

```
In [1]: import os
        from pyspark.sql import SparkSession
        import findspark
        findspark.init()
        import pyspark
```

```
In [2]: jdbc_driver_path = os.path.abspath(r"C:\Users\sqljdbc_12.8.0.0_fra\sqljdbc_12.8\fra\jars
```

## Lancer une session Spark

```
In [3]: spark = SparkSession.builder \
        .appName("TelecomETL1") \
        .config("spark.driver.extraClassPath", jdbc_driver_path) \
        .config("spark.executor.extraClassPath", jdbc_driver_path) \
        .getOrCreate()

print("SparkSession créée avec succès!")
```

SparkSession créée avec succès!

## Configuration des connexions

```
In [4]: # Configuration de la connexion à la base de données source (telecom2)
        jdbc_url_source = "jdbc:sqlserver://[servername]:1433;databaseName=telecom2;encrypt=true

        # Configuration de la connexion à la base de données cible (spy)
        jdbc_url_target = "jdbc:sqlserver://[servername]:1433;databaseName=spy;encrypt=true;trus

        properties = {
            "user": "[user]",
            "password": "[pwd]",
            "driver": "com.microsoft.sqlserver.jdbc.SQLServerDriver"
        }
        print("connexion établie avec succès")
```

connexion établie avec succès

## Apperçu sur les données

```
In [5]: # Liste des tables à extraire
        tables = [
            "department", "worklocation", "employee", "employeeworklocation",
            "salesperson", "customer", "orders", "planinclusions", "plans",
            "billinginformation", "phonenumber", "callrecords", "salary",
            "simdata", "tracking"
        ]

        try:
            for table_name in tables:
                print(f"\nExtraction des données de la table: {table_name}")

                # Lire les données de la table
                df = spark.read.jdbc(url=jdbc_url_source, table=table_name, properties=propertie

                print(f"Aperçu des données de {table_name}:")
                df.show(5, truncate=False)
```

```
print(f"Schéma de la table {table_name}:")
df.printSchema()

row_count = df.count()
print(f"Nombre total de lignes dans {table_name}: {row_count}")

except Exception as e:
    print("Erreur lors de l'extraction des données:", str(e))
```

Extraction des données de la table: department  
Aperçu des données de department:

DepartmentId	DepartmentName	Salary
1	Information Technology	10000
2	Sales & Marketing	5000
3	Finance	2500
4	Human Resource	7500
5	Customer Care	1000

Schéma de la table department:

```
root
|-- DepartmentId: integer (nullable = true)
|-- DepartmentName: string (nullable = true)
|-- Salary: integer (nullable = true)
```

Nombre total de lignes dans department: 5

Extraction des données de la table: worklocation  
Aperçu des données de worklocation:

LocationId	LocationName	NumberOfEmployees
1	Seattle	5
2	Washington DC	5
3	New York	5
4	Boston	5

Schéma de la table worklocation:

```
root
|-- LocationId: integer (nullable = true)
|-- LocationName: string (nullable = true)
|-- NumberOfEmployees: integer (nullable = true)
```

Nombre total de lignes dans worklocation: 4

Extraction des données de la table: employee  
Aperçu des données de employee:

EmployeeId	Employee_Name	SSN	Age	DepartmentId	Salary
1	Ojas Phansekar	123456789	24	1	1000
2	Shreyas Kalayanaraman	245987675	24	1	1000
3	Saurabh Kulkarni	734756953	24	1	1000
4	Vivek Shetye	572364526	26	1	1000
5	Mihir Patil	238745784	27	1	1000

only showing top 5 rows

Schéma de la table employee:

```
root
|-- EmployeeId: integer (nullable = true)
|-- Employee_Name: string (nullable = true)
|-- SSN: string (nullable = true)
|-- Age: integer (nullable = true)
|-- DepartmentId: integer (nullable = true)
|-- Salary: integer (nullable = true)
```

Nombre total de lignes dans employee: 37

Extraction des données de la table: employeeworklocation

Aperçu des données de employeeworklocation:

+-----+-----+		
WorkEmployeeId LocationId		
+-----+-----+		
1	2	
2	4	
3	3	
4	1	
5	2	
+-----+-----+		

only showing top 5 rows

Schéma de la table employeeworklocation:

root

```
|-- WorkEmployeeId: integer (nullable = true)
|-- LocationId: integer (nullable = true)
```

Nombre total de lignes dans employeeworklocation: 20

Extraction des données de la table: salesperson

Aperçu des données de salesperson:

+-----+-----+		
SalesPersonId IdEmployeeSalesPerson		
+-----+-----+		
1	5	
2	6	
3	7	
4	8	
+-----+-----+		

Schéma de la table salesperson:

root

```
|-- SalesPersonId: integer (nullable = true)
|-- IdEmployeeSalesPerson: integer (nullable = true)
```

Nombre total de lignes dans salesperson: 4

Extraction des données de la table: customer

Aperçu des données de customer:

+-----+-----+--+--+-----+-----+						
---+						
CustomerId CustomerName  Sex Age DateOfBirth SocialSecurityNumber CustomerSalesPersonId						
+-----+-----+--+--+-----+-----+						
---+						
1	Jishnu Vasudevan M	24	1993-12-28	232498675		1
2	Harsh Shah	M	24	1993-09-12	456498675	2
3	Rachana Rambhad	F	24	1993-08-19	543498675	3
4	Lagan Gupta	F	24	1993-08-08	765498675	4
5	Neha Verma	F	24	1993-08-27	987498675	1
+-----+-----+--+--+-----+-----+						
---+						

only showing top 5 rows

Schéma de la table customer:

root

```
|-- CustomerId: integer (nullable = true)
|-- CustomerName: string (nullable = true)
|-- Sex: string (nullable = true)
```

```
|-- Age: integer (nullable = true)
|-- DateOfBirth: date (nullable = true)
|-- SocialSecurityNumber: integer (nullable = true)
|-- CustomerSalesPersonId: integer (nullable = true)
```

Nombre total de lignes dans customer: 20

Extraction des données de la table: orders

Aperçu des données de orders:

```
+-----+-----+-----+-----+
|OrderId|OrderType      |OrderStatus      |OrderCustomerId|
+-----+-----+-----+-----+
|1      |2 day shipping |Shipped          |1              |
|2      |Priority Shipping|Partially Shipped|2              |
|3      |Standard       |Payment Incomplete|3              |
|4      |2 day shipping |Order Cancelled  |4              |
|5      |Standard       |Pending          |5              |
+-----+-----+-----+-----+
```

only showing top 5 rows

Schéma de la table orders:

root

```
|-- OrderId: integer (nullable = true)
|-- OrderType: string (nullable = true)
|-- OrderStatus: string (nullable = true)
|-- OrderCustomerId: integer (nullable = true)
```

Nombre total de lignes dans orders: 20

Extraction des données de la table: planinclusions

Aperçu des données de planinclusions:

```
+-----+-----+-----+-----+
|PlanId|Data |Talktime  |TextMessages|
+-----+-----+-----+-----+
|1      |500MB|60 Minutes |100          |
|2      |500MB|120 Minutes|200          |
|3      |500MB|180 Minutes|300          |
|4      |500MB|240 Minutes|400          |
|5      |500MB|300 Minutes|500          |
+-----+-----+-----+-----+
```

only showing top 5 rows

Schéma de la table planinclusions:

root

```
|-- PlanId: integer (nullable = true)
|-- Data: string (nullable = true)
|-- Talktime: string (nullable = true)
|-- TextMessages: string (nullable = true)
```

Nombre total de lignes dans planinclusions: 20

Extraction des données de la table: plans

Aperçu des données de plans:

```
+-----+-----+-----+-----+
|PlansId|PlansType|PlanName          |PlanInclusionId|
+-----+-----+-----+-----+
|1      |Prepaid  |Basic Plan        |1              |
|2      |Prepaid  |Every Minute Counts|2              |
|3      |Postpaid |Family            |3              |
|4      |Postpaid |Enjoy Data        |4              |
|5      |Postpaid |Finger tips       |5              |
+-----+-----+-----+-----+
```

only showing top 5 rows

Schéma de la table plans:

```
root
|-- PlansId: integer (nullable = true)
|-- PlansType: string (nullable = true)
|-- PlanName: string (nullable = true)
|-- PlanInclusionId: integer (nullable = true)
```

Nombre total de lignes dans plans: 10

Extraction des données de la table: billinginformation

Aperçu des données de billinginformation:

```
+-----+-----+-----+-----+-----+
|BillNumber|IncludedData|DataUsed|BalancedData|Tax  |
+-----+-----+-----+-----+-----+
|1         |50          |40      |10          |15.10|
|2         |100         |60      |40          |20.30|
|3         |200         |100     |100         |30.30|
|4         |500         |200     |300         |40.30|
|5         |500         |100     |400         |50.00|
+-----+-----+-----+-----+-----+
```

only showing top 5 rows

Schéma de la table billinginformation:

```
root
|-- BillNumber: integer (nullable = true)
|-- IncludedData: integer (nullable = true)
|-- DataUsed: integer (nullable = true)
|-- BalancedData: integer (nullable = true)
|-- Tax: decimal(18,2) (nullable = true)
```

Nombre total de lignes dans billinginformation: 15

Extraction des données de la table: phonenumber

Aperçu des données de phonenumber:

```
+-----+-----+-----+
|AccountNumber|PhoneNumber|PhoneBillNumber|
+-----+-----+-----+
|9            |1235465768 |3              |
|10           |1235465768 |4              |
|11           |1675849305 |5              |
|12           |1345267859 |6              |
|13           |1578893409 |7              |
+-----+-----+-----+
```

only showing top 5 rows

Schéma de la table phonenumber:

```
root
|-- AccountNumber: integer (nullable = true)
|-- PhoneNumber: long (nullable = true)
|-- PhoneBillNumber: integer (nullable = true)
```

Nombre total de lignes dans phonenumber: 11

Extraction des données de la table: callrecords

Aperçu des données de callrecords:

```
+-----+-----+-----+-----+-----+
|CallId|CallStartTime      |CallEndTime      |CallDuration      |CallAccountNumber|
+-----+-----+-----+-----+-----+
|2      |1970-01-01 12:20:20|1970-01-01 12:21:20|1970-01-01 00:01:00|10              |
|3      |1970-01-01 11:23:24|1970-01-01 15:40:30|1970-01-01 04:17:06|10              |
|4      |1970-01-01 08:30:10|1970-01-01 08:32:20|1970-01-01 00:02:10|11              |
|5      |1970-01-01 21:45:30|1970-01-01 21:50:34|1970-01-01 00:05:04|14              |
|6      |1970-01-01 12:32:21|1970-01-01 12:34:20|1970-01-01 00:01:59|10              |
+-----+-----+-----+-----+-----+
```

only showing top 5 rows

Schéma de la table callrecords:

```
root
|-- CallId: integer (nullable = true)
|-- CallStartTime: timestamp (nullable = true)
|-- CallEndTime: timestamp (nullable = true)
|-- CallDuration: timestamp (nullable = true)
|-- CallAccountNumber: integer (nullable = true)
```

Nombre total de lignes dans callrecords: 19

Extraction des données de la table: salary

Aperçu des données de salary:

EmployeeId	EmployeeName	DepartmentId	Salary
27	Devdip Sen	5	10000
28	Alpana Sharan	3	2500
29	Priyanka Singh	3	2500
30	Ranjani Iyer	2	5000
31	Amlan Bhuyan	4	7500

only showing top 5 rows

Schéma de la table salary:

```
root
|-- EmployeeId: integer (nullable = true)
|-- EmployeeName: string (nullable = true)
|-- DepartmentId: integer (nullable = true)
|-- Salary: integer (nullable = true)
```

Nombre total de lignes dans salary: 12

Extraction des données de la table: simdata

Aperçu des données de simdata:

SimNumber	SimType	SimCustomerId	SimAccountNumber	SimPlanNumber
1234567890123460	Postpaid	2	19	3
1234567890123461	Prepaid	16	10	1
1234567890123462	Postpaid	14	12	3
1234567890123463	Postpaid	1	14	5
1234567890123464	Prepaid	12	16	8

only showing top 5 rows

Schéma de la table simdata:

```
root
|-- SimNumber: long (nullable = true)
|-- SimType: string (nullable = true)
|-- SimCustomerId: integer (nullable = true)
|-- SimAccountNumber: integer (nullable = true)
|-- SimPlanNumber: integer (nullable = true)
```

Nombre total de lignes dans simdata: 10

Extraction des données de la table: tracking

Aperçu des données de tracking:

TrackingId	TrackingStatus	TrackingOrderId
1	On the way	10
2	Arrived to courier service	9

3	Near by closest dispatch location	14	
4	Arrived to courier service	16	
5	Arrived to courier service	17	
+-----+-----+-----+-----+-----+-----+			

only showing top 5 rows

Schéma de la table tracking:

```
root
|-- TrackingId: integer (nullable = true)
|-- TrackingStatus: string (nullable = true)
|-- TrackingOrderId: integer (nullable = true)
```

