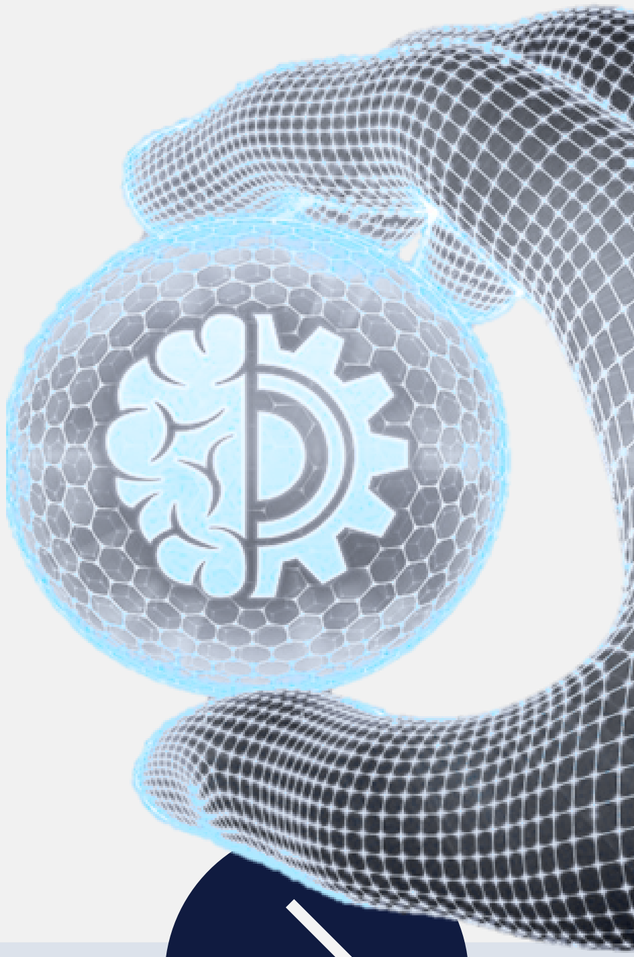
IBM Cloud watsonx Power BI

Hackaton IBM BI Pipeline

Credit Card Fraud Detection



Team 20:
Lisa NACCACHE (DIA 4): Team Leader
Hiba NEJJARI (DIA 4)
Neil MAHCER (DIA 4)
Wendy DUONG (DIA 4)
Cyprien MOUTON (DIA 4)
Safa HORMI BOUAICHI (DIA 3)

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Objective

Automatically identify suspicious financial transactions

Dataset

IBM dataset (2016–2018)

Key Challenge

The evaluation set contains new customers not seen during training, the model must generalize well.

Approach

Machine Learning (LightGBM), advanced feature engineering, and final results visualized through a Power BI dashboard.

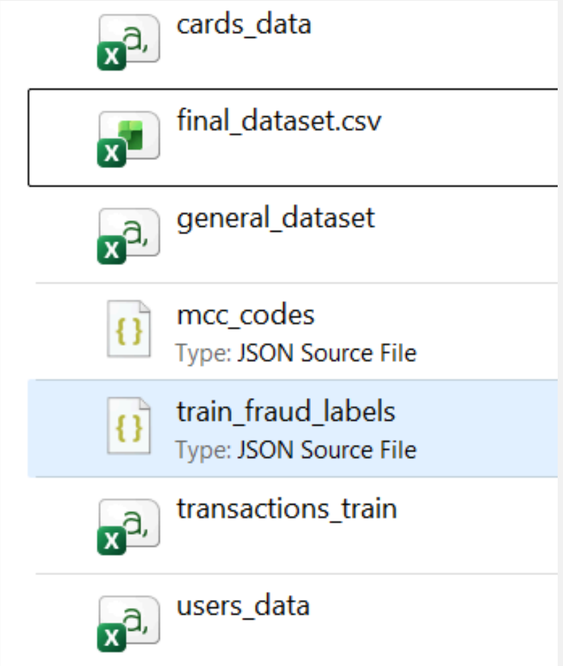
Team Task Distribution

Phase	Main tasks	Responsible members
Introduction & Context	Presentation of the project and the IBM dataset	Lisa & Cyprien
Data Exploration	Exploratory analysis and initial visualization	Hiba & Safa
Data Preparation	Cleaning, merging, feature engineering	Hiba & safa
Machine Learning Modeling	Training, model selection, tuning	Neil & Wendy
Evaluation & Generalization	Robustness testing and comparison	Neil & Wendy
Data Visualization & Dashboard	Creation of the dashboard in Power BI	Safa
Generation of the submission file	Production of the final CSV for evaluation	Hiba & Cyprien
Documentation & Presentation	Report and oral presentation	All members

Data Exploration

WE DIVIDED THE EDA INTO THREE MAIN PARTS:

- *Transactions analysis*: focus on spending behavior and fraud occurrence patterns.
- *Cards analysis*: study card characteristics, credit limits, and chip usage.
- *Users analysis*: explore demographic and financial indicators linked to fraud.



