipment	F	35	5 Married	Professional
60271	Mountaineering Equipment	M	20) Single	Sales
60272	Mountaineering Equipment	М	20) Single	Sales
60273	Mountaineering Equipment	M	20) Single	Sales
60274	Personal Accessories	F	37	7 Single	Other
60275	Camping Equipment	M	42	2 Married	Other
60276	Camping Equipment	F	24	+ Married	Retail
60277	Personal Accessories	F	24	+ Married	Retail
60278	Mountaineering Equipment	М	29) Single	Retail
60279	Camping Equipment	M	29) Single	Retail
60280	Camping Equipment	М	43	8 Married	Trades
60281	Camping Equipment	M	43	8 Married	Trades
60282	Camping Equipment	F	43	3 Unspecified	Hospitality
60283	Camping Equipment	F	43	3 Unspecified	Hospitality
60284	Camping Equipment	F	43	3 Unspecified	Hospitality
60285	Camping Equipment	F	43	3 Unspecified	Hospitality
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60288	Camping Equipment	М	32	2 Married	Other
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60290	Personal Accessories	F	18	3 Single	Student
60291	Camping Equipment	F	31	Married	Executive
60292	Camping Equipment	М	28	3 Single	Trades
60293	Mountaineering Equipment	F	24	i Single	Student
60294	Camping Equipment	F	29	Single	Other

- The goal is to extract data for building & training our predictive model.
- The data is in the GOSALES library, table SALES, containing past sales summary (not a normalized table: requires SQL Preprocessing)
- Extraction using ACS & SQL

Data Transfer				
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🟦 To IBM i - 1 🗶 🕭 From IB	BM i - 2 🕱			= If
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Alternative: Direct Connection to IBM i







Alternative: Direct Connection to IBM i

 \bigotimes

Name APPDB





Data Asset (from Db2 for i)

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Personal Accessories	М	27	Single	Professional	<u>^</u>	Tags				
Personal Accessories	F	39	Married	Other		No tags	available f	or this ass	et	
Mountaineering Equipment	F	39	Married	Other		Creator	benoit.m	arolleau@	fr.ibm.cor	m
Personal Accessories	F	56	Unspecified	Hospitality		Added:	10:49 Al	ч UTC, 201 в	.8/04/09	
Golf Equipment	М	45	Married	Retired		01201	2177011	5		
Golf Equipment	М	45	Married	Retired						
Camping Equipment	F	39	Married	Other						
Camping Equipment	F	49	Married	Other						
Outdoor Protection	F	49	Married	Other						
Golf Equipment	Μ	47	Married	Retired						
Golf Equipment	Μ	47	Married	Retired						
Mountaineering Equipment	Μ	21	Single	Retail						
Personal Accessories	F	66	Married	Other						

Data Asset (from Db2 for i) vears 👸 IBM Watson 1.11 Projects À Tools Community Services 믭 My Projects / Project IBM i / GoSales_Tx_NaiveBayes_IBMi.csv P Q Refine Ø Preview Profile 🗙 📷 Data Asset GoSales_Tx_NaiveBayes _IBMi.csv Description No description available for this asset Tags Creating data profile No tags available for this asset Feel free to continue working or stay here and refresh the page Creator: benoit.marolleau@fr.ibm.com occasionally to get an update on the profile's status. When the 10:49 AM UTC, 2018/04/09 Added: profile's ready, you'll be able to view it. Size: 2.993 MB

Data Asset (from Db2 for i)

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FREQUENCY Camping Equipment Personal Accessories Mountaineering Equipm	ent		FREQUENCY	, ,		FREQUENCY 29 28 26 25 27 37 33			FREQUENC Married Single					

years

Work on your data: Data Refinery (Data Flow for Cleaning, Labeling...)



- □ Work on your data **graphically** using Data Flows & Data Refinery
- □ From a CSV data asset or from a Connection to Db2 for i

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Work on your data: Data Refinery (Data Flow for Cleaning, Labeling...)