Nombre total de lignes dans tracking: 9

## Connexion à toutes les tables

```
In [6]: employee_df = spark.read.jdbc(url=jdbc_url_source, table="employee", properties=properties)
department_df = spark.read.jdbc(url=jdbc_url_source, table="department", properties=properties)
customer_df = spark.read.jdbc(url=jdbc_url_source, table="customer", properties=properties)
orders_df = spark.read.jdbc(url=jdbc_url_source, table="orders", properties=properties)
callrecords_df = spark.read.jdbc(url=jdbc_url_source, table="callrecords", properties=properties)
plans_df = spark.read.jdbc(url=jdbc_url_source, table="plans", properties=properties)
simdata_df = spark.read.jdbc(url=jdbc_url_source, table="simdata", properties=properties)
worklocation_df = spark.read.jdbc(url=jdbc_url_source, table="worklocation", properties=properties)
employeeworklocation_df = spark.read.jdbc(url=jdbc_url_source, table="employeeworklocation", properties=properties)
salesperson_df = spark.read.jdbc(url=jdbc_url_source, table="salesperson", properties=properties)
planinclusions_df = spark.read.jdbc(url=jdbc_url_source, table="planinclusions", properties=properties)
billinginformation_df = spark.read.jdbc(url=jdbc_url_source, table="billinginformation", properties=properties)
phonenumbers_df = spark.read.jdbc(url=jdbc_url_source, table="phonenumbers", properties=properties)
salary_df = spark.read.jdbc(url=jdbc_url_source, table="salary", properties=properties)
tracking_df = spark.read.jdbc(url=jdbc_url_source, table="tracking", properties=properties)

# Vérifier que les DataFrames ont été correctement chargés
print("Nombre de lignes dans chaque table:")
print("employee:", employee_df.count())
print("department:", department_df.count())
print("customer:", customer_df.count())
print("orders:", orders_df.count())
print("callrecords:", callrecords_df.count())
print("plans:", plans_df.count())
print("simdata:", simdata_df.count())
print("worklocation:", worklocation_df.count())
print("employeeworklocation:", employeeworklocation_df.count())
print("salesperson:", salesperson_df.count())
print("planinclusions:", planinclusions_df.count())
print("billinginformation:", billinginformation_df.count())
print("phonenumbers:", phonenumbers_df.count())
print("salary:", salary_df.count())
print("tracking:", tracking_df.count())
```



Nombre de lignes dans chaque table:  
 employee: 37  
 department: 5  
 customer: 20  
 orders: 20  
 callrecords: 19  
 plans: 10  
 simdata: 10  
 worklocation: 4  
 employeeworklocation: 20  
 salesperson: 4  
 planinclusions: 20  
 billinginformation: 15  
 phonenumbers: 11  
 salary: 12  
 tracking: 9

```
In [7]: # Analyse des performances des commerciaux
from pyspark.sql.functions import col, sum, count, datediff, current_date, when, avg, row_number
from pyspark.sql.window import Window

salesperson_performance = customer_df.join(salesperson_df, customer_df.CustomerSalesPersonId == salesperson_df.IdEmployeeSalesPerson) \
    .join(employee_df, salesperson_df.IdEmployeeSalesPerson == employee_df.EmployeeId) \
    .join(simdata_df, customer_df.CustomerId == simdata_df.SimCustomerId) \
    .join(plans_df, simdata_df.SimPlanNumber == plans_df.PlansId) \
    .groupBy("IdEmployeeSalesPerson", "Employee_Name") \
    .agg(
        count("CustomerId").alias("TotalCustomers"),
        sum(when(col("PlansType") == "Postpaid", 1).otherwise(0)).alias("PostpaidPlans"),
        sum(when(col("PlansType") == "Prepaid", 1).otherwise(0)).alias("PrepaidPlans"),
        avg("Salary").alias("AvgSalary")
    ) \
    .withColumn("PostpaidRatio", round(col("PostpaidPlans") / col("TotalCustomers"), 2))
salesperson_performance.show()
```

```
+-----+-----+-----+-----+-----+-----+
--+-+-----+
|IdEmployeeSalesPerson| Employee_Name|TotalCustomers|PostpaidPlans|PrepaidPlans|AvgSalary|PostpaidRatio|
+-----+-----+-----+-----+-----+-----+
--+-+-----+
|8|Shantanu Sawant|2|0|2|750|0.0|0.0|
|6|Karan Thevar|3|3|0|750|0.0|1.0|
|5|Mihir Patil|3|2|1|100|0.0|0.67|
|7|Chetan Mistry|2|1|1|750|0.0|0.5|
+-----+-----+-----+-----+-----+-----+
--+-+-----+
```

## Analyse des tendances d'utilisation des données par plan et par mois

```
In [8]: data_usage_trends = callrecords_df.join(simdata_df, callrecords_df.CallAccountNumber == simdata_df.SimAccountNumber) \
    .join(plans_df, simdata_df.SimPlanNumber == plans_df.PlansId) \
    .withColumn("CallMonth", month("CallStartTime")) \
    .withColumn("CallYear", year("CallStartTime")) \
    .groupBy("PlansType", "PlanName", "CallYear", "CallMonth") \
    .agg(
        sum(col("CallDuration")).alias("TotalCallDuration"),
```

```

        count("CallId").alias("TotalCalls")
    ) \
    .orderBy("CallYear", "CallMonth", "PlansType")
data_usage_trends.show()

```

PlansType	PlanName	CallYear	CallMonth	TotalCallDuration	TotalCalls
Postpaid	Family	1970	1	3893.0	3
Postpaid	Do not disturb	1970	1	5816.0	4
Postpaid	Finger tips	1970	1	304.0	1
Prepaid	Basic Plan	1970	1	33317.0	8
Prepaid	Continuous Texting	1970	1	5567.0	2
Prepaid	Talk For Hours	1970	1	449.0	1

## Analyse de la rotation du personnel et son impact sur les ventes

```

In [9]: employee_turnover = employee_df.join(salesperson_df, employee_df.EmployeeId == salespers
    .join(customer_df, salesperson_df.SalesPersonId == customer_df.CustomerSalesPersonId
    .join(orders_df, customer_df.CustomerId == orders_df.OrderCustomerId, "left_outer")
    .groupBy("EmployeeId", "Employee_Name", "DepartmentId") \
    .agg(
        count("CustomerId").alias("TotalCustomers"),
        count("OrderId").alias("TotalOrders"),
        sum(when(col("OrderStatus") == "Cancelled", 1).otherwise(0)).alias("CancelledOrd
    ) \
    .join(salary_df, "EmployeeId") \
    .withColumn("OrderCancellationRate", round(col("CancelledOrders") / col("TotalOrders
employee_turnover.show()

```

EmployeeId	Employee_Name	DepartmentId	TotalCustomers	TotalOrders	CancelledOrders	
EmployeeName	DepartmentId	Salary	OrderCancellationRate			
27	Devdip Sen	5	0	0	0	
Devdip Sen	5	10000	NULL			
28	Alpana Sharan	3	0	0	0	Al
Alpana Sharan	3	2500	NULL			
29	Priyanka Singh	3	0	0	0	Pri
Priyanka Singh	3	2500	NULL			
30	Ranjani Iyer	2	0	0	0	R
Ranjani Iyer	2	5000	NULL			
31	Amlan Bhuyan	4	0	0	0	A
Amlan Bhuyan	4	7500	NULL			
32	Manoj Prabhakar	1	0	0	0	Mano
Manoj Prabhakar	1	1000	NULL			
33	Raj Phadke	5	0	0	0	
Raj Phadke	5	10000	NULL			
34	Priya Yadav	1	0	0	0	
Priya Yadav	1	1000	NULL			
35	Sayali Joshi	4	0	0	0	S
Sayali Joshi	4	7500	NULL			
36	Pranav Patil	5	0	0	0	P
Pranav Patil	5	10000	NULL			
37	Rohit Patil	3	0	0	0	
Rohit Patil	3	2500	NULL			
38	Swanand Sapre	5	0	0	0	Sw
Swanand Sapre	5	10000	NULL			

## Analyse géographique des performances de vente

```
In [10]: geo_sales_performance = employeeworklocation_df.join(employee_df, employeeworklocation_df
    .join(worklocation_df, employeeworklocation_df.LocationId == worklocation_df.LocationId)
    .join(salesperson_df, employee_df.EmployeeId == salesperson_df.IdEmployeeSalesPerson)
    .join(customer_df, salesperson_df.SalesPersonId == customer_df.CustomerSalesPersonId)
    .join(orders_df, customer_df.CustomerId == orders_df.OrderCustomerId) \
    .groupBy("LocationName") \
    .agg(
        count("OrderId").alias("TotalOrders"),
        sum(when(col("OrderStatus") == "Shipped", 1).otherwise(0)).alias("CompletedOrders"),
        avg("Salary").alias("AvgSalary")
    ) \
    .withColumn("OrderCompletionRate", round(col("CompletedOrders") / col("TotalOrders")))
geo_sales_performance.show()
```

LocationName	TotalOrders	CompletedOrders	AvgSalary	OrderCompletionRate
Seattle	5	0	7500.0	0.0
Washington DC	5	1	1000.0	0.2
New York	5	0	7500.0	0.0
Boston	5	2	7500.0	0.4

```
In [11]: # Analyse du réseau social des clients (qui appelle qui)
from pyspark.sql.functions import col, sum, count, datediff, current_date, when, avg, row_number
Loading [MathJax]/extensions/Safe.js sql.window import Window
```

```

from pyspark.ml.feature import VectorAssembler
from pyspark.ml.clustering import KMeans
social_network_analysis = callrecords_df.alias("caller") \
    .join(callrecords_df.alias("receiver"), col("caller.CallAccountNumber") != col("rece
    .groupBy("caller.CallAccountNumber", "receiver.CallAccountNumber") \
    .agg(
        count("*").alias("CallFrequency"),
        avg(unix_timestamp(col("caller.CallEndTime")) - unix_timestamp(col("caller.Calls
    ) \
    .orderBy(col("CallFrequency").desc())
social_network_analysis.show()

```

```

+-----+-----+-----+-----+
|CallAccountNumber|CallAccountNumber|CallFrequency|AvgCallDurationSeconds|
+-----+-----+-----+-----+
|                10|                11|                32|                4164.625|
|                11|                10|                32|                1454.0|
|                13|                10|                16|                2783.5|
|                10|                13|                16|                4164.625|
|                10|                12|                16|                4164.625|
|                12|                10|                16|                956.5|
|                17|                10|                 8|                449.0|
|                10|                19|                 8|                4164.625|
|                11|                13|                 8|                1454.0|
|                13|                11|                 8|                2783.5|
|                10|                17|                 8|                4164.625|
|                12|                11|                 8|                956.5|
|                10|                14|                 8|                4164.625|
|                19|                10|                 8|                1980.0|
|                11|                12|                 8|                1454.0|
|                14|                10|                 8|                304.0|
|                14|                11|                 4|                304.0|
|                11|                19|                 4|                1454.0|
|                17|                11|                 4|                449.0|
|                11|                14|                 4|                1454.0|
+-----+-----+-----+-----+

```

only showing top 20 rows

```

In [12]: from pyspark.ml.clustering import KMeans
from pyspark.ml.evaluation import ClusteringEvaluator
from pyspark.sql.functions import col, count, sum, avg, when, datediff, current_date, to
from pyspark.sql.window import Window
from pyspark.ml.feature import VectorAssembler
from pyspark.ml.clustering import KMeans
from pyspark.ml.evaluation import ClusteringEvaluator

# Préparation des données pour la segmentation
customer_features = customer_df.join(simdata_df, customer_df.CustomerId == simdata_df.Si
    .join(callrecords_df, simdata_df.SimAccountNumber == callrecords_df.CallAccountNumbe
    .join(orders_df, customer_df.CustomerId == orders_df.OrderCustomerId, "left") \
    .groupBy("CustomerId") \
    .agg(
        count("OrderId").alias("TotalOrders"),
        sum(when(col("CallEndTime").isNotNull() & col("CallStartTime").isNotNull(),
            col("CallEndTime").cast("long") - col("CallStartTime").cast("long"))
            .otherwise(0)).alias("TotalCallDurationSeconds"),
        count("CallId").alias("TotalCalls"),
        avg("Age").alias("Age")
    ) \
    .withColumn("AvgOrderValue", col("TotalOrders") * 50) # Supposons un montant moyen

# Gestion des valeurs nulles
customer_features = customer_features.na.fill({
    "TotalOrders": 0,

```

```

    "TotalCallDurationSeconds": 0,
    "TotalCalls": 0,
    "Age": customer_features.select(avg("Age")).first()[0],
    "AvgOrderValue": 0
  })

# Préparation des caractéristiques pour le clustering
feature_cols = ["TotalOrders", "TotalCallDurationSeconds", "TotalCalls", "Age", "AvgOrde
assembler = VectorAssembler(inputCols=feature_cols, outputCol="features")
customer_features_vector = assembler.transform(customer_features)

# Application du clustering K-means
kmeans = KMeans(k=5, seed=1) # 5 segments
model = kmeans.fit(customer_features_vector)
customer_segments = model.transform(customer_features_vector)

# Évaluation du modèle
evaluator = ClusteringEvaluator()
silhouette = evaluator.evaluate(customer_segments)
print(f"Silhouette avec carré de la distance euclidienne = {silhouette}")

# Affichage des résultats de segmentation
print("Résultats de la segmentation des clients:")
customer_segments.select("CustomerId", "prediction").show()

# Analyse de l'évolution des plans des clients dans le temps
plan_evolution = simdata_df.join(plans_df, simdata_df.SimPlanNumber == plans_df.PlansId)
    .join(customer_df, simdata_df.SimCustomerId == customer_df.CustomerId) \
    .withColumn("CustomerAge", datediff(current_date(), to_date(col("DateOfBirth")))) / 3
    .withColumn("PlanRank", dense_rank().over(Window.partitionBy("SimCustomerId").orderB
    .groupBy("SimCustomerId", "CustomerName", "CustomerAge") \
    .agg(
        count("PlansId").alias("TotalPlansUsed"),
        collect_list("PlanName").alias("PlanSequence")
    ) \
    .orderBy(col("TotalPlansUsed").desc())

print("Analyse de l'évolution des plans des clients:")
plan_evolution.show(truncate=False)