Dataset	Content	Goal
transactions	Transaction details	Spot fraud patterns & risky behaviors
cards	Card info (type, limit, chip)	Link card features to fraud risk
users	Demographic & financial data	Identify user profiles prone to fraud

Data Preparation

- The data preparation phase was divided into two key parts: **general cleaning** and **feature engineering**.
- This ensured a consistent, reliable dataset and enriched it with predictive features for fraud detection.

PHASE 1 : CLEANING AND PREPROCESSING

Step	Action	Goal
Remove duplicates	Keep unique transactions	Avoid repetition
Clean amounts	Remove $, fix negatives	Normalize values
Convert dates	Use proper date format	Enable time analysis
Handle missing data	Fill or drop NaNs	Ensure completeness
Drop useless columns	Remove IDs & addresses	Keep relevant info
Remove constant columns	Drop same-value fields	Reduce noise
Clean JSON files	Merge mcc & fraud	Add key info
Standardize types	Align numeric & text	Prepare for ML
Merge files	Combine all sources	One clean dataset

PHASE 2 : FEATURE ENGINEERING

Feature	Meaning	Fraud Insight
log_amount	Scaled amount	Flags extreme values
is_night	Night transaction	Higher fraud activity
is_weekend	Weekend payment	More off-hour frauds
amount_ratio_limit	Amount vs. card limit	Detects overspending
mcc_encoded	Merchant frequency	Unusual merchants
debt_to_income	Debt vs. income	Financial stress
credit_risk_index	Credit health score	Vulnerable users
account_age_days	Account age	New = higher risk
fraud_risk_index	Combined score	Overall fraud risk

Machine Learning Modeling

We trained several models to predict fraudulent transactions and evaluated them using ROC-AUC, AUPRC, and F1-score.

Three data splits classic, temporal, and cold-start were used to test performance and generalization on unseen clients, with differents models.

Machine Learning Modeling

Metrics

WHAT ARE THE METRICS USED ?

ROC-AUC — Measures the model's ability to distinguish between fraudulent and legitimate transactions

AUPRC — Evaluates performance on the highly imbalanced fraud class

F1-score — Balances precision and recall in identifying fraud cases

Machine Learning Modeling

Splits

WHAT ARE THE SPLITS ?

CLASSIC — Random train/test split mixing all data to get a baseline performance

TEMPORAL — Train on older data and test on newer data to simulate real-world future prediction

COLD-START — Train on a set of users and test on completely unseen users to measure the model's ability to generalize to new customers

Machine Learning Modeling

Models

WHICH MODEL DID WE SELECT ?

CatBoost

LightGBM

XGBoost

Machine Learning Modeling

Models

```
✅ CatBoost (split classique) Metrics :
AUROC : 0.8134 | AUPRC : 0.0193 | F1-score : 0.0563
Confusion Matrix :
 [[39595   320]
 [   49    11]]
```

CatBoost interpretal variables efficiently.

LightGBM stood out for its speed and strong generalization, making it highly suitable for large-scale fraud detection.

CATBOOST (SPLIT CLASSIQUE)

```
Metrics :
3 | F1-score : 0.0563
```

CATBOOST (TEMPORAL SPLIT)

```
) Metrics :
0854 | F1-score : 0.0633
```

CATBOOST (COLD-START SPLIT)

```
📌 CatBoost (cold-start split)
ROC AUC        : 0.7325
AUPRC          : 0.0117
F1 @ 0.5       : 0.0315
Best Threshold (F1 max): 0.463
```

Machine Learning Modeling
Models

XGBoost

XGBoost achieved robust and consistent results, effectively detecting subtle fraud behaviors within transactions.

XGBOOST (SPLIT CLASSIQUE)

```
✅ XGBoost (split classique) Metrics :
AUROC : 0.8006 | AUPRC : 0.0216 | F1-score : 0.0658
```

XGBOOST (TEMPORAL SPLIT)

```
✅ XGBoost (temporal split) Metrics :
AUROC : 0.7353 | AUPRC : 0.0518 | F1-score : 0.0796
```

XGBOOST (COLD-START SPLIT)

```
✅ XGBoost (cold-start split) Metrics :
AUROC : 0.6989 | AUPRC : 0.0093 | F1-score : 0.0563
```

Machine Learning Modeling
Models

LightGBM

LightGBM provided fast and accurate predictions, showing excellent adaptability to complex fraud detection patterns.