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Data Refinery							
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APPDB IBM COS Connection	ID Type: Integer	PRODUCT_LINE Type: String	GENDER Type: Char	AGE Type: Smallint	MARITAL_STATUS Type: String	PROFESSION Type: String	
15791306-7fba-4e95-97bb	60257	Personal Accessories	Μ	27	Single	Professional	^
c85f7031-1cc4-4308-a16b	60258	Personal Accessories	F	39	Married	Other	=
00017001 1007 1000 d100.	60259	Mountaineering Equipment	F	39	Married	Other	
	60260	Personal Accessories	F	56	Unspecified	Hospitality	
	60261	Golf Equipment	М	45	Married	Retired	
	60262	Golf Equipment	М	45	Married	Retired	
	60263	Camping Equipment	F	39	Married	Other	
	60264	Camping Equipment	F	49	Married	Other	
	60265	Outdoor Protection	F	49	Married	Other	
	60266	Golf Equipment	М	47	Married	Retired	
	60267	Golf Equipment	Μ	47	Married	Retired	
	60268	Mountaineering Equipment	Μ	21	Single	Retail	

Work on your data: Jupyter Notebook



AND/OR : Work on your data using your favorite language & ML/DL libraries & frameworks

ts / Proje	ct IBM i / From spark ml mod	lel to onlir	ie scori			1	8	<	0 -	
										~
	As you can see, the data conta	ains five fi	elds. PRODUCT_LIN	E field is the one v	e would like to predict (label).					
In [35]:	df_data.show()									
				DDOFESSION						
	++-	+	-+	+						
	Personal Accessories	M 2'	7 Single	Professional						
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	Golf Equipment	M 4	5 Married	Retired						
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	Camping Equipment	F 3	9 Married	Other						
	Camping Equipment	F 4	9 Married	Other						
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	Camping Equipment	F 3	5 Married	Professional						
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	Mountaineering Eq	M 20) Single	Sales						
	Mountaineering Eq	M 20) Single	Sales						
	[Personal Accessories]	E 3	/ Single	Other						
	Camping Equipment	M 42	2) Married	Otner						
	Camping Equipment	E 24	H Married	Retail						
	+			·+						
	only showing top 20 rows									

Number of records: 60252

Data Preparation / Model Training & Deployment using a Python Jupyter Notebook



y Projects /	Project IBM i / Online Scoring with Spark ML	<u>↑</u>
e Edit V	/iew Insert Cell Kernel Help	Trusted Python 2 with \$
) 🕀 નં	· 📄 💽 🚱 🕑 Run (●) C → 😭 Format Markdown 🗸 🖽	
	4. Persist model	
	In this section you will learn how to store your pipeline and model in Watson Machine Learning repository by using	python client libraries.
	First, you must import client libraries.	
	Note: Python 2 and Apache® Spark 2.0 or higher is required.	
In [63]:	<pre>from repository_v3.mlrepositoryclient import MLRepositoryClient from repository_v3.mlrepositoryartifact import MLRepositoryArtifact</pre>	
	Authenticate to Watson Machine Learning service on Bluemix.	
	Action: Put authentication information from your instance of Watson Machine Learning service here.	
In [64]:	<pre>wml_credentials={ "url": "https://ibm-watson-ml.mybluemix.net", "access_key": "mN3bwIsi/xpOh08Bd8D8Zah6UF++y/ZqlqTlJDmJQr6dqC83AFnAyPemGJw9js0JHxGxQ3pIc "username": "75693a81-d133-4c15-8570-3dc0f0f092c1", "password": "13cb03fd-2b6b-4b24-a17f-49eb2efaf7b9", "instance_id": "366f855c-745d-4820-9b10-975dac91d5f7" </pre>	gjgE0jN0TGDTcL0h32gVzPkwMb
	}	

in Serice Credentials generate new credentials by pressing New credential (+) button.