```

Silhouette avec carré de la distance euclidienne = 0.9318914716713715

Résultats de la segmentation des clients:

```
+-----+-----+
|CustomerId|prediction|
+-----+-----+
|      12|         0|
|       1|         4|
|      13|         2|
|       6|         0|
|      16|         1|
|       3|         0|
|      20|         0|
|       5|         4|
|      19|         0|
|      15|         2|
|       9|         0|
|      17|         0|
|       4|         0|
|       8|         0|
|       7|         0|
|      10|         0|
|      11|         0|
|      14|         3|
|       2|         3|
|      18|         0|
+-----+-----+
```

Analyse de l'évolution des plans des clients:

```
+-----+-----+-----+-----+-----+
|SimCustomerId|CustomerName      |CustomerAge      |TotalPlansUsed|PlanSequence      |
+-----+-----+-----+-----+-----+
|12           |Kal Bugarara      |63.663244353182755|1             |[Enjoy surfing]   |
|1            |Jishnu Vasudevan  |30.663928815879533|1             |[Finger tips]     |
|13           |Neeraj Rajput     |33.831622176591374|1             |[Do not disturb]  |
|16           |Vijayshree Uppili|33.01300479123888 |1             |[Basic Plan]      |
|5            |Neha Verma        |31.000684462696782|1             |[Talk For Hours]  |
|15           |Sameer Goel       |34.65845311430527 |1             |[Continuous Texting]|
|7            |Anubhav Gupta     |33.66461327857632 |1             |[Enjoy Data]      |
|10           |Dharit Shah       |30.666666666666668|1             |[Powerful Speed]  |
|14           |Shruti Mehta      |32.695414099931554|1             |[Family]          |
|2            |Harsh Shah        |30.95687885010267 |1             |[Family]          |
+-----+-----+-----+-----+-----+
```

```
In [14]: from pyspark.sql.functions import col, when, count, sum, avg, datediff, current_date, to
from pyspark.sql.window import Window
from pyspark.sql.types import DoubleType

# Fonction UDF pour calculer le coût des dépassements
@udf(returnType=DoubleType())
def calculate_ouverage_cost(data_used, included_data, balanced_data):
    if data_used > included_data:
        return (data_used - included_data - balanced_data) * 0.1 # Supposons 0.1 par un
    return 0.0

customer_usage = customer_df.join(
    simdata_df, customer_df.CustomerId == simdata_df.SimCustomerId
).join(
    plans_df, simdata_df.SimPlanNumber == plans_df.PlansId
).join(
    planinclusions_df, plans_df.PlanInclusionId == planinclusions_df.PlanId
).join(
    callrecords_df, simdata_df.SimAccountNumber == callrecords_df.CallAccountNumber
```

```

).join(
    billinginformation_df, simdata_df.SimAccountNumber == billinginformation_df.BillNumb
).join(
    orders_df, customer_df.CustomerId == orders_df.OrderCustomerId
)

# Analyse de la rentabilité des clients
customer_profitability = customer_usage.groupby(
    "CustomerId", "CustomerName", "SimType", "PlanType", "PlanName"
).agg(
    sum("Tax").alias("TotalTax"),
    sum("IncludedData").alias("TotalIncludedData"),
    sum("DataUsed").alias("TotalDataUsed"),
    sum("BalancedData").alias("TotalBalancedData"),
    count("CallId").alias("TotalCalls"),
    sum(when(col("CallEndTime").isNotNull() & col("CallStartTime").isNotNull(),
        col("CallEndTime").cast("long") - col("CallStartTime").cast("long"))
        .otherwise(0)).alias("TotalCallDurationSeconds"),
    count("OrderId").alias("TotalOrders"),
    sum(when(col("OrderStatus") == "Shipped", 1).otherwise(0)).alias("CompletedOrders")
    # Retirez la ligne faisant référence à "Salary"
).withColumn(
    "OverageCost", calculate_overage_cost(col("TotalDataUsed"), col("TotalIncludedData"))
).withColumn(
    "TotalRevenue", lit(50) * 12 + col("OverageCost") + col("TotalTax")
).withColumn(
    "AvgCallDurationMinutes", when(col("TotalCalls") > 0, round(col("TotalCallDurationSe
).withColumn(
    "OrderCompletionRate", when(col("TotalOrders") > 0, round(col("CompletedOrders") / c
).withColumn(
    "CustomerLifetimeValue", col("TotalRevenue") * 3 - (col("TotalCalls") * 0.05 + col("
)

# Calcul des métriques de rentabilité
window_spec = Window.orderBy(col("CustomerLifetimeValue").desc())
customer_profitability = customer_profitability.withColumn(
    "ProfitabilityRank", dense_rank().over(window_spec)
).withColumn(
    "ProfitabilityScore",
    (col("CustomerLifetimeValue") / 1000 * 0.4) +
    (col("OrderCompletionRate") * 0.3) +
    (col("AvgCallDurationMinutes") / 10 * 0.3)
).withColumn(
    "ProfitabilityCategory",
    when(col("ProfitabilityScore") >= 0.8, "High Value")
    .when(col("ProfitabilityScore") >= 0.6, "Medium Value")
    .when(col("ProfitabilityScore") >= 0.4, "Average Value")
    .otherwise("Low Value")
)

# Affichage des résultats
print("Analyse de la rentabilité des clients:")
customer_profitability.select(
    "CustomerName", "SimType", "PlanName", "TotalRevenue", "OverageCost",
    "TotalCalls", "TotalOrders", "AvgCallDurationMinutes", "OrderCompletionRate",
    format_number("CustomerLifetimeValue", 2).alias("CustomerLifetimeValue"),
    "ProfitabilityRank", format_number("ProfitabilityScore", 2).alias("ProfitabilityScor
    "ProfitabilityCategory"
).show(truncate=False)

# Analyse des caractéristiques des clients les plus rentables
top_customers = customer_profitability.filter(col("ProfitabilityCategory") == "High Valu
print("\nCaractéristiques des clients les plus rentables:")

```

```

top_customers.groupBy("SimType", "PlanType").agg(
  count("CustomerId").alias("CustomerCount"),
  avg("TotalRevenue").alias("AvgRevenue"),
  avg("TotalCalls").alias("AvgCalls"),
  avg("TotalOrders").alias("AvgOrders"),
  avg("AvgCallDurationMinutes").alias("AvgCallDuration"),
  avg("OrderCompletionRate").alias("AvgOrderCompletionRate")
).orderBy(col("CustomerCount").desc()).show(truncate=False)

# Analyse de l'impact des dépassements sur la rentabilité
print("\nImpact des dépassements sur la rentabilité:")
customer_profitability.groupBy("ProfitabilityCategory").agg(
  avg("OverageCost").alias("AvgOverageCost"),
  avg("TotalRevenue").alias("AvgRevenue"),
  avg("CustomerLifetimeValue").alias("AvgLifetimeValue"),
  (avg("OverageCost") / avg("TotalRevenue") * 100).alias("OverageCostPercentage")
).orderBy("ProfitabilityCategory").show(truncate=False)

```



Analyse de la rentabilité des clients:

CustomerName  SimType  PlanName  TotalRevenue OverageCost TotalCalls TotalOrders AvgCallDurationMinutes OrderCompletionRate CustomerLifetimeValue ProfitabilityRank ProfitabilityScore ProfitabilityCategory													
Vijayshree Uppili Prepaid  Basic Plan  3000.0  0.0  8  8  69.41  0.0  8,983.60  1  5.68  High Value													
Neeraj Rajput  Postpaid Do not disturb  1320.0  0.0  4  4  24.23  0.0  3,951.80  2  2.31  High Value													
Shruti Mehta  Postpaid Family  960.0  0.0  2  2  15.94  1.0  2,875.90  3  1.93  High Value													
Sameer Goel  Prepaid  Continuous Texting 940.0  0.0  2  2  46.39  0.0  2,815.90  4  2.52  High Value													
Jishnu Vasudevan  Postpaid Finger tips  800.0  0.0  1  1  5.07  1.0  2,397.95  5  1.41  High Value													

Caractéristiques des clients les plus rentables:

SimType  PlansType CustomerCount AvgRevenue				AvgCalls		AvgOrders	
AvgCallDuration AvgOrderCompletionRate							
Postpaid Postpaid  3  1026.6666666666667				2.3333333333333335		2.333333333333333	
35 15.08  0.6666666666666666							
Prepaid  Prepaid  2  1970.0				5.0		5.0	
57.9  0.0							

Impact des dépassements sur la rentabilité:

ProfitabilityCategory AvgOverageCost AvgRevenue AvgLifetimeValue  OverageCostPercentage				
High Value  0.0  1404.0  4205.030000000001 0.0				

# Performances de vente par localisation et département

```
In [15]: from pyspark.sql.functions import count, sum, avg, col

sales_performance = (
    customer_df
    .join(salesperson_df, customer_df.CustomerSalesPersonId == salesperson_df.SalesPersonId)
    .join(employee_df, salesperson_df.IdEmployeeSalesPerson == employee_df.EmployeeId)
    .join(department_df, employee_df.DepartmentId == department_df.DepartmentId)
    .join(employeeworklocation_df, employee_df.EmployeeId == employeeworklocation_df.WorkLocationId)
    .join(worklocation_df, employeeworklocation_df.LocationId == worklocation_df.LocationId)
    .join(orders_df, customer_df.CustomerId == orders_df.OrderCustomerId)
)

# Analyser les performances
performance_metrics = (
    sales_performance
    .groupBy("LocationName", "DepartmentName")
    .agg(
        count("CustomerId").alias("TotalCustomers"),
        count("OrderId").alias("TotalOrders"),
        sum(when(col("OrderStatus") == "Shipped", 1).otherwise(0)).alias("CompletedOrders"),
        avg(when(col("OrderStatus") == "Shipped", 1).otherwise(0)).alias("OrderCompletionRate")
    )
    .orderBy(col("TotalOrders").desc())
)

performance_metrics.show()
```

```
+-----+-----+-----+-----+-----+-----+
+-----+
| LocationName | DepartmentName | TotalCustomers | TotalOrders | CompletedOrders | OrderCompletionRate |
+-----+-----+-----+-----+-----+-----+
| New York | Human Resource | 5 | 5 | 0 | 0.0 |
| Washington DC | Information Techn... | 5 | 5 | 1 | 0.2 |
| Boston | Human Resource | 5 | 5 | 2 | 0.4 |
| Seattle | Human Resource | 5 | 5 | 0 | 0.0 |
+-----+-----+-----+-----+-----+-----+
+-----+
```

## Analyse des plans en termes d'utilisation des données et de contribution aux revenus

```
In [16]: from pyspark.sql.functions import sum, avg, col, round

data_usage_revenue = (
    simdata_df
    .join(plans_df, simdata_df.SimPlanNumber == plans_df.PlansId)
    .join(planinclusions_df, plans_df.PlanInclusionId == planinclusions_df.PlanId)
    .join(phonenumbers_df, simdata_df.SimAccountNumber == phonenumbers_df.AccountNumber)
    .join(billinginformation_df, phonenumbers_df.PhoneBillNumber == billinginformation_df.PhoneBillNumber)
)

usage_revenue_metrics = (
    data_usage_revenue
    .groupBy("PlansType", "PlanName")
    .agg(
        sum("Usage").alias("TotalUsage"),
        sum("Revenue").alias("TotalRevenue")
    )
    .orderBy(col("TotalRevenue").desc())
)

usage_revenue_metrics.show()
```

```

    .agg(
        count("SimNumber").alias("TotalSubscribers"),
        round(avg("IncludedData"), 2).alias("AvgIncludedData"),
        round(avg("DataUsed"), 2).alias("AvgDataUsed"),
        round(avg(col("DataUsed") / col("IncludedData")), 2).alias("AvgDataUsageRate"),
        round(sum("Tax"), 2).alias("TotalRevenue")
    )
    .orderBy(col("TotalRevenue").desc())
)

usage_revenue_metrics.show()

```

```

+-----+-----+-----+-----+-----+-----+
---+-----+
|PlansType|          PlanName|TotalSubscribers|AvgIncludedData|AvgDataUsed|AvgDataUsageRate|TotalRevenue|
+-----+-----+-----+-----+-----+-----+
---+-----+
|  Prepaid|    Enjoy surfing|              1|          1500.0|          600.0|              0.4|          300.00|
| Postpaid|          Family|              2|          1500.0|          300.0|              0.18|          240.00|
|  Prepaid|    Talk For Hours|              1|          1500.0|          800.0|              0.53|          180.00|
| Postpaid|    Powerful Speed|              1|          2000.0|          900.0|              0.45|          180.00|
| Postpaid|    Finger tips|              1|          1200.0|          400.0|              0.33|          100.00|
| Postpaid|    Enjoy Data|              1|          1500.0|          400.0|              0.27|          100.00|
|  Prepaid|Continuous Texting|              1|           800.0|          300.0|              0.38|           60.00|
| Postpaid|    Do not disturb|              1|           500.0|          100.0|              0.2|           50.00|
|  Prepaid|      Basic Plan|              1|           500.0|          200.0|              0.4|           40.30|
+-----+-----+-----+-----+-----+-----+
---+-----+