LIGHTGBM (SPLIT CLASSIQUE)

```
✅ LightGBM (split classique) Metrics :
AUROC : 0.82 | AUPRC : 0.037 | F1-score : 0.0875
```

LIGHTGBM (TEMPORAL SPLIT)

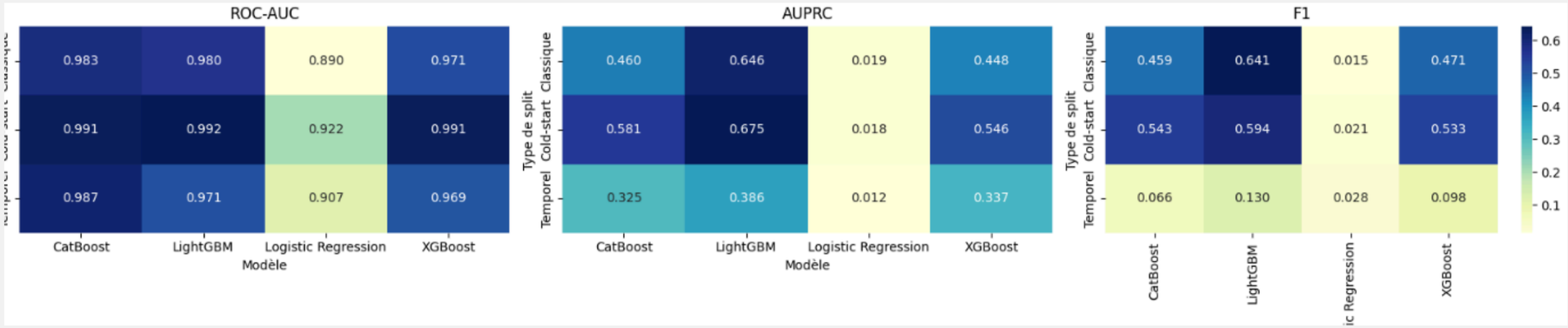
```
✅ LightGBM (temporal split) Metrics :
AUROC : 0.7993 | AUPRC : 0.0511 | F1-score : 0.125
```

LIGHTGBM (COLD-START SPLIT)

```
✅ LightGBM (cold-start split) Metrics :
AUROC : 0.7711 | AUPRC : 0.0214 | F1-score : 0.0637
```