Demo Notebook: <u>https://github.com/bmarolleau/gosales-ibmi</u>

Model Training & Deployment



using the Model Building Wizard

Ö IBM Watson	Projects Tools Community	Services					US South	E	111		۲
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Select Data	Select a technique			Sele	ect the features				(±) A	dd Estima	itors
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Evaluate	PRODUCT_LINE (String)			····P		Config	gurea esti	imators	6		
	Feature columns GENDER (String), AGE (Integer PROFESSION (String) ⊗), MARITAL_STATUS (String),	,	pre	dict)						
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	categories.	number of categories.	values.								
	Validation Split Train: 60	Test: 20	Holdout: 20	Dat	a Split (Training – T	ēst)					

Model Training & Evaluation

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	0	DecisionTreeClassifier	Trained & Evaluated	Poor	0.56219	0.23524	0.52019	0.5128	0.56219	9 A 1:4	pr 201 8, 3 PM	÷	
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												C)



Model deployment, test, publication



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Overview Implementation Test								
Enter input data								>
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1 MARITAL_STATUS_index 1		Mountaineering Eq 18.48% Camping Equipment 16.86% Outdoor Protection 1.44% Golf Equipment 1.03%						E.
PROFESSION_index 1		. What recommendation for a 27 year	old sinc		man	work	ing i	n Pr
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Model deployment, test, publication

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year.

Product Line Prediction IBMi App



Model deployment, test, publication **API Specs (Swagger)**



IBM Watson Machine Learning API

Service Instance URL or ID

Authorize

Authorization

Step by step instruction how to use Watson Machine Learning service can be found here

IBM Watson Machine Learning Credentials

To start working with API one needs to generate an access token using the username and password available on the Service Credentials tab of the IBM Watson Machine Learning service instance or also available in the VCAP environment variable.

Example of the Service Credentials:

"url": "https://ibm-watson-ml.mybluemix.net", "access key": "ERY9vcBfE4sE+F4g8hcotF9L+j81WXWeZv", "username": "c1ef4b80-2ee2-458e-ab92-e9ca97ec657d", "password": "030528d4-5a3e-4d4c-9258-5d553513be6f", "instance_id": "a751c209-954e-dc32-b441-ad56ce7a9f40"

Example of obtaining access token from Token Endpoint using HTTP Basic Auth (for details please refer to Token section below):

curl --basic --user username:password https://ibm-watson-ml.mybluemix.net/v3/identity/token

The obtained access token needs to be prepended with Bearer word and it needs to be passed in the Authorization header for API calls.

Example of API request with Bearer access token

curl https://ibm-watson-ml.mybluemix.net/v3/wml_instances/00fd89e6-8cf2-4712-a068-ade10277b649/published_models -H "Authorization: Bearer eyJhbGciOiJSUzUxMiIsInR5cCI6IkpXVCJ9.eyJ0ZW5hbnRJZCI6ImU4YmQzZGM3LWI5Y2UtNDY10C1iZ..."

Apache Spark Service Credentials

The IBM Watson Machine Learning co-operates with the Apache Spark as a Service to create batch, stream deployments and for learning configuration functionality.

For API methods requiring Apache Spark Service instance a custom header: X-Spark-Service-Instance with Service Credentials must be specified. The header value is a base64 encoded string with the JSON data containing Service Credentials and Spark version.

Model Integration with IBM i Apps



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Manage	🛞 WatsonML	-						:
Service credentials	Location: US South	Org: benoit.marolleau@fr.ibm.com	Space: DataSciX					•
Plan Connections	Credentials are provide	d in JSON format. The JSON snippet lists o	credentials, such as the API key and s	secret, as well as connection information for t	ne service.		View	More
	Service credentials					New c	redential 🕀	:
	10 - Items per page	1-1 of 1 items			1	of 1 pages	< 1	>
	KEY NAME	DATE CREATED		ACTIONS				
	v apsx-data	Sep 13, 2017 - 02:4	10:49	View credentials 🔺			1	Ē
	<pre>{ "url": "htt "access_key kwMbmHXNpi+FQ "username": "password": "instance_i }</pre>	cps://ibm-watson-ml.mybluemi /": "mN3bwIsi/xpOh08Bd8D8Zah)YUqQmv73SQJrb1WXWeZv", : "75693a81-d133-4c15-8570-3 : "13cb03fd-2b6b-4b24-a17f-4 id": "366f855c-745d-4820-9b1	x.net", 6UF++y/ZqlqTlJDmJQr6dqC8 dc0f0f092c1", 9eb2efaf7b9", 0-975dac91d5f7"	33AFnAyPemGJw9js0JHxGxQ3pIogjgH	ΞΟϳΝΘΤGDT	cL0h32g\	VzP	Ē