```

## la relation entre les interactions d'appels et la satisfaction des client

```

In [17]: from pyspark.sql.functions import count, sum, avg, col, datediff, to_timestamp, when

# Joindre les tables nécessaires
call_customer_data = (
    callrecords_df
    .join(phonenumbers_df, callrecords_df.CallAccountNumber == phonenumbers_df.AccountNumber)
    .join(simdata_df, phonenumbers_df.AccountNumber == simdata_df.SimAccountNumber)
    .join(customer_df, simdata_df.SimCustomerId == customer_df.CustomerId)
    .join(orders_df, customer_df.CustomerId == orders_df.OrderCustomerId)
)

# Calculer les métriques d'appels et de satisfaction client
call_satisfaction_metrics = (
    call_customer_data
    .withColumn("CallDurationMinutes", (col("CallDuration").cast("long") / 60))
    .withColumn("CustomerAge", datediff(to_timestamp(lit("2023-05-23")), col("DateOfBirth")))
    .groupBy("CustomerId", "CustomerName", "Sex")
    .agg(
        count("CallId").alias("TotalCalls"),

```

```

        round(sum("CallDurationMinutes"), 2).alias("TotalCallDurationMinutes"),
        round(avg("CallDurationMinutes"), 2).alias("AvgCallDurationMinutes"),
        sum(when(col("OrderStatus") == "Shipped", 1).otherwise(0)).alias("CompletedOrder"),
        sum(when(col("OrderStatus") == "Order Cancelled", 1).otherwise(0)).alias("CancelledOrders")
    )
    .withColumn("CustomerSatisfactionScore",
        when(col("CompletedOrders") > col("CancelledOrders"), "High")
        .when(col("CompletedOrders") == col("CancelledOrders"), "Medium")
        .otherwise("Low"))
    .orderBy(col("TotalCallDurationMinutes").desc())
)

call_satisfaction_metrics.show()

```

```

+-----+-----+-----+-----+-----+-----+-----+-----+-----+-----+
+-----+-----+-----+-----+-----+-----+-----+-----+-----+-----+
|CustomerId|CustomerName|Sex|TotalCalls|TotalCallDurationMinutes|AvgCallDurationMin|
|utes|CompletedOrders|CancelledOrders|CustomerSatisfactionScore|
+-----+-----+-----+-----+-----+-----+-----+-----+-----+-----+
+-----+-----+-----+-----+-----+-----+-----+-----+-----+-----+
|16|Vijayshree Uppili|F|8|555.28|6
9.41|0|8|Low|
|13|Neeraj Rajput|M|4|96.93|2
4.23|0|0|Medium|
|15|Sameer Goel|M|2|92.78|4
6.39|0|0|Medium|
|2|Harsh Shah|M|1|33.0|
33.0|0|0|Medium|
|14|Shruti Mehta|F|2|31.88|1
5.94|2|0|High|
|5|Neha Verma|F|1|7.48|
7.48|0|0|Medium|
|1|Jishnu Vasudevan|M|1|5.07|
5.07|1|0|High|
+-----+-----+-----+-----+-----+-----+-----+-----+-----+-----+
+-----+-----+-----+-----+-----+-----+-----+-----+-----+-----+

```

## Envoyer les résultats vers la destination

```

In [18]: def send_to_sql_server(df, table_name, mode="append"):
        """
        Envoie un DataFrame PySpark vers une table SQL Server.

        :param df: Le DataFrame PySpark à envoyer
        :param table_name: Le nom de la table dans SQL Server
        :param mode: Le mode d'écriture ('overwrite', 'append', 'ignore', 'error')
        """
        df.write.jdbc(url=jdbc_url_target, table=table_name, mode=mode, properties=propertie
        print(f"Les données ont été envoyées avec succès à la table {table_name} dans la bas

# 1. Analyse des performances de vente
send_to_sql_server(performance_metrics, "sales_performance_analysis")

# 2. Analyse de l'utilisation des données et des revenus
send_to_sql_server(usage_revenue_metrics, "data_usage_revenue_analysis")

# 3. Analyse des tendances d'appels et de la satisfaction client
send_to_sql_server(call_satisfaction_metrics, "call_trends_customer_satisfaction")

```

Les données ont été envoyées avec succès à la table sales\_performance\_analysis dans la base de données spy.  
Les données ont été envoyées avec succès à la table data\_usage\_revenue\_analysis dans la base de données spy.  
Les données ont été envoyées avec succès à la table call\_trends\_customer\_satisfaction dans la base de données spy.

## Analyse complète

```
In [19]: # Fonction pour charger un DataFrame depuis la base de données source (telecom2)
def load_dataframe(table_name):
    return spark.read.jdbc(url=jdbc_url_source, table=table_name, properties=properties)

# Fonction pour envoyer les données à la base de données cible (spy)
def send_to_sql_server(df, table_name, mode="append"):
    df.write.jdbc(url=jdbc_url_target, table=table_name, mode=mode, properties=properties)
    print(f"Les données ont été envoyées avec succès à la table {table_name} dans la base de données spy.")

# Test de connexion
print("Test de connexion réussi. Aperçu de la table customer de telecom2 :")
customer_df.show(5)

try:
    # 1. Joindre les tables nécessaires
    comprehensive_analysis = (
        customer_df
        .join(simdata_df, customer_df.CustomerId == simdata_df.SimCustomerId)
        .join(phonenumber_df, simdata_df.SimAccountNumber == phonenumber_df.AccountNumber)
        .join(billinginformation_df, phonenumber_df.PhoneBillNumber == billinginformation_df.BillNumber)
        .join(plans_df, simdata_df.SimPlanNumber == plans_df.PlansId)
        .join(planinclusions_df, plans_df.PlanInclusionId == planinclusions_df.PlanId)
        .join(orders_df, customer_df.CustomerId == orders_df.OrderCustomerId)
        .join(callrecords_df, phonenumber_df.AccountNumber == callrecords_df.CallAccountNumber)
        .join(salesperson_df, customer_df.CustomerSalesPersonId == salesperson_df.SalesPersonId)
        .join(employee_df, salesperson_df.IdEmployeeSalesPerson == employee_df.EmployeeId)
        .join(department_df, employee_df.DepartmentId == department_df.DepartmentId)
    )

    # 2. Calculer les métriques
    comprehensive_metrics = (
        comprehensive_analysis
        .groupBy("CustomerId", "CustomerName", "Employee_Name", "DepartmentName", "Plans")
        .agg(
            count("OrderId").alias("TotalOrders"),
            sum(when(col("OrderStatus") == "Shipped", 1).otherwise(0)).alias("CompletedOrders"),
            round(avg("DataUsed"), 2).alias("AvgDataUsed"),
            round(sum("Tax"), 2).alias("TotalRevenue"),
            count("CallId").alias("TotalCalls"),
            round(avg(col("CallDuration").cast("long") / 60), 2).alias("AvgCallDurationM"),
            round(avg(col("DataUsed") / col("IncludedData")), 2).alias("DataUsageRate")
        )
        .withColumn("CustomerSatisfactionScore",
            when(col("CompletedOrders") / col("TotalOrders") > 0.8, "High")
            .when(col("CompletedOrders") / col("TotalOrders") > 0.5, "Medium")
            .otherwise("Low"))
        .withColumn("RevenuePerCall", round(col("TotalRevenue") / col("TotalCalls"), 2))
        .withColumn("RevenuePerDataUnit", round(col("TotalRevenue") / col("AvgDataUsed"), 2))
    )

    # 3. Ajouter des indicateurs de performance
    final_analysis = comprehensive_metrics.withColumn(
        "PerformanceIndicator",

```

```
        when((col("CustomerSatisfactionScore") == "High") & (col("RevenuePerDataUnit") >
        .when((col("CustomerSatisfactionScore") == "High") | (col("RevenuePerDataUnit")
        .when((col("CustomerSatisfactionScore") == "Low") & (col("RevenuePerDataUnit") <
        .otherwise("Average")
    )

    # Afficher les résultats
    print("Analyse complète :")
    final_analysis.show(truncate=False)

    # 4. Envoyer les résultats à la base de données spy
    send_to_sql_server(final_analysis, "comprehensive_telecom_analysis")

except Exception as e:
    print("Erreur lors de l'analyse :", str(e))
```

Test de connexion réussi. Aperçu de la table customer de telecom2 :

CustomerId	CustomerName	Sex	Age	DateOfBirth	SocialSecurityNumber	CustomerSalesPersonId
1	Jishnu Vasudevan	M	24	1993-12-28	232498675	
2	Harsh Shah	M	24	1993-09-12	456498675	
3	Rachana Rambhad	F	24	1993-08-19	543498675	
4	Lagan Gupta	F	24	1993-08-08	765498675	
5	Neha Verma	F	24	1993-08-27	987498675	

only showing top 5 rows

Analyse complète :

CustomerId	CustomerName	Employee_Name	DepartmentName	PlansType	PlanName	TotalOrders	CompletedOrders	AvgDataUsed	TotalRevenue	TotalCalls	AvgCallDurationMinutes	DataUsageRate	CustomerSatisfactionScore	RevenuePerCall	RevenuePerDataUnit	PerformanceIndicator
15	Sameer Goel	Chetan Mistry	Human Resource	Prepaid	Continuous Texting	2	0	300.0	120.00	2	46.39	0.38	Low	60.00	0.4	Poor
13	Neeraj Rajput	Mihir Patil	Information Technology	Postpaid	sturb	4	0	100.0	200.00	4	24.23	0.2	Low	50.00	2.0	Poor
5	Neha Verma	Mihir Patil	Information Technology	Prepaid	Hours	1	0	800.0	180.00	1	7.48	0.53	Low	180.00	0.23	Poor
2	Harsh Shah	Karan Thevar	Human Resource	Postpaid	Family	1	0	500.0	170.00	1	33.0	0.25	Low	170.00	0.34	Poor
14	Shruti Mehta	Karan Thevar	Human Resource	Postpaid	Family	2	2	100.0	140.00	2	15.94	0.1	High	70.00	1.4	Good
16	Vijayshree Uppili	Shantanu Sawant	Human Resource	Prepaid	Basic Plan	8	0	200.0	322.40	8	69.41	0.4	Low	40.30	1.61	Poor
1	Jishnu Vasudevan	Mihir Patil	Information Technology	Postpaid	Finger tips	1	1	400.0	100.00	1	5.07	0.33	High	100.00	0.25	Good

Les données ont été envoyées avec succès à la table comprehensive\_telecom\_analysis dans la base de données spy.

## envoyer les résultats en format csv

```
In [20]: import os
import csv
from pyspark.sql import SparkSession

# Configurer HADOOP_HOME (ajustez le chemin si nécessaire)
os.environ['HADOOP_HOME'] = r"C:\hadoop"
os.environ['PATH'] = r"C:\hadoop\bin;" + os.environ['PATH']

# Charger la table employee depuis SQL Server
query = "(SELECT * FROM employee) as employee_data"
df_employee = spark.read.jdbc(url=jdbc_url_source, table=query, properties=properties)

# Afficher le schéma et quelques lignes pour vérification
df_employee.printSchema()
df_employee.show(5)

# Convertir le DataFrame en RDD et collecter les résultats
results = df_employee.rdd.collect()

# Chemin de sortie spécifié
output_path = r"C:\Users\ELITEBOOK\Desktop\stage\jupy\employee_dataa1.csv"

def write_csv(path):
    try:
        # Créer le répertoire parent si nécessaire
        os.makedirs(os.path.dirname(path), exist_ok=True)

        with open(path, 'w', newline='') as csvfile:
            writer = csv.writer(csvfile)
            writer.writerow(df_employee.columns)
            for row in results:
                writer.writerow(row)
            print(f"Résultats sauvegardés dans {path}")
            return True
    except PermissionError:
        print(f"Erreur de permission pour {path}. Essayez d'exécuter le script en tant q
            return False
    except Exception as e:
        print(f"Erreur lors de l'écriture dans {path}: {str(e)}")
        return False

# Écrire le fichier CSV
write_csv(output_path)
```



```

root
|-- EmployeeId: integer (nullable = true)
|-- Employee_Name: string (nullable = true)
|-- SSN: string (nullable = true)
|-- Age: integer (nullable = true)
|-- DepartmentId: integer (nullable = true)
|-- Salary: integer (nullable = true)

```

```

+-----+-----+-----+-----+-----+
|EmployeeId|      Employee_Name|      SSN|Age|DepartmentId|Salary|
+-----+-----+-----+-----+-----+
|      1|      Ojas Phansekar|123456789| 24|      1|   1000|
|      2|Shreyas Kalayanar...|245987675| 24|      1|   1000|
|      3|      Saurabh Kulkarni|734756953| 24|      1|   1000|
|      4|      Vivek Shetye|572364526| 26|      1|   1000|
|      5|      Mihir Patil|238745784| 27|      1|   1000|
+-----+-----+-----+-----+-----+

```

only showing top 5 rows

Résultats sauvegardés dans C:\Users\ELITEB00K\Desktop\stage\jupy\employee\_dataa1.csv  
 Out[20]: True

```

In [21]: import os
import csv
from pyspark.sql import SparkSession
from pyspark.sql.functions import col, when, avg, round, lit, concat, substring

# Configurer HADOOP_HOME (ajustez le chemin si nécessaire)
os.environ['HADOOP_HOME'] = r"C:\hadoop"
os.environ['PATH'] = r"C:\hadoop\bin;" + os.environ['PATH']

# Charger la table employee depuis SQL Server
query = "(SELECT * FROM employee) as employee_data"
df_employee = spark.read.jdbc(url=jdbc_url_source, table=query, properties=properties)

# Afficher le schéma initial
print("Schéma initial:")
df_employee.printSchema()

# Transformations
df_transformed = df_employee \
    .withColumn("SalaryCategory", when(col("Salary") < 5000, "Low")
        .when((col("Salary") >= 5000) & (col("Salary") < 10000), "Medium")
        .otherwise("High")) \
    .withColumn("AdjustedSalary", round(col("Salary") * 1.1, 2)) \
    .withColumn("AgeBracket", when(col("Age") < 30, "Young")
        .when((col("Age") >= 30) & (col("Age") < 50), "Middle-aged")
        .otherwise("Senior")) \
    .withColumn("MaskedSSN", concat(substring(col("SSN"), 1, 3), lit("*****"))) \
    .withColumn("FullName", concat(col("Employee_Name"), lit(" (ID: ") , col("EmployeeId"))) \
    .drop("SSN") # Supprimer la colonne SSN originale pour des raisons de confidentialité

# Calculer le salaire moyen par département
avg_salary_by_dept = df_transformed.groupBy("DepartmentId").agg(round(avg("Salary"), 2).alias("avg_salary"))

# Joindre le salaire moyen du département
df_final = df_transformed.join(avg_salary_by_dept, "DepartmentId")

# Afficher le nouveau schéma et quelques lignes
print("\nNouveau schéma après transformations:")
df_final.printSchema()

# Afficher quelques données transformées:
df_final.show(5)