Machine Learning Modeling

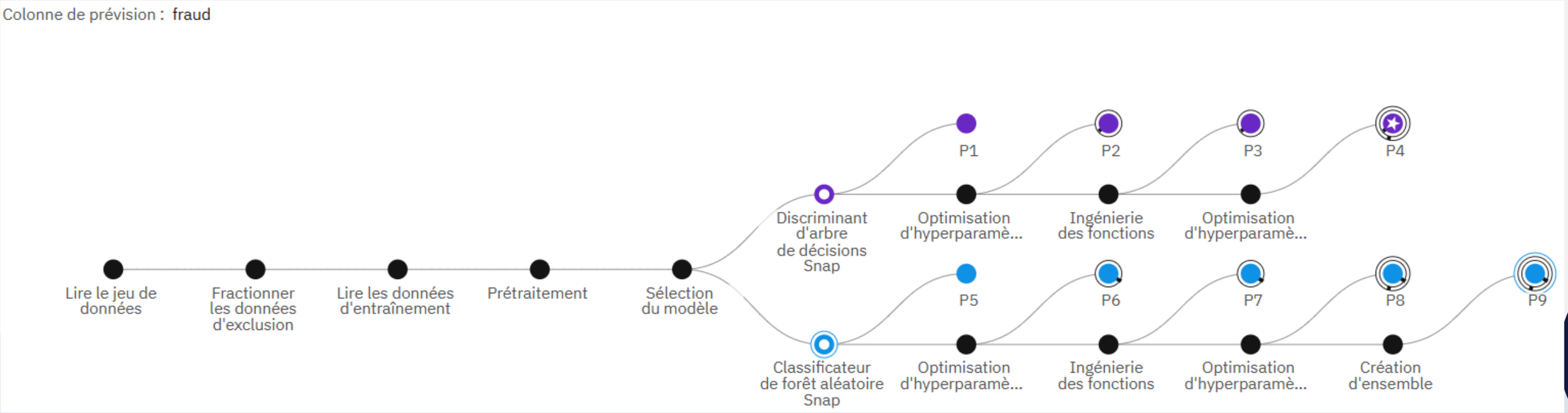
Comparison



MODEL COMPARISON

Progress Map

with Model Training Agent



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Analysis Result

with Model Training Agent

FEATURE IMPORTANCE IN THE MODEL

Toutes les fonctions

Rechercher des noms de fonction ou de transformateur

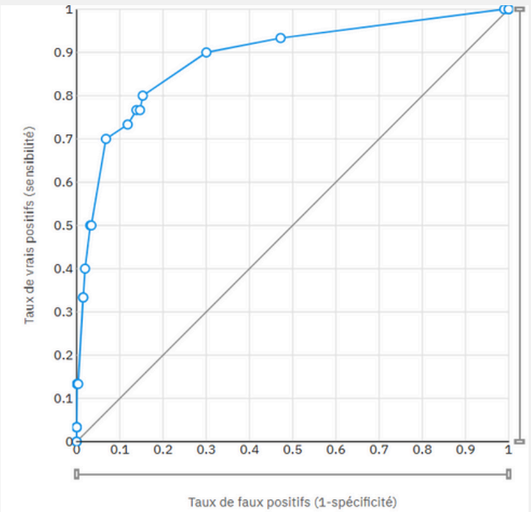
Nom de fonction	Transformation	Importance des fonctions
mcc	None	30.63%
fraud_risk_index	None	27.47%
mcc_encoded	None	20.02%
is_high_spender	None	15.93%
NewFeature_17	sum(round(amount),round(current_age))	5.96%

CONFUSION MATRIX OF THE MODEL

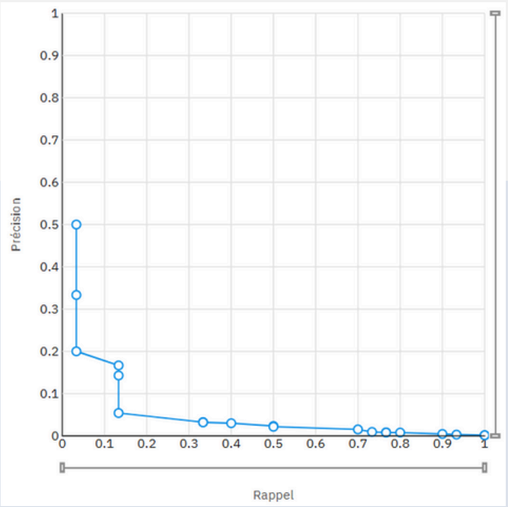
Observé	Prédit		
	1	0	Pourcentage correct
1	0	30	0.0%
0	0	19958	100.0%
Pourcentage correct	0.0%	99.8%	99.8%