Model Integration with IBM i Apps *Example with Node.js on IBM i : Node-RED Prototype*



Sold-RED Edit WML node > Edit wml-config node Delete Cancel Update link Name Initial mqtt Instance Method http Username 75693a81-d133-4c15-8570-3dc0f0f092c1 Password Published Model Methods Host URL https://ibm-watson-ml.mybluemix.net Access Key VzPkwMbmHXNpi+FQYUqQmv73SQJrb1WXWeZv Instance ID 366f855c-745d-4820-9b10-975dac91d5f7 output Scoring - Prediction Run Prediction Build Payload Values timestamp

Fig. Graphical coding: let's invoke our model from Node-RED Left: json input values + Watson ML node for invocation. Right: API call result in json

05/2018 à 18:41:11 node: d0861edf.f95ad8
g : Object
object
_msgid: "4b7c6d15.f5aae4"
topic: ""
payload: object
<pre>fields: array[10]</pre>
<pre>values: array[1]</pre>
▼0: array[10]
0: 27
1: 0
2: 1
3: 1
▶ 4: array[4]
▶ 5: array[5]
▶ 6: array[5]
7: 0
8: "Camping Equipment"
▶ 9: array[5]
_event: "node:3d4e884c.9f8908"

Model Integration with IBM i Apps *Example with Node.js on IBM i*





How to get started? Q&A





Sessions connexes à venir

S28 - IA sur vos données DB2 avec Watson Analytics – Lab

par Christophe Lalevee



- S34 Comment développer les applications de demain ? IBM Cloud Private, Docker etc. par Benoit Marolleau
- S45 Prototypez un dashboard "social" avec Node-RED, Db2, Watson par Benoit Marolleau



Backup Slides

The Machine Learning Tasks & algorithms



years

Supervised learning

"right answers" given

Classification

- The output variable takes class labels (discrete valued output)

Breast Cancer (malignant, benign)

Regression

- Predict continuous valued output.

Housing price prediction





PCA for dimensionality reduction

thirty

Principal Components Analysis



Spark Technology Center

IBM established Spark Technology Center to contribute to the Apache® Spark[™] ecosystem – June 2015

505 Howard Street, San Francisco



IBM Spark Technology Center (STC) San Francisco, USA

Growing pool of contributors ~50 world wide, and 3 committers

Apache SystemML now an official Apache Incubator project Founding member of AMPLab (and upcoming RISE Lab) Member of R Consortium Founding member of Scala Center Partnerships in the ecosystem


Spark Technology Center contributions have grown over 400% since start in June 2015

STC Spark Contribution Progress



IBM had a significant impact on Spark 2.0

- IBM is #2 contributor to Apache Spark
- IBM was the leading contributor in Spark 2.0 to SparkML, PySpark, and SparkR

years



IBM impact on SparkML / MLlib 2.0



- Spark Machine Learning (ML) provides a toolset to create pipelines of different ML related transformations on your data
- IBM is #1 contributor in the Spark (ML)
- Distinction between ML and MLlib:
 - MLlib is based on RDDs; ML is based on data frames.
 - The distinction between both is fading out. In general they usually combine both under the name "Spark ML"



Machine Learning framework in Apache Spark

thirty

Pipeline components:

• **Transformers (e.g. indexing, normalization):** Dataframe -> Dataframe with features

• Estimators: Dataframe -> ML model

• **Models:** Dataframe -> Dataframe with predictions

• Pipelines:

Dataframe -> (chained transformers and estimators) -> ML model

• Evaluators:

Dataframe -> ML model



IBM Watson Studio & Machine Learning Pricing

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- Watson Studio
 - Per user licensing + Processing Units
 - https://www.ibm.com/cloud/watson-studio/pricing
- Watson Machine Learning
 - Per prediction licensing + Processing Units
 - https://www.ibm.com/cloud/machine-learning/pricing

IBM Data Science Experience Local (includes IBM Machine Learning*)

Per user licensing

*IBM Machine Learning = on premises Watson Machine Learning