```

```

df_final.show(5, truncate=False)

# Convertir le DataFrame en RDD et collecter les résultats
results = df_final.rdd.collect()

# Chemin de sortie spécifié
output_path = r"C:\Users\ELITEBOOK\Desktop\stage\jupy\employee_data_transformed11.csv"

def write_csv(path, data, columns):
    try:
        os.makedirs(os.path.dirname(path), exist_ok=True)
        with open(path, 'w', newline='') as csvfile:
            writer = csv.writer(csvfile)
            writer.writerow(columns)
            for row in data:
                writer.writerow(row)
        print(f"Résultats transformés sauvegardés dans {path}")
        return True
    except PermissionError:
        print(f"Erreur de permission pour {path}. Essayez d'exécuter le script en tant q
        return False
    except Exception as e:
        print(f"Erreur lors de l'écriture dans {path}: {str(e)}")
        return False

# Écrire le fichier CSV
write_csv(output_path, results, df_final.columns)

```

Schéma initial:

```
root
|-- EmployeeId: integer (nullable = true)
|-- Employee_Name: string (nullable = true)
|-- SSN: string (nullable = true)
|-- Age: integer (nullable = true)
|-- DepartmentId: integer (nullable = true)
|-- Salary: integer (nullable = true)
```

Nouveau schéma après transformations:

```
root
|-- DepartmentId: integer (nullable = true)
|-- EmployeeId: integer (nullable = true)
|-- Employee_Name: string (nullable = true)
|-- Age: integer (nullable = true)
|-- Salary: integer (nullable = true)
|-- SalaryCategory: string (nullable = false)
|-- AdjustedSalary: double (nullable = true)
|-- AgeBracket: string (nullable = false)
|-- MaskedSSN: string (nullable = true)
|-- FullName: string (nullable = true)
|-- AvgDeptSalary: double (nullable = true)
```

Aperçu des données transformées:

```
+-----+-----+-----+-----+-----+-----+-----+
+-----+-----+-----+-----+-----+-----+-----+
|DepartmentId|EmployeeId|Employee_Name          |Age|Salary|SalaryCategory|AdjustedSalary|
AgeBracket|MaskedSSN|FullName              |AvgDeptSalary|
+-----+-----+-----+-----+-----+-----+-----+
+-----+-----+-----+-----+-----+-----+-----+
|1          |1          |Ojas Phansekar        |24 |1000 |Low           |1100.0        |
Young      |123*****|Ojas Phansekar (ID: 1)|    |1000.0|              |              |
|1          |2          |Shreyas Kalayanaraman|24 |1000 |Low           |1100.0        |
Young      |245*****|Shreyas Kalayanaraman (ID: 2)|1000.0|      |              |              |
|1          |3          |Saurabh Kulkarni      |24 |1000 |Low           |1100.0        |
Young      |734*****|Saurabh Kulkarni (ID: 3)|    |1000.0|              |              |
|1          |4          |Vivek Shetye          |26 |1000 |Low           |1100.0        |
Young      |572*****|Vivek Shetye (ID: 4)  |    |1000.0|              |              |
|1          |5          |Mihir Patil           |27 |1000 |Low           |1100.0        |
Young      |238*****|Mihir Patil (ID: 5)   |    |1000.0|              |              |
+-----+-----+-----+-----+-----+-----+-----+
+-----+-----+-----+-----+-----+-----+-----+
```

only showing top 5 rows

Résultats transformés sauvegardés dans C:\Users\ELITEBOOK\Desktop\stage\jupy\employee\_data\_transformed11.csv

Out[21]: True

## envoyer les résultats en format JSON

```
In [22]: import os
import json
from pyspark.sql import SparkSession
from pyspark.sql.functions import col, when, avg, round, lit, concat, substring, to_json

query = "(SELECT * FROM employee) as employee_data"
df_employee = spark.read.jdbc(url=jdbc_url_source, table=query, properties=properties)
```

```

df_employee.printSchema()

# Transformations
df_transformed = df_employee \
    .withColumn("performance_score", (col("Salary") / 1000 + col("Age") / 10).cast("int")
    .withColumn("experience_level", when(col("Age") < 25, "Junior")
        .when((col("Age") >= 25) & (col("Age") < 35), "Interm")
        .when((col("Age") >= 35) & (col("Age") < 45), "Senior")
        .otherwise("Expert")) \
    .withColumn("salary_bracket", when(col("Salary") < 3000, "Entry")
        .when((col("Salary") >= 3000) & (col("Salary") < 6000)
        .when((col("Salary") >= 6000) & (col("Salary") < 9000)
        .otherwise("Executive")) \
    .withColumn("department_size", when(col("DepartmentId").isin([1, 2]), "Small")
        .when(col("DepartmentId").isin([3, 4]), "Medium")
        .otherwise("Large")) \
    .withColumn("employee_code", concat(substring(col("Employee_Name"), 1, 3), lit("-"),

# Calculer des statistiques par département
dept_stats = df_transformed.groupBy("DepartmentId") \
    .agg(round(avg("Salary"), 2).alias("avg_salary"),
        round(avg("Age"), 2).alias("avg_age"))

# Joindre les statistiques du département
df_final = df_transformed.join(dept_stats, "DepartmentId")

# Afficher le nouveau schéma et quelques lignes
print("\nNouveau schéma après transformations:")
df_final.printSchema()
print("\nAperçu des données transformées:")
df_final.show(5, truncate=False)

# Chemin de sortie spécifié
output_path = r"C:\Users\ELITEBOOK\Desktop\stage\jupy\employee_data2_transformed11.json"

# Écriture manuelle du JSON
try:
    data = df_final.toJSON().collect()
    with open(output_path, 'w') as f:
        json.dump(data, f)
    print(f"Résultats transformés sauvegardés en JSON dans {output_path}")
except Exception as e:
    print(f"Erreur lors de l'écriture du JSON: {str(e)}")

```

Schéma initial:

```
root
|-- EmployeeId: integer (nullable = true)
|-- Employee_Name: string (nullable = true)
|-- SSN: string (nullable = true)
|-- Age: integer (nullable = true)
|-- DepartmentId: integer (nullable = true)
|-- Salary: integer (nullable = true)
```

Nouveau schéma après transformations:

```
root
|-- DepartmentId: integer (nullable = true)
|-- EmployeeId: integer (nullable = true)
|-- Employee_Name: string (nullable = true)
|-- SSN: string (nullable = true)
|-- Age: integer (nullable = true)
|-- Salary: integer (nullable = true)
|-- performance_score: integer (nullable = true)
|-- experience_level: string (nullable = false)
|-- salary_bracket: string (nullable = false)
|-- department_size: string (nullable = false)
|-- employee_code: string (nullable = true)
|-- avg_salary: double (nullable = true)
|-- avg_age: double (nullable = true)
```

Aperçu des données transformées:

```
+-----+-----+-----+-----+-----+-----+-----+-----+
|DepartmentId|EmployeeId|Employee_Name      |SSN      |Age|Salary|performance_score|ex
perience_level|salary_bracket|department_size|employee_code|avg_salary|avg_age|
+-----+-----+-----+-----+-----+-----+-----+-----+
|1           |1         |Ojas Phansekar     |123456789|24 |1000 |3               |Ju
nior         |Entry      |Small             |Oja-1    |    |1000.0 |25.57 |
|1           |2         |Shreyas Kalayanaraman|245987675|24 |1000 |3               |Ju
nior         |Entry      |Small             |Shr-2    |    |1000.0 |25.57 |
|1           |3         |Saurabh Kulkarni   |734756953|24 |1000 |3               |Ju
nior         |Entry      |Small             |Sau-3    |    |1000.0 |25.57 |
|1           |4         |Vivek Shetye       |572364526|26 |1000 |3               |In
termediate   |Entry      |Small             |Viv-4    |    |1000.0 |25.57 |
|1           |5         |Mihir Patil        |238745784|27 |1000 |3               |In
termediate   |Entry      |Small             |Mih-5    |    |1000.0 |25.57 |
+-----+-----+-----+-----+-----+-----+-----+-----+
-----+-----+-----+-----+-----+-----+-----+-----+
only showing top 5 rows
```

Résultats transformés sauvegardés en JSON dans C:\Users\ELITEBOOK\Desktop\stage\jupy\employee\_data2\_tansformed11.json

## analyse de la rétention des clients

```
In [23]: from pyspark.sql.functions import col, lag, datediff, current_date, count, avg, to_date,
from pyspark.sql.window import Window

# Charger les données
orders_df = spark.read.jdbc(url=jdbc_url_source, table="orders", properties=properties)
customer_df = spark.read.jdbc(url=jdbc_url_source, table="customer", properties=properties)

# Ajouter une colonne de date à orders_df
orders_with_date = orders_df.withColumn("OrderDate", to_date(from_unixtime(col("OrderId"))
```

```
# Analyse de la rétention des clients
```

```
window_spec = Window.partitionBy("OrderCustomerId").orderBy("OrderId")
```

```
customer_retention = orders_with_date.withColumn("PreviousOrderDate", lag("OrderDate").o  
    .withColumn("DaysSinceLastOrder", datediff(col("OrderDate"), col("PreviousOrderDate"  
    .groupBy("OrderCustomerId") \  
    .agg(  
        count("OrderId").alias("TotalOrders"),  
        avg("DaysSinceLastOrder").alias("AvgDaysBetweenOrders")  
    ) \  
    .join(customer_df, orders_df.OrderCustomerId == customer_df.CustomerId) \  
    .withColumn("CustomerLifetime", datediff(current_date(), col("DateOfBirth"))))
```

```
print("Analyse de la rétention des clients:")
```

```
customer_retention.show()
```

```
# Quelques statistiques supplémentaires
```

```
print("\nStatistiques globales:")
```

```
customer_retention.select(  
    avg("TotalOrders").alias("AvgOrdersPerCustomer"),  
    avg("AvgDaysBetweenOrders").alias("OverallAvgDaysBetweenOrders"),  
    avg("CustomerLifetime").alias("AvgCustomerLifetime")  
) .show()
```

OrderDate	CustomerId	TotalOrders	AvgDaysBetweenOrders	CustomerId	CustomerName	Sex	Age	DateOfBirth	SocialSecurityNumber	CustomerSalesPersonId	CustomerLifetime
	12	1	NULL	12	Kal Bugrara	M	57	1960-12-28	145498675	4	23253
	1	1	NULL	1	Jishnu Vasudevan	M	24	1993-12-28	232498675	1	11200
	13	1	NULL	13	Neeraj Rajput	M	27	1990-10-28	232555675	1	12357
	6	1	NULL	6	Aniel Patel	M	24	1993-11-28	235468675	2	11230
	16	1	NULL	16	Vijayshree Uppili	F	26	1991-08-23	654498675	4	12058
	3	1	NULL	3	Rachana Rambhad	F	24	1993-08-19	543498675	3	11331
	20	1	NULL	20	Simmah Kazi	F	22	1995-12-28	232834675	4	10470
	5	1	NULL	5	Neha Verma	F	24	1993-08-27	987498675	1	11323
	19	1	NULL	19	Komal Shirodkar	F	26	1991-02-27	678498675	3	12235
	15	1	NULL	15	Sameer Goel	M	28	1989-12-30	276578675	3	12659
	9	1	NULL	9	Parnal Dighe	F	24	1993-09-28	232498765	1	11291
	17	1	NULL	17	Rohit Kamble	M	24	1993-06-28	453498675	1	11383
	4	1	NULL	4	Lagan Gupta	F	24	1993-08-08	765498675	4	11342
	8	1	NULL	8	Aditya Joshi	M	24	1993-10-28	232434575	4	11261
	7	1	NULL	7	Anubhav Gupta	M	27	1990-12-28	555698675	3	12296
	10	1	NULL	10	Dharit Shah	M	24	1993-12-27	123498675	2	11201
	11	1	NULL	11	Girish Sanai	M	24	1993-07-22	645498675	3	11359
	14	1	NULL	14	Shruti Mehta	F	26	1991-12-17	232444375	2	11942
	2	1	NULL	2	Harsh Shah	M	24	1993-09-12	456498675	2	11307
	18	1	NULL	18	Priyanka Desai	F	26	1991-04-23	189498675	2	12180

AvgOrdersPerCustomer	OverallAvgDaysBetweenOrders	AvgCustomerLifetime
1.0	NULL	12183.9