moins correct — Le plus

RECEIVER OPERATING CHARACTERISTIC CURVE OF THE CLASSIFICATION MODEL



PRECISION-RECALL CURVE



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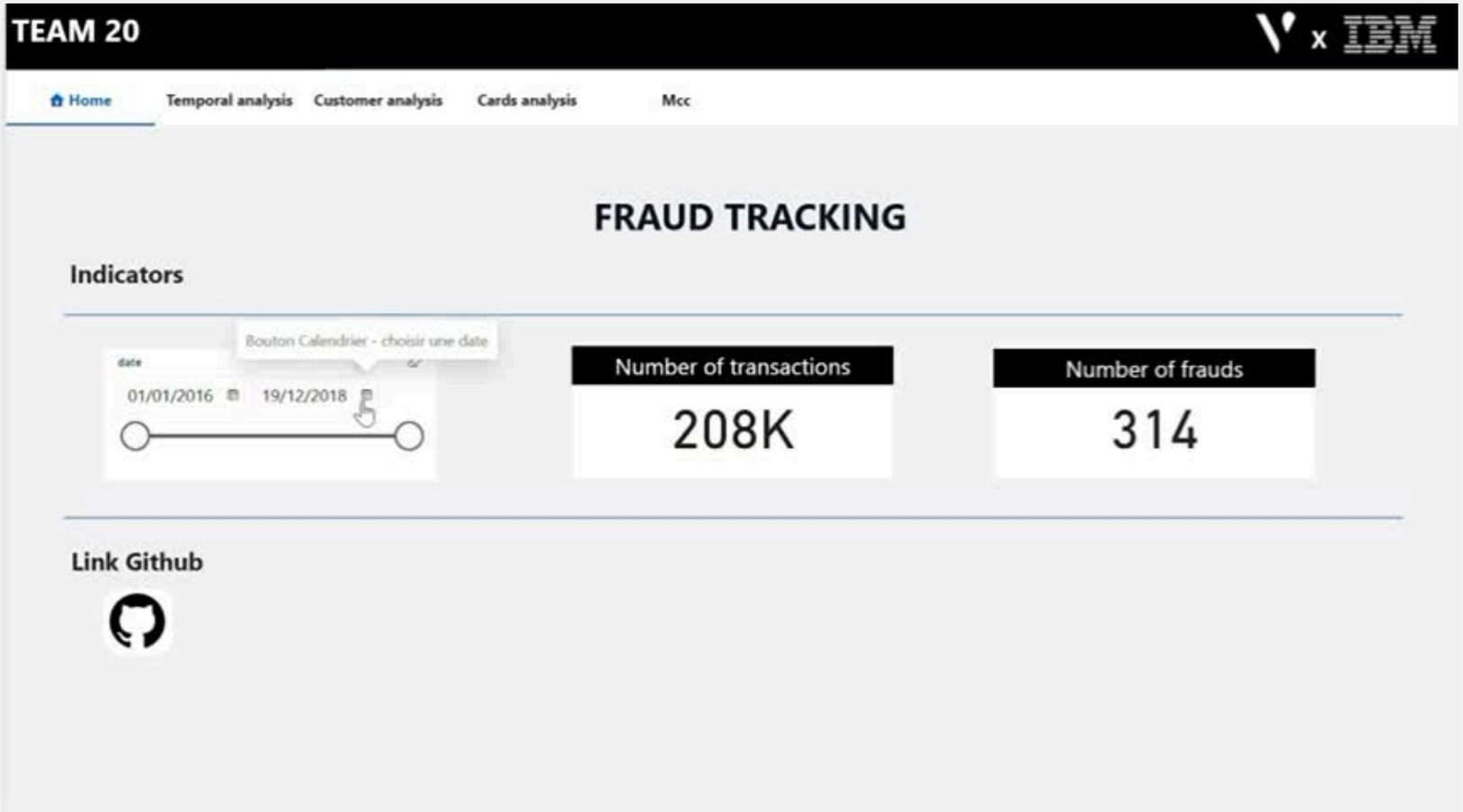
Dashboard PowerBI



Power BI

STRUCTURE OF OUR PROJECT ON WATSON

Types d'actif

- **Données** 8
  - Actifs de données 8
- Visualisations 1
  - Visualisation 1
- Expérimentations 2
  - Expérimentations Aut... 2
- Notebooks 5
- Modèles 2
  - Modèles 2

STATISTICS ON OUR ACTIVITY

Utilisation des ressources

Récapitulatif de l'utilisation

Pour ce mois dans ce projet

13.6 **Unités de capacité/heure**

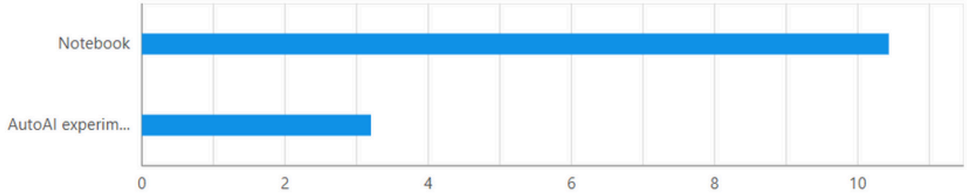
0 **Jetons**

0 **Heures d'hébergement**

0 **Pages**

Utilisation par type

CUH



SERVICES AND INTEGRATIONS

Services et intégrations

Services IBM (1) | Intégrations tierces

Associez les services IBM Cloud à ce projet pour ajouter des outils, des environnements informatiques ou d'autres capacités. En savoir plus.

Rechercher des services

Associer un service +

Nom	Type de service
WatsonMachineLearning	watsonx.ai Runtime

MEMBER OF OUR GROUP

Contrôle d'accès

Collaborateurs (6) | Jetons d'accès

Rechercher des collaborateurs

Nom	Rôle
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Wendy Duong wendy.duong@edu.devinci.fr	Administrateur

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Difficulties encountered

New Tool

DIFFICULTIES IN GETTING TO GRIPS WITH THE NEW WATSONX TOOL & WATSONX CREDIT

Time Project

DIFFICULTY MANAGING TIME FOR THE PROJECT, LACK OF TIME

Task distribution

FOR DEVELOPMENT AND INTEGRATION.

Objective achieved

Creation of an agent

LEARNING IN THE CREATION OF AN AGENT USING WATSONX

Good work structure

WELL-ORGANIZED GITHUB & WATSONX PROJECT REPOSITORY

Development of multiple models

USE OF MULTIPLE MODELS: CATBOOST, XGBOOST, AND LIGHTGBM