Loading [MathJax]/extensions/Safe.js

```
In [24]: salesperson_performance = customer_df.join(salesperson_df, customer_df.CustomerSalesPers
        .join(orders_df, customer_df.CustomerId == orders_df.OrderCustomerId) \
        .join(employee_df, salesperson_df.IdEmployeeSalesPerson == employee_df.EmployeeId) \
        .groupBy("IdEmployeeSalesPerson", "Employee_Name") \
        .agg(
            count("CustomerId").alias("TotalCustomers"),
            count("OrderId").alias("TotalOrders"),
            sum(when(col("OrderStatus") == "Shipped", 1).otherwise(0)).alias("CompletedOrder
        ) \
        .withColumn("OrderCompletionRate", round(col("CompletedOrders") / col("TotalOrders")

print("Performance des vendeurs:")
salesperson_performance.show()
```

Performance des vendeurs:

IdEmployeeSalesPerson	Employee_Name	TotalCustomers	TotalOrders	CompletedOrders	OrderC ompletionRate
5	Mihir Patil	5	5	1	0.2
6	Karan Thevar	5	5	2	0.4
7	Chetan Mistry	5	5	0	0.0
8	Shantanu Sawant	5	5	0	0.0

## Analyse des salaires par département

```
In [26]: from pyspark.sql.functions import avg, count, desc, col

salary_analysis = employee_df.join(department_df, "DepartmentId") \
    .groupBy("DepartmentName") \
    .agg(
        avg(employee_df.Salary).alias("AvgSalary"),
        count("EmployeeId").alias("EmployeeCount")
    ) \
    .orderBy(desc("AvgSalary"))

print("Analyse des salaires par département:")
salary_analysis.show()
```

Analyse des salaires par département:

	DepartmentName	AvgSalary	EmployeeCount
	Customer Care	10000.0	10
	Human Resource	7500.0	7
	Sales & Marketing	5000.0	6
	Finance	2500.0	7
	Information Techn...	1000.0	7



# Catégorisation des employés par âge

```
In [27]: from pyspark.sql.functions import col, expr, when, concat, lit, datediff, current_date,
from pyspark.sql.window import Window
from pyspark.sql.functions import col, when

def display_df(df, n=10):
    return df.limit(n).toPandas()

employee_category = employee_df.withColumn(
    "age_category",
    when(col("Age") < 30, "Junior")
    .when((col("Age") >= 30) & (col("Age") < 45), "Mid-level")
    .when(col("Age") >= 45, "Senior")
    .otherwise("Unknown")
)

print("Catégorisation des employés par âge:")
print(display_df(employee_category))
```

Catégorisation des employés par âge:

	EmployeeId	Employee_Name	SSN	Age	DepartmentId	Salary	\
0	1	Ojas Phansekar	123456789	24	1	1000	
1	2	Shreyas Kalayanaraman	245987675	24	1	1000	
2	3	Saurabh Kulkarni	734756953	24	1	1000	
3	4	Vivek Shetye	572364526	26	1	1000	
4	5	Mihir Patil	238745784	27	1	1000	
5	6	Karan Thevar	968374657	28	4	7500	
6	7	Chetan Mistry	623784983	30	4	7500	
7	8	Shantanu Sawant	527473298	24	4	7500	
8	9	Pooja Patil	286436778	24	4	7500	
9	10	Kalpita Malvankar	863476236	34	4	7500	

	age_category
0	Junior
1	Junior
2	Junior
3	Junior
4	Junior
5	Junior
6	Mid-level
7	Junior
8	Junior
9	Mid-level

## Classement des employés par salaire dans chaque département

```
In [30]: salary_ranking = employee_df.withColumn(
    "SalaryRank",
    rank().over(Window.partitionBy("DepartmentId").orderBy(col("Salary").desc()))
)

print("\n3. Classement des employés par salaire dans chaque département:")
print(display_df(salary_ranking))
```

3. Classement des employés par salaire dans chaque département:

	EmployeeId	Employee_Name	SSN	Age	DepartmentId	Salary	\
0	1	Ojas Phansekar	123456789	24	1	1000	
1	2	Shreyas Kalayanaraman	245987675	24	1	1000	
2	3	Saurabh Kulkarni	734756953	24	1	1000	
3	4	Vivek Shetye	572364526	26	1	1000	
4	5	Mihir Patil	238745784	27	1	1000	
5	32	Manoj Prabhakar	444787654	21	1	1000	
6	34	Priya Yadav	228787654	33	1	1000	
7	11	Vaibhav Parkar	123456789	24	2	5000	
8	12	Sayali Sakhalkar	674378987	24	2	5000	
9	13	Khushi Chavan	652134897	45	2	5000	

	SalaryRank
0	1
1	1
2	1
3	1
4	1
5	1
6	1
7	1
8	1
9	1

## Identification des employés les mieux payés par département (Top 3)

```
In [31]: top_earners = employee_df.withColumn(
    "SalaryRank",
    dense_rank().over(Window.partitionBy("DepartmentId").orderBy(col("Salary").desc()))
).filter(col("SalaryRank") <= 3)

print("\n5. Top 3 des employés les mieux payés par département:")
print(display_df(top_earners))
```

5. Top 3 des employés les mieux payés par département:

	EmployeeId	Employee_Name	SSN	Age	DepartmentId	Salary	\
0	1	Ojas Phansekar	123456789	24	1	1000	
1	2	Shreyas Kalayanaraman	245987675	24	1	1000	
2	3	Saurabh Kulkarni	734756953	24	1	1000	
3	4	Vivek Shetye	572364526	26	1	1000	
4	5	Mihir Patil	238745784	27	1	1000	
5	32	Manoj Prabhakar	444787654	21	1	1000	
6	34	Priya Yadav	228787654	33	1	1000	
7	11	Vaibhav Parkar	123456789	24	2	5000	
8	12	Sayali Sakhalkar	674378987	24	2	5000	
9	13	Khushi Chavan	652134897	45	2	5000	

	SalaryRank
0	1
1	1
2	1
3	1
4	1
5	1
6	1
7	1
8	1
9	1

# Analyse de la distribution des âges

```
In [32]: age_distribution = employee_df.withColumn(
    "AgeGroup",
    when(col("Age") < 25, "18-24")
    .when((col("Age") >= 25) & (col("Age") < 35), "25-34")
    .when((col("Age") >= 35) & (col("Age") < 45), "35-44")
    .when((col("Age") >= 45) & (col("Age") < 55), "45-54")
    .otherwise("55+")
).groupBy("AgeGroup").count().orderBy("AgeGroup")

print("\n6. Distribution des âges:")
print(display_df(age_distribution))
```

6. Distribution des âges:

	AgeGroup	count
0	18-24	13
1	25-34	9
2	35-44	3
3	45-54	4
4	55+	8

# Analyse des employés par tranche de salaire

```
In [33]: salary_brackets = employee_df.withColumn(
    "SalaryBracket",
    when(col("Salary") < 3000, "Low")
    .when((col("Salary") >= 3000) & (col("Salary") < 6000), "Medium")
    .when((col("Salary") >= 6000) & (col("Salary") < 9000), "High")
    .otherwise("Very High")
).groupBy("SalaryBracket").count().orderBy("SalaryBracket")

print("\n8. Analyse des employés par tranche de salaire:")
print(display_df(salary_brackets))
```

8. Analyse des employés par tranche de salaire:

	SalaryBracket	count
0	High	7
1	Low	14
2	Medium	6
3	Very High	10

# Analyse du nombre d'employés par département

```
In [34]: employees_per_dept = employee_df.join(department_df, "DepartmentId") \
    .groupBy("DepartmentName") \
    .agg(count("EmployeeId").alias("EmployeeCount")) \
    .orderBy(col("EmployeeCount").desc())

print("\n9. Nombre d'employés par département:")
print(display_df(employees_per_dept))
```

9. Nombre d'employés par département:		
	DepartmentName	EmployeeCount
0	Customer Care	10
1	Information Technology	7
2	Finance	7
3	Human Resource	7
4	Sales & Marketing	6

## Calcul de la masse salariale totale par département

```
In [35]: from pyspark.sql.functions import col, sum as sum_

total_salary_by_dept = employee_df.join(department_df, "DepartmentId") \
    .groupBy(department_df.DepartmentName) \
    .agg(sum_(employee_df.Salary).alias("TotalSalary")) \
    .orderBy(col("TotalSalary").desc())

print("\n10. Masse salariale totale par département:")
print(display_df(total_salary_by_dept))
```

10. Masse salariale totale par département:		
	DepartmentName	TotalSalary
0	Customer Care	100000
1	Human Resource	52500
2	Sales & Marketing	30000
3	Finance	17500
4	Information Technology	7000

## normalisation des noms d'employés

```
In [36]: from pyspark.sql.functions import col, when, regexp_replace, trim, lower, upper, to_date
from pyspark.sql.window import Window

cleaned_employee_df = employee_df.withColumn(
    "CleanedName",
    trim(regexp_replace(lower(col("Employee_Name")), r'^\w\s', ''))
)
cleaned_employee_df.show()
```

EmployeeId	Employee_Name	SSN	Age	DepartmentId	Salary	CleanedName
1	Ojas Phansekar	123456789	24	1	1000	ojas phansekar
2	Shreyas Kalayanar...	245987675	24	1	1000	shreyas kalayanar...
3	Saurabh Kulkarni	734756953	24	1	1000	saurabh kulkarni
4	Vivek Shetye	572364526	26	1	1000	vivek shetye
5	Mihir Patil	238745784	27	1	1000	mihir patil
6	Karan Thevar	968374657	28	4	7500	karan thevar
7	Chetan Mistry	623784983	30	4	7500	chetan mistry
8	Shantanu Sawant	527473298	24	4	7500	shantanu sawant
9	Pooja Patil	286436778	24	4	7500	pooja patil
10	Kalpita Malvankar	863476236	34	4	7500	kalpita malvankar
11	Vaibhav Parkar	123456789	24	2	5000	vaibhav parkar
12	Sayali Sakhalkar	674378987	24	2	5000	sayali sakhalkar
13	Khushi Chavan	652134897	45	2	5000	khushi chavan
14	Pratik Patre	677435432	24	2	5000	pratik patre
15	Pushkar	564321879	43	2	5000	pushkar
16	Tushar Gupta	444777651	24	5	10000	tushar gupta
17	Pranav Swaminathan	990077663	34	3	2500	pranav swaminathan
18	Victor	563477778	44	3	2500	victor
19	Yusuf Ozbek	995912563	45	3	2500	yusuf ozbek
20	Sudharshan Poojary	763459876	24	3	2500	sudharshan poojary

only showing top 20 rows

## Gestion des valeurs manquantes dans la colonne Salary

```
In [37]: salary_stats = employee_df.agg(
    avg("Salary").alias("avg_salary"),
    stddev("Salary").alias("stddev_salary")
)
avg_salary = salary_stats.collect()[0]["avg_salary"]
stddev_salary = salary_stats.collect()[0]["stddev_salary"]

imputed_salary_df = employee_df.withColumn(
    "ImputedSalary",
    when(col("Salary").isNull(),
        when(col("Age") < 30, avg_salary - stddev_salary)
        .when(col("Age") >= 30, avg_salary + stddev_salary)
        .otherwise(avg_salary)
    ).otherwise(col("Salary"))
)
print("\nSalaires imputés :")
imputed_salary_df.select("EmployeeId", "Salary", "ImputedSalary").show(5)
```

Salaires imputés :

EmployeeId	Salary	ImputedSalary
1	1000	1000.0
2	1000	1000.0
3	1000	1000.0
4	1000	1000.0
5	1000	1000.0

only showing top 5 rows

# Détection des valeurs aberrantes de salaire

```
In [38]: salary_outliers_df = imputed_salary_df.withColumn(
        "IsSalaryOutlier",
        abs(col("ImputedSalary") - avg_salary) > (3 * stddev_salary)
    )
print("\nDétection des valeurs aberrantes de salaire :")
salary_outliers_df.select("EmployeeId", "ImputedSalary", "IsSalaryOutlier").show(5)
```

Détection des valeurs aberrantes de salaire :

EmployeeId	ImputedSalary	IsSalaryOutlier
1	1000.0	false
2	1000.0	false
3	1000.0	false
4	1000.0	false
5	1000.0	false

only showing top 5 rows

## Gestion des valeurs vides dans la colonne Salary

```
In [39]: from pyspark.sql.functions import col, when, regexp_replace, trim, lower, length, isnan,
        from pyspark.sql.window import Window

salary_stats = employee_df.agg(
    avg("Salary").alias("avg_salary"),
    stddev("Salary").alias("stddev_salary")
)
avg_salary = salary_stats.collect()[0]["avg_salary"]
stddev_salary = salary_stats.collect()[0]["stddev_salary"]

df_with_imputed_salary = employee_df.withColumn(
    "ImputedSalary",
    when(col("Salary").isNull() | isnan("Salary"),
        when(col("Age") < 35, lit(avg_salary - stddev_salary))
        .when(col("Age") >= 35, lit(avg_salary + stddev_salary))
        .otherwise(lit(avg_salary))
    ).otherwise(col("Salary"))
)
df_with_imputed_salary.show()
```

EmployeeId	Employee_Name	SSN	Age	DepartmentId	Salary	ImputedSalary
1	Ojas Phansekar	123456789	24	1	1000	1000.0
2	Shreyas Kalayanar...	245987675	24	1	1000	1000.0
3	Saurabh Kulkarni	734756953	24	1	1000	1000.0
4	Vivek Shetye	572364526	26	1	1000	1000.0
5	Mihir Patil	238745784	27	1	1000	1000.0
6	Karan Thevar	968374657	28	4	7500	7500.0
7	Chetan Mistry	623784983	30	4	7500	7500.0
8	Shantanu Sawant	527473298	24	4	7500	7500.0
9	Pooja Patil	286436778	24	4	7500	7500.0
10	Kalpita Malvankar	863476236	34	4	7500	7500.0
11	Vaibhav Parkar	123456789	24	2	5000	5000.0
12	Sayali Sakhalkar	674378987	24	2	5000	5000.0
13	Khushi Chavan	652134897	45	2	5000	5000.0
14	Pratik Patre	677435432	24	2	5000	5000.0
15	Pushkar	564321879	43	2	5000	5000.0
16	Tushar Gupta	444777651	24	5	10000	10000.0
17	Pranav Swaminathan	990077663	34	3	2500	2500.0
18	Victor	563477778	44	3	2500	2500.0
19	Yusuf Ozbek	995912563	45	3	2500	2500.0
20	Sudharshan Poojary	763459876	24	3	2500	2500.0

only showing top 20 rows

## Calcul de l'ancienneté

```
In [40]: from pyspark.sql.functions import col, when, current_date, datediff, round, lit
from pyspark.sql.types import DateType

print("Schéma actuel du DataFrame:")
df_with_imputed_salary.printSchema()

if "HireDate" not in df_with_imputed_salary.columns:
    df_with_hire_date = df_with_imputed_salary.withColumn(
        "HireDate",
        lit("2020-01-01").cast(DateType()) # Date fictive, à ajuster selon vos besoins
    )
else:
    df_with_hire_date = df_with_imputed_salary

df_with_tenure = df_with_hire_date.withColumn(
    "HireDate",
    when(col("HireDate").isNull(), current_date()).otherwise(col("HireDate"))
).withColumn(
    "TenureYears",
    round(datediff(current_date(), col("HireDate")) / 365, 2)
)

print("DataFrame avec ancienneté calculée:")
df_with_tenure.show()
```

Schéma actuel du DataFrame:

```
root
|-- EmployeeId: integer (nullable = true)
|-- Employee_Name: string (nullable = true)
|-- SSN: string (nullable = true)
|-- Age: integer (nullable = true)
|-- DepartmentId: integer (nullable = true)
|-- Salary: integer (nullable = true)
|-- ImputedSalary: double (nullable = true)
```

DataFrame avec ancienneté calculée:

EmployeeId	Employee_Name	SSN	Age	DepartmentId	Salary	ImputedSalary	HireDate	TenureYears
1	Ojas Phansekar	123456789	24	1	1000	1000.0	2020-01-01	4.66
2	Shreyas Kalayanar...	245987675	24	1	1000	1000.0	2020-01-01	4.66
3	Saurabh Kulkarni	734756953	24	1	1000	1000.0	2020-01-01	4.66
4	Vivek Shetye	572364526	26	1	1000	1000.0	2020-01-01	4.66
5	Mihir Patil	238745784	27	1	1000	1000.0	2020-01-01	4.66
6	Karan Thevar	968374657	28	4	7500	7500.0	2020-01-01	4.66
7	Chetan Mistry	623784983	30	4	7500	7500.0	2020-01-01	4.66
8	Shantanu Sawant	527473298	24	4	7500	7500.0	2020-01-01	4.66
9	Pooja Patil	286436778	24	4	7500	7500.0	2020-01-01	4.66
10	Kalpita Malvankar	863476236	34	4	7500	7500.0	2020-01-01	4.66
11	Vaibhav Parkar	123456789	24	2	5000	5000.0	2020-01-01	4.66
12	Sayali Sakhalkar	674378987	24	2	5000	5000.0	2020-01-01	4.66
13	Khushi Chavan	652134897	45	2	5000	5000.0	2020-01-01	4.66
14	Pratik Patre	677435432	24	2	5000	5000.0	2020-01-01	4.66
15	Pushkar	564321879	43	2	5000	5000.0	2020-01-01	4.66
16	Tushar Gupta	444777651	24	5	10000	10000.0	2020-01-01	4.66
17	Pranav Swaminathan	990077663	34	3	2500	2500.0	2020-01-01	4.66
18	Victor	563477778	44	3	2500	2500.0	2020-01-01	4.66
19	Yusuf Ozbek	995912563	45	3	2500	2500.0	2020-01-01	4.66
20	Sudharshan Poojary	763459876	24	3	2500	2500.0	2020-01-01	4.66

only showing top 20 rows

Durée moyenne des appels par compte



```
In [41]: avg_call_duration = callrecords_df \
    .withColumn("DurationSeconds",
        expr("hour(CallDuration) * 3600 + minute(CallDuration) * 60 + second(CallDuration)")) \
    .groupBy("CallAccountNumber") \
    .agg(
        avg("DurationSeconds").alias("AvgCallDurationSeconds"),
        count("CallId").alias("CallCount")
    ) \
    .orderBy(col("AvgCallDurationSeconds").desc())

print("4. Durée moyenne des appels par compte:")
avg_call_duration.show()
```

```
4. Durée moyenne des appels par compte:
+-----+-----+-----+
|CallAccountNumber|AvgCallDurationSeconds|CallCount|
+-----+-----+-----+
|10|4164.625|8|
|13|2783.5|2|
|19|1980.0|1|
|11|1454.0|4|
|12|956.5|2|
|17|449.0|1|
|14|304.0|1|
+-----+-----+-----+
```

## Analyse des commandes par statut

```
In [42]: order_status = orders_df.groupBy("OrderStatus") \
    .agg(count("OrderId").alias("OrderCount")) \
    .orderBy(col("OrderCount").desc())

print("3. Analyse des commandes par statut:")
order_status.show()
```

```
3. Analyse des commandes par statut:
+-----+-----+
|OrderStatus|OrderCount|
+-----+-----+
|Order Cancelled|4|
|Shipped|3|
|Partially Shipped|3|
|Pending|3|
|On The way|2|
|Refund Initiated|2|
|Payment Incomplete|2|
|Order Declined|1|
+-----+-----+
```

## Top 5 des employés avec le plus de clients

```
In [43]: top_salespeople = customer_df.join(employee_df, customer_df.CustomerSalesPersonId == emp
    .groupBy("EmployeeId", "Employee_Name") \
    .agg(count("CustomerId").alias("CustomerCount")) \
    .orderBy(col("CustomerCount").desc()) \
    .limit(5)
```

```
print("6. Top 5 des employés avec le plus de clients:")
top_salespeople.show()
```

6. Top 5 des employés avec le plus de clients:

```
+-----+-----+-----+
|EmployeeId|      Employee_Name|CustomerCount|
+-----+-----+-----+
|          1|      Ojas Phansekar|          5|
|          2|Shreyas Kalayanar...|          5|
|          3|      Saurabh Kulkarni|          5|
|          4|      Vivek Shetye|          5|
+-----+-----+-----+
```

## Calcul du salaire moyen par département et du ratio de salaire

```
In [44]: window_spec = Window.partitionBy("DepartmentId")
df_with_salary_ratio = df_with_tenure.withColumn(
    "AvgDeptSalary", avg("Salary").over(window_spec)
).withColumn(
    "SalaryRatio", col("Salary") / col("AvgDeptSalary")
)
df_with_salary_ratio.show()
```

```

+-----+-----+-----+-----+-----+-----+-----+-----+
|EmployeeId|      Employee_Name|      SSN|Age|DepartmentId|Salary|ImputedSalary|  HireD
ate|TenureYears|AvgDeptSalary|SalaryRatio|
+-----+-----+-----+-----+-----+-----+-----+-----+
+-----+-----+-----+-----+-----+-----+-----+-----+
|      1|      Ojas Phansekar|123456789| 24|      1|  1000|      1000.0|2020-01
-01|      4.66|      1000.0|      1.0|
|      2|Shreyas Kalayanar...|245987675| 24|      1|  1000|      1000.0|2020-01
-01|      4.66|      1000.0|      1.0|
|      3|      Saurabh Kulkarni|734756953| 24|      1|  1000|      1000.0|2020-01
-01|      4.66|      1000.0|      1.0|
|      4|      Vivek Shetye|572364526| 26|      1|  1000|      1000.0|2020-01
-01|      4.66|      1000.0|      1.0|
|      5|      Mihir Patil|238745784| 27|      1|  1000|      1000.0|2020-01
-01|      4.66|      1000.0|      1.0|
|     32|      Manoj Prabhakar|444787654| 21|      1|  1000|      1000.0|2020-01
-01|      4.66|      1000.0|      1.0|
|     34|      Priya Yadav|228787654| 33|      1|  1000|      1000.0|2020-01
-01|      4.66|      1000.0|      1.0|
|     11|      Vaibhav Parkar|123456789| 24|      2|  5000|      5000.0|2020-01
-01|      4.66|      5000.0|      1.0|
|     12|      Sayali Sakhalkar|674378987| 24|      2|  5000|      5000.0|2020-01
-01|      4.66|      5000.0|      1.0|
|     13|      Khushi Chavan|652134897| 45|      2|  5000|      5000.0|2020-01
-01|      4.66|      5000.0|      1.0|
|     14|      Pratik Patre|677435432| 24|      2|  5000|      5000.0|2020-01
-01|      4.66|      5000.0|      1.0|
|     15|      Pushkar|564321879| 43|      2|  5000|      5000.0|2020-01
-01|      4.66|      5000.0|      1.0|
|     30|      Ranjani Iyer|777787654| 34|      2|  5000|      5000.0|2020-01
-01|      4.66|      5000.0|      1.0|
|     17|      Pranav Swaminathan|990077663| 34|      3|  2500|      2500.0|2020-01
-01|      4.66|      2500.0|      1.0|
|     18|      Victor|563477778| 44|      3|  2500|      2500.0|2020-01
-01|      4.66|      2500.0|      1.0|
|     19|      Yusuf Ozbek|995912563| 45|      3|  2500|      2500.0|2020-01
-01|      4.66|      2500.0|      1.0|
|     20|      Sudharshan Poojary|763459876| 24|      3|  2500|      2500.0|2020-01
-01|      4.66|      2500.0|      1.0|
|     28|      Alpana Sharan|987787654| 45|      3|  2500|      2500.0|2020-01
-01|      4.66|      2500.0|      1.0|
|     29|      Priyanka Singh|238787654| 43|      3|  2500|      2500.0|2020-01
-01|      4.66|      2500.0|      1.0|
|     37|      Rohit Patil|222787654| 45|      3|  2500|      2500.0|2020-01
-01|      4.66|      2500.0|      1.0|
+-----+-----+-----+-----+-----+-----+-----+-----+
+-----+-----+-----+-----+-----+-----+-----+-----+
only showing top 20 rows

```

## Création d'une catégorie de performance

```

In [46]: df_with_performance = df_with_salary_ratio.withColumn(
    "PerformanceCategory",
    when((col("SalaryRatio") > 1.2) & (col("TenureYears") > 5), "High Performer")
    .when((col("SalaryRatio") < 0.8) & (col("TenureYears") <= 2), "Needs Improvement")
    .otherwise("Average Performer")
)

# Affichage des résultats

```

```
print("Employés avec catégories de performance:")
df_with_performance.select("EmployeeId", "Employee_Name", "Salary", "TenureYears", "Sala
```

Employés avec catégories de performance:

EmployeeId	Employee_Name	Salary	TenureYears	SalaryRatio	PerformanceCategory
1	Ojas Phansekar	1000	4.66	1.0	Average Performer
2	Shreyas Kalayanar...	1000	4.66	1.0	Average Performer
3	Saurabh Kulkarni	1000	4.66	1.0	Average Performer
4	Vivek Shetye	1000	4.66	1.0	Average Performer
5	Mihir Patil	1000	4.66	1.0	Average Performer
32	Manoj Prabhakar	1000	4.66	1.0	Average Performer
34	Priya Yadav	1000	4.66	1.0	Average Performer
11	Vaibhav Parkar	5000	4.66	1.0	Average Performer
12	Sayali Sakhalkar	5000	4.66	1.0	Average Performer
13	Khushi Chavan	5000	4.66	1.0	Average Performer
14	Pratik Patre	5000	4.66	1.0	Average Performer
15	Pushkar	5000	4.66	1.0	Average Performer
30	Ranjani Iyer	5000	4.66	1.0	Average Performer
17	Pranav Swaminathan	2500	4.66	1.0	Average Performer
18	Victor	2500	4.66	1.0	Average Performer
19	Yusuf Ozbek	2500	4.66	1.0	Average Performer
20	Sudharshan Poojary	2500	4.66	1.0	Average Performer
28	Alpana Sharan	2500	4.66	1.0	Average Performer
29	Priyanka Singh	2500	4.66	1.0	Average Performer
37	Rohit Patil	2500	4.66	1.0	Average Performer

only showing top 20 rows

## Statistiques sur les catégories de performance

```
In [47]: performance_stats = df_with_performance.groupBy("PerformanceCategory").agg(
    count("*").alias("EmployeeCount"),
    avg("Salary").alias("AvgSalary"),
    avg("TenureYears").alias("AvgTenure")
)
```

```
print("\nStatistiques par catégorie de performance:")
performance_stats.show()
```

Statistiques par catégorie de performance:

PerformanceCategory	EmployeeCount	AvgSalary	AvgTenure
Average Performer	37	5594.594594594595	4.6599999999999997

## standarizer ssn

```
In [49]: from pyspark.sql.functions import col, when, avg, regexp_replace, concat, substring, lit

employee_cleaned = employee_df.na.fill({
    "DepartmentId": 0,
    "Salary": employee_df.select(avg("Salary")).collect()[0][0]
})

employee_cleaned = employee_cleaned.withColumn(
```

```

        regex_replace(col("SSN"), r'^[0-9]', '')
    ).withColumn(
        "SSN",
        when(length(col("SSN")) == 9,
            concat(substring(col("SSN"), 1, 3), lit("-"),
                substring(col("SSN"), 4, 2), lit("-"),
                substring(col("SSN"), 6, 4)))
            .otherwise(lit(None))
    )

print("Données des employés nettoyées :")
employee_cleaned.show(truncate=False)

```

Données des employés nettoyées :

EmployeeId	Employee_Name	SSN	Age	DepartmentId	Salary
1	Ojas Phansekar	123-45-6789	24	1	1000
2	Shreyas Kalayanaraman	245-98-7675	24	1	1000
3	Saurabh Kulkarni	734-75-6953	24	1	1000
4	Vivek Shetye	572-36-4526	26	1	1000
5	Mihir Patil	238-74-5784	27	1	1000
6	Karan Thevar	968-37-4657	28	4	7500
7	Chetan Mistry	623-78-4983	30	4	7500
8	Shantanu Sawant	527-47-3298	24	4	7500
9	Pooja Patil	286-43-6778	24	4	7500
10	Kalpita Malvankar	863-47-6236	34	4	7500
11	Vaibhav Parkar	123-45-6789	24	2	5000
12	Sayali Sakhalkar	674-37-8987	24	2	5000
13	Khushi Chavan	652-13-4897	45	2	5000
14	Pratik Patre	677-43-5432	24	2	5000
15	Pushkar	564-32-1879	43	2	5000
16	Tushar Gupta	444-77-7651	24	5	10000
17	Pranav Swaminathan	990-07-7663	34	3	2500
18	Victor	563-47-7778	44	3	2500
19	Yusuf Ozbek	995-91-2563	45	3	2500
20	Sudharshan Poojary	763-45-9876	24	3	2500

only showing top 20 rows

## Clean customer data

```

In [51]: customer_cleaned = customer_df.withColumn(
        "Sex", upper(trim(col("Sex")))
    ).withColumn(
        "DateOfBirth", to_date(col("DateOfBirth"))
    ).withColumn(
        "Age", round(datediff(current_date(), col("DateOfBirth")) / 365.25)
    )
customer_cleaned.show()

```

CustomerId  sonId	CustomerName	Sex	Age	DateOfBirth	SocialSecurityNumber	CustomerSalesPer
1	Jishnu Vasudevan	M	31.0	1993-12-28	232498675	
2	Harsh Shah	M	31.0	1993-09-12	456498675	
3	Rachana Rambhad	F	31.0	1993-08-19	543498675	
4	Lagan Gupta	F	31.0	1993-08-08	765498675	
1	Neha Verma	F	31.0	1993-08-27	987498675	
2	Aniel Patel	M	31.0	1993-11-28	235468675	
3	Anubhav Gupta	M	34.0	1990-12-28	555698675	
4	Aditya Joshi	M	31.0	1993-10-28	232434575	
1	Parnal Dighe	F	31.0	1993-09-28	232498765	
2	Dharit Shah	M	31.0	1993-12-27	123498675	
3	Girish Sanai	M	31.0	1993-07-22	645498675	
4	Kal Bugarara	M	64.0	1960-12-28	145498675	
1	Neeraj Rajput	M	34.0	1990-10-28	232555675	
2	Shruti Mehta	F	33.0	1991-12-17	232444375	
3	Sameer Goel	M	35.0	1989-12-30	276578675	
4	Vijayshree Uppili	F	33.0	1991-08-23	654498675	
1	Rohit Kamble	M	31.0	1993-06-28	453498675	
2	Priyanka Desai	F	33.0	1991-04-23	189498675	
3	Komal Shirodkar	F	33.0	1991-02-27	678498675	
4	Simmah Kazi	F	29.0	1995-12-28	232834675	

## gérer les incohérences dans order status

```
In [52]: orders_cleaned = orders_df.withColumn(
    "OrderStatus",
    when(col("OrderStatus").isin("Shipped", "On The way"), "In Transit")
    .when(col("OrderStatus") == "Order Cancelled", "Cancelled")
    .when(col("OrderStatus").isin("Pending", "Payment Incomplete"), "Pending")
    .otherwise(col("OrderStatus"))
)
orders_cleaned.show()
```

OrderId	OrderType	OrderStatus	OrderCustomerId
1	2 day shipping	In Transit	1
2	Priority Shipping	Partially Shipped	2
3	Standard	Pending	3
4	2 day shipping	Cancelled	4
5	Standard	Pending	5
6	Priority Shipping	Refund Initiated	6
7	2 day shipping	Cancelled	7
8	Standard	Pending	8
9	Priority Shipping	Partially Shipped	9
10	2 day shipping	In Transit	10
11	Standard	Cancelled	11
12	Priority Shipping	Partially Shipped	12
13	2 day shipping	Pending	13
14	Standard	In Transit	14
15	Priority Shipping	In Transit	15
16	2 day shipping	Cancelled	16
17	Standard	Order Decilned	17
18	Priority Shipping	Refund Initiated	18
19	2 day shipping	Pending	19
20	Standard	In Transit	20

## identifie les doublons potentiels

```
In [53]: window_spec = Window.partitionBy("Employee_Name", "SSN").orderBy("EmployeeId")

employee_deduped = employee_cleaned.withColumn(
    "IsPotentialDuplicate",
    row_number().over(window_spec) > 1
)

print("Employés avec identification des doublons potentiels:")
employee_deduped.show(truncate=False)

# Afficher uniquement les doublons potentiels
print("\nDoublons potentiels:")
employee_deduped.filter(col("IsPotentialDuplicate") == True).show(truncate=False)
```

Employés avec identification des doublons potentiels:

EmployeeId	Employee_Name	SSN	Age	DepartmentId	Salary	IsPotentialDuplicate
28	Alpana Sharan	987-78-7654	45	3	2500	false
31	Amlan Bhuyan	555-78-7654	23	4	7500	false
7	Chetan Mistry	623-78-4983	30	4	7500	false
22	Devdip Sen	458-78-7654	56	5	10000	false
23	Devdip Sen	458-78-7654	56	5	10000	true
24	Devdip Sen	458-78-7654	56	5	10000	true
26	Devdip Sen	458-78-7654	56	5	10000	true
27	Devdip Sen	458-78-7654	56	5	10000	true
10	Kalpita Malvankar	863-47-6236	34	4	7500	false
6	Karan Thevar	968-37-4657	28	4	7500	false
13	Khushi Chavan	652-13-4897	45	2	5000	false
32	Manoj Prabhakar	444-78-7654	21	1	1000	false
5	Mihir Patil	238-74-5784	27	1	1000	false
1	Ojas Phansekar	123-45-6789	24	1	1000	false
21	Parth Mehta	458-78-7654	56	5	10000	false
9	Pooja Patil	286-43-6778	24	4	7500	false
36	Pranav Patil	658-78-7654	25	5	10000	false
17	Pranav Swaminathan	990-07-7663	34	3	2500	false
14	Pratik Patre	677-43-5432	24	2	5000	false
34	Priya Yadav	228-78-7654	33	1	1000	false

only showing top 20 rows

Doublons potentiels:

EmployeeId	Employee_Name	SSN	Age	DepartmentId	Salary	IsPotentialDuplicate
23	Devdip Sen	458-78-7654	56	5	10000	true
24	Devdip Sen	458-78-7654	56	5	10000	true
26	Devdip Sen	458-78-7654	56	5	10000	true
27	Devdip Sen	458-78-7654	56	5	10000	true

## Analyse de la performance des vendeurs

```
In [54]: salesperson_performance = customer_df.join(salesperson_df, customer_df.CustomerSalesPers
        .join(orders_df, customer_df.CustomerId == orders_df.OrderCustomerId) \
        .join(employee_df, salesperson_df.IdEmployeeSalesPerson == employee_df.EmployeeId) \
        .groupBy("IdEmployeeSalesPerson", "Employee_Name") \
        .agg(
            count("CustomerId").alias("TotalCustomers"),
            count("OrderId").alias("TotalOrders"),
            sum(when(col("OrderStatus") == "Shipped", 1).otherwise(0)).alias("CompletedOrder
        ) \
        .withColumn("OrderCompletionRate", round(col("CompletedOrders") / col("TotalOrders"))

print("Performance des vendeurs:")
salesperson_performance.show()
```



Performance des vendeurs:

Performance des vendeurs					
IdEmployeeSalesPerson	Employee_Name	TotalCustomers	TotalOrders	CompletedOrders	OrderCompletionRate
5	Mihir Patil	5	5	1	0.2
6	Karan Thevar	5	5	2	0.4
7	Chetan Mistry	5	5	0	0.0
8	Shantanu Sawant	5	5	0	0.0

## Analyse des employés par département

```
In [55]: employee_dept = employee_df.join(department_df, "DepartmentId")
employee_dept.groupBy("DepartmentName").count().show()
```

Employee by Department	
DepartmentName	count
Information Techn...	7
Finance	7
Human Resource	7
Sales & Marketing	6
Customer Care	10

## Analyse des ventes par vendeur

```
In [56]: sales_analysis = customer_df.join(salesperson_df, customer_df.CustomerSalesPersonId == salesperson_df.IdEmployeeSalesPerson)
sales_analysis = sales_analysis.join(employee_df, salesperson_df.IdEmployeeSalesPerson == employee_df.IdEmployeeSalesPerson)
sales_analysis.groupBy("Employee_Name").count().orderBy("count", ascending=False).show()
```

Sales by Employee	
Employee_Name	count
Karan Thevar	5
Shantanu Sawant	5
Mihir Patil	5
Chetan Mistry	5

## Analyse des appels par client

```
In [57]: call_analysis = callrecords_df.join(phonenumbers_df, callrecords_df.CallAccountNumber == phonenumbers_df.AccountNumber)
call_analysis = call_analysis.join(simdata_df, phonenumbers_df.AccountNumber == simdata_df.AccountNumber)
call_analysis = call_analysis.join(customer_df, simdata_df.SimCustomerId == customer_df.SimCustomerId)

from pyspark.sql.functions import sum, col
```

```
call_duration = call_analysis.groupBy("CustomerName").agg(sum(col("CallDuration").cast("call_duration.orderBy("TotalDuration", ascending=False).show()
```

CustomerName	TotalDuration
Vijayshree Uppili	33317
Neeraj Rajput	5816
Sameer Goel	5567
Harsh Shah	1980
Shruti Mehta	1913
Neha Verma	449
Jishnu Vasudevan	304

## Analyse des plans les plus populaires

```
In [58]: popular_plans = simdata_df.join(plans_df, simdata_df.SimPlanNumber == plans_df.PlansId)
popular_plans.groupBy("PlanName").count().orderBy("count", ascending=False).show()
```

PlanName	count
Family	2
Do not disturb	1
Finger tips	1
Enjoy surfing	1
Talk For Hours	1
Enjoy Data	1
Continuous Texting	1
Powerful Speed	1
Basic Plan	1

```
In [59]: # Calcul de l'écart salarial par rapport à la moyenne du département
avg_salary_by_dept = employee_df.groupBy("DepartmentId").agg(avg("Salary").alias("AvgDeptSalary"))
salary_comparison = employee_df.join(avg_salary_by_dept, "DepartmentId") \
    .withColumn("SalaryDifference", col("Salary") - col("AvgDeptSalary")) \
    .withColumn("SalaryDifferencePercent", (col("Salary") - col("AvgDeptSalary")) / col("Salary"))

print("\n4. Comparaison des salaires avec la moyenne du département:")
print(display_df(salary_comparison))
```

4. Comparaison des salaires avec la moyenne du département:

	DepartmentId	EmployeeId	Employee_Name	SSN	Age	Salary	\
0	1	1	Ojas Phansekar	123456789	24	1000	
1	1	2	Shreyas Kalayanaraman	245987675	24	1000	
2	1	3	Saurabh Kulkarni	734756953	24	1000	
3	1	4	Vivek Shetye	572364526	26	1000	
4	1	5	Mihir Patil	238745784	27	1000	
5	1	32	Manoj Prabhakar	444787654	21	1000	
6	1	34	Priya Yadav	228787654	33	1000	
7	3	17	Pranav Swaminathan	990077663	34	2500	
8	3	18	Victor	563477778	44	2500	
9	3	19	Yusuf Ozbek	995912563	45	2500	

	AvgDeptSalary	SalaryDifference	SalaryDifferencePercent
0	1000.0	0.0	0.0
1	1000.0	0.0	0.0
2	1000.0	0.0	0.0
3	1000.0	0.0	0.0
4	1000.0	0.0	0.0
5	1000.0	0.0	0.0
6	1000.0	0.0	0.0
7	2500.0	0.0	0.0
8	2500.0	0.0	0.0
9	2500.0	0.0	0.0

```
In [60]: # Calcul du ratio salaire/âge
salary_age_ratio = employee_df.withColumn("SalaryAgeRatio", col("Salary") / col("Age"))

print("\n7. Ratio salaire/âge:")
print(display_df(salary_age_ratio))
```

7. Ratio salaire/âge:

	EmployeeId	Employee_Name	SSN	Age	DepartmentId	Salary	\
0	1	Ojas Phansekar	123456789	24	1	1000	
1	2	Shreyas Kalayanaraman	245987675	24	1	1000	
2	3	Saurabh Kulkarni	734756953	24	1	1000	
3	4	Vivek Shetye	572364526	26	1	1000	
4	5	Mihir Patil	238745784	27	1	1000	
5	6	Karan Thevar	968374657	28	4	7500	
6	7	Chetan Mistry	623784983	30	4	7500	
7	8	Shantanu Sawant	527473298	24	4	7500	
8	9	Pooja Patil	286436778	24	4	7500	
9	10	Kalpita Malvankar	863476236	34	4	7500	

	SalaryAgeRatio
0	41.666667
1	41.666667
2	41.666667
3	38.461538
4	37.037037
5	267.857143
6	250.000000
7	312.500000
8	312.500000
9	220.588235

In [ ]: