BABU BANARASI DAS UNIVERSITY

Predictive Insights into Customer Churn: A Telecom Case Study

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Definition:- Customer Churn Prediction is a data mining task where the goal is to identify customers who are likely to leave (churn) a telecommunications service provider.

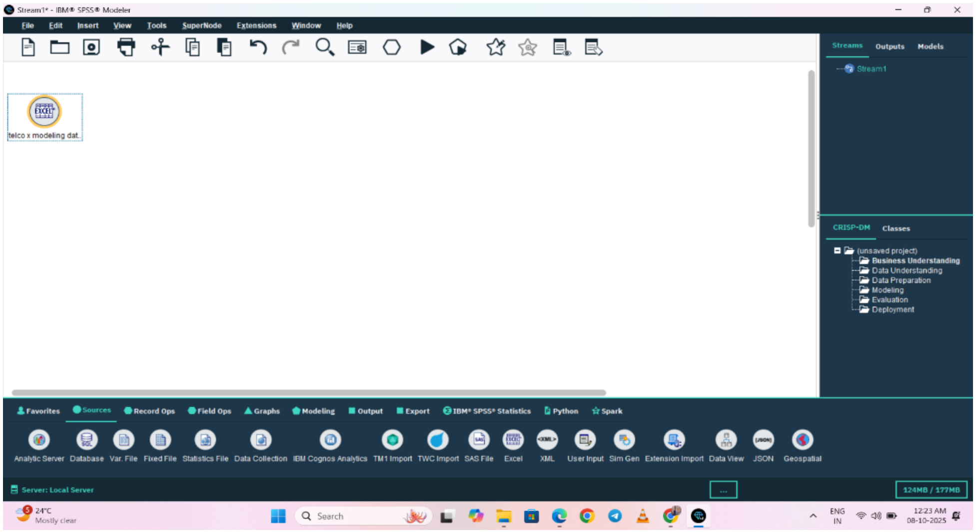
Outcomes/Learning:- Gained experience in cleaning data, training models, making predictions, evaluating results, and exporting the outcomes.

Required tools:- IBM SPSS Modeler tool.

Working:- We used it to examine the field measurement level and assess the data quality, identifying whether it is flag, nominal, ordinal, continuous, or typeless.

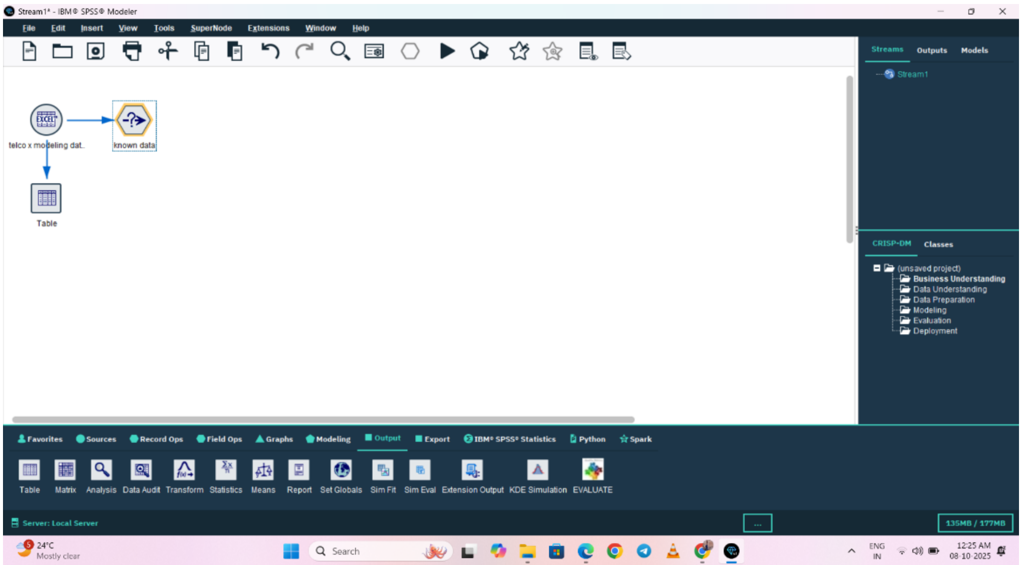
Step 1: Import Excel Data

- Open IBM SPSS Modeler.
- Go to **Source palette → Excel Node**.
- Drag the **Excel Node** to the canvas.
- Import the telecom dataset from an Excel file.



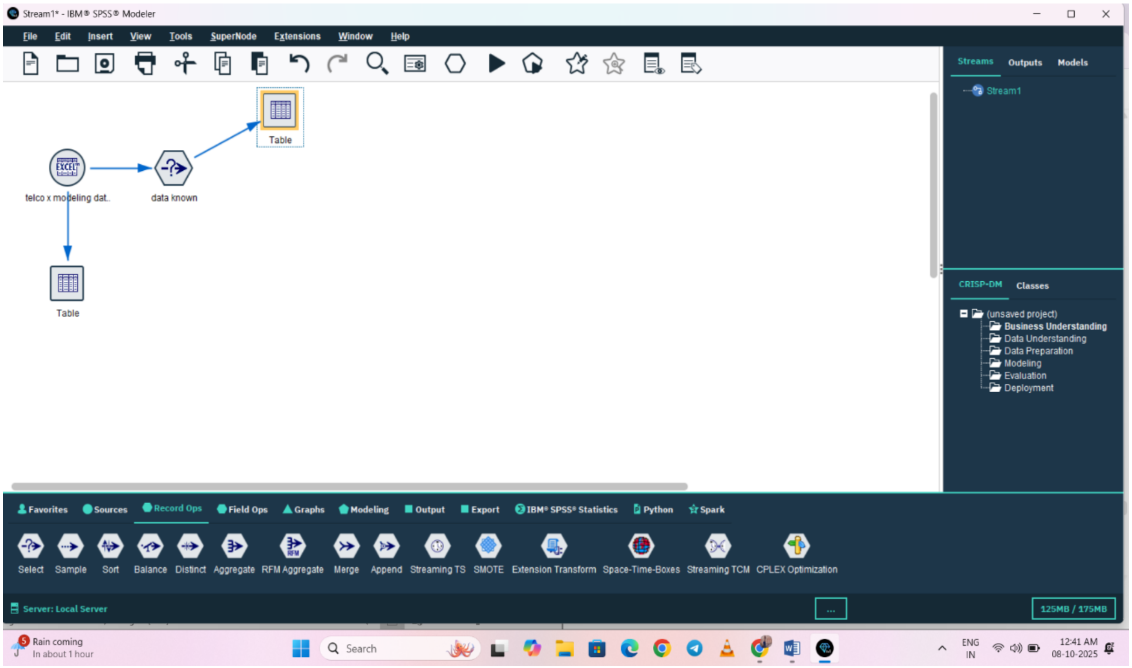
Step 2: Apply Select Node for Filtering Data

- From **Record Ops palette**, drag a **Select Node**.
- Connect it to the **Excel Node**.
- Open the Select Node and set condition: `data_known = "yes"`.



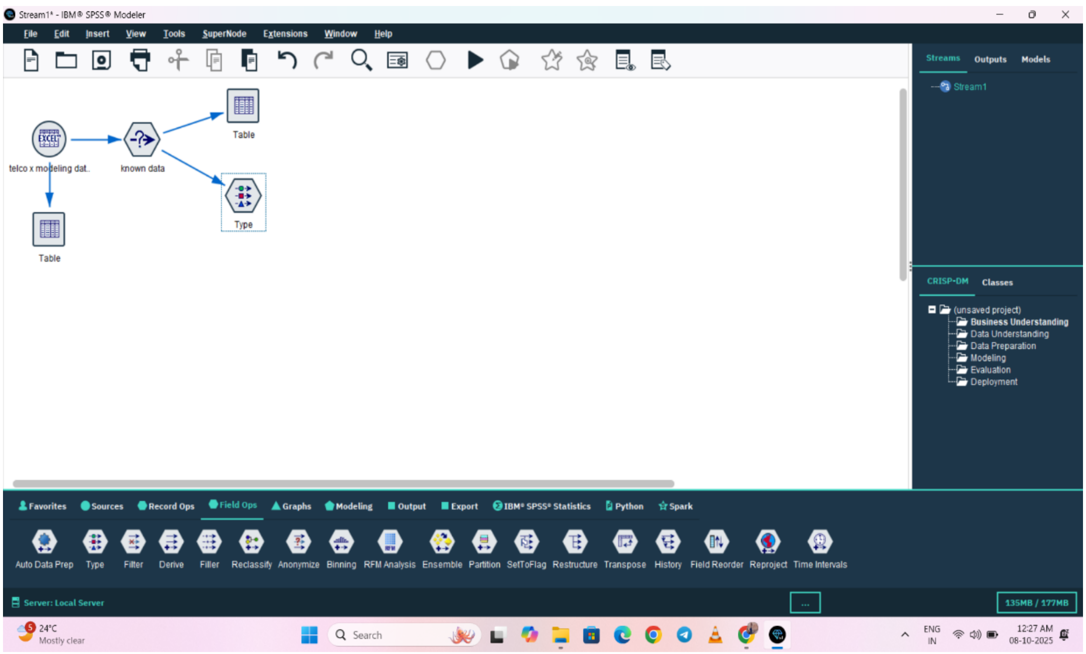
Step 3: View Data in Table Node

- From **Output palette**, drag a **Table Node**.
- Connect it to the **Select Node**.
- Click **Run** to see the filtered data in table form.



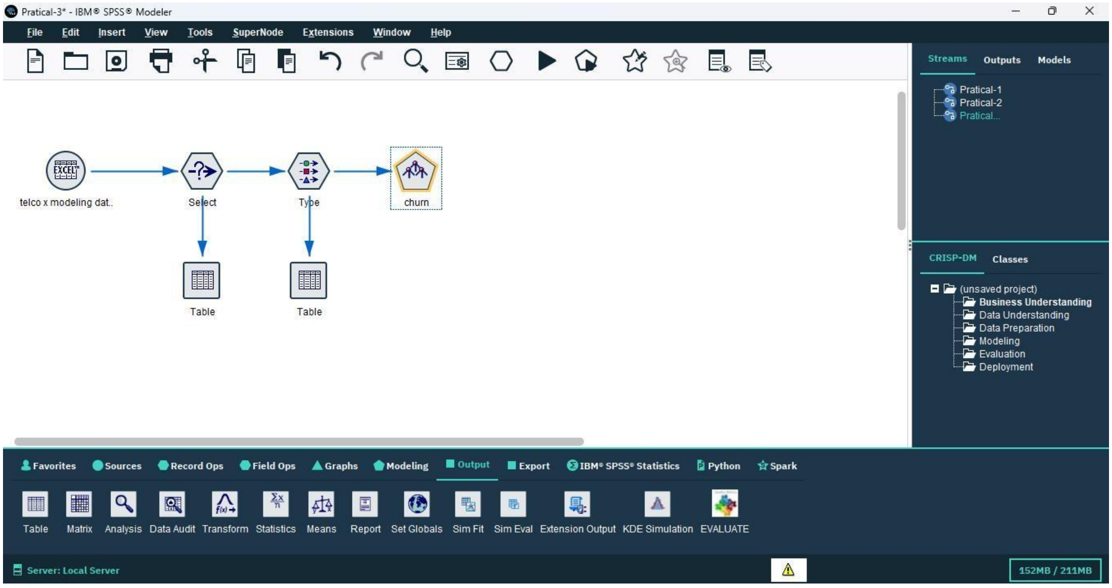
Step 4: **Add and Configure Type Node**

- From **Field palette**, drag a **Type Node**.
- Connect it to the **Select Node**.
- In the Type Node, select input fields: `data_known`, `age`, `gender`, `handsets`.
- Set `churn` as the **target field**.



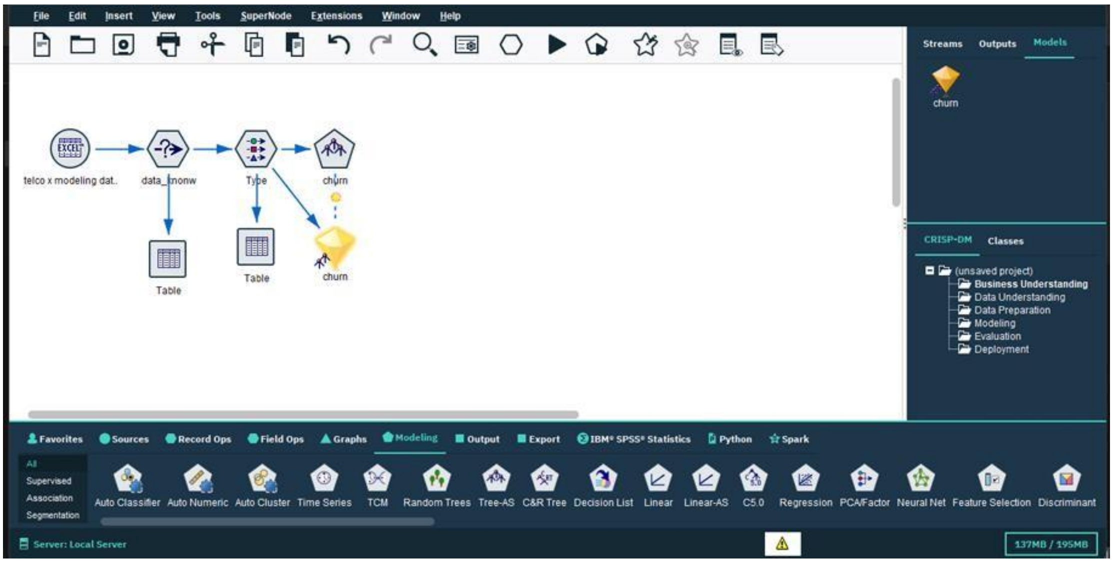
Step 5: Add Churn Node for Modeling

- From **Modeling palette**, drag a **Churn Node**.
- Connect it to the **Type Node**.
- This will create a predictive churn model using the selected fields.



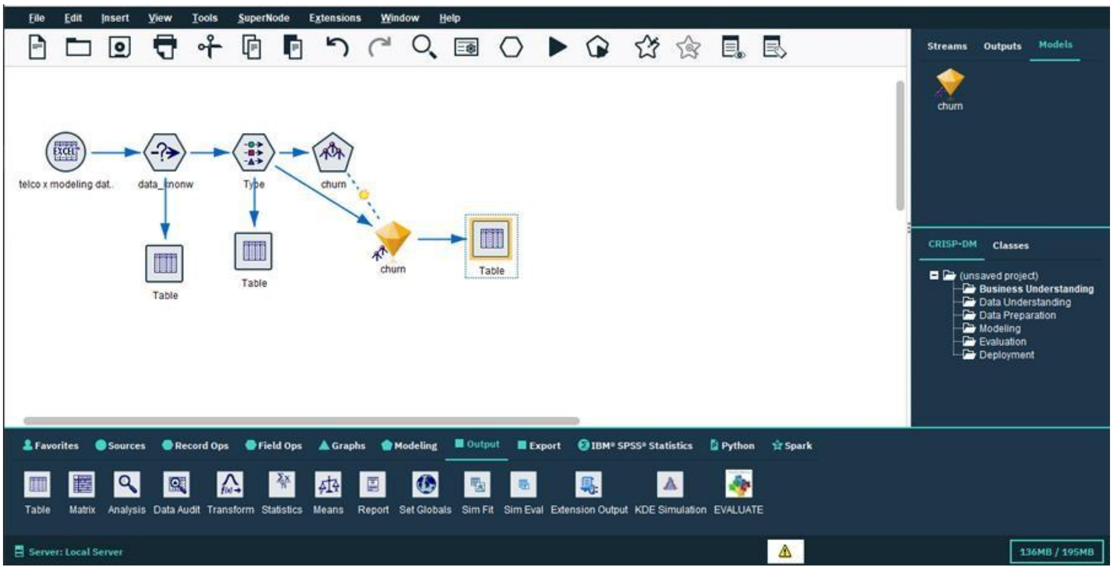
Step 6: Run Churn Node

- Right-click the **Churn Node** → select **Run**.
- This creates a **churn nugget** (trained churn model).



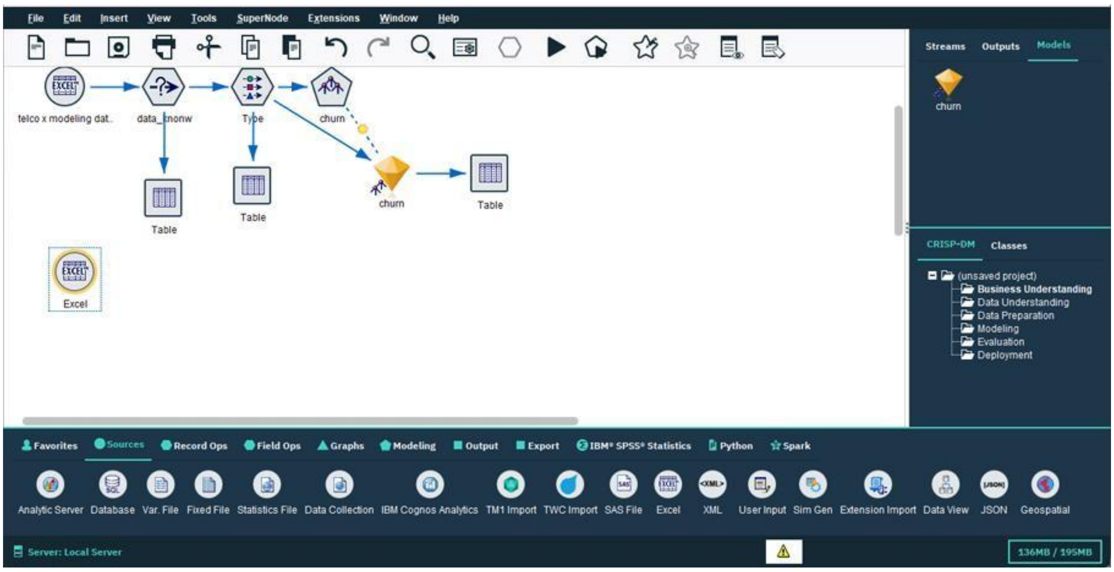
Step 7: View Churn Output Table

- Drag another **Table Node** from the **Output palette**.
- Connect it to the **Churn Node**.
- Click **Run** to see new fields such as $R-churn, $RC-churn, $RI-churn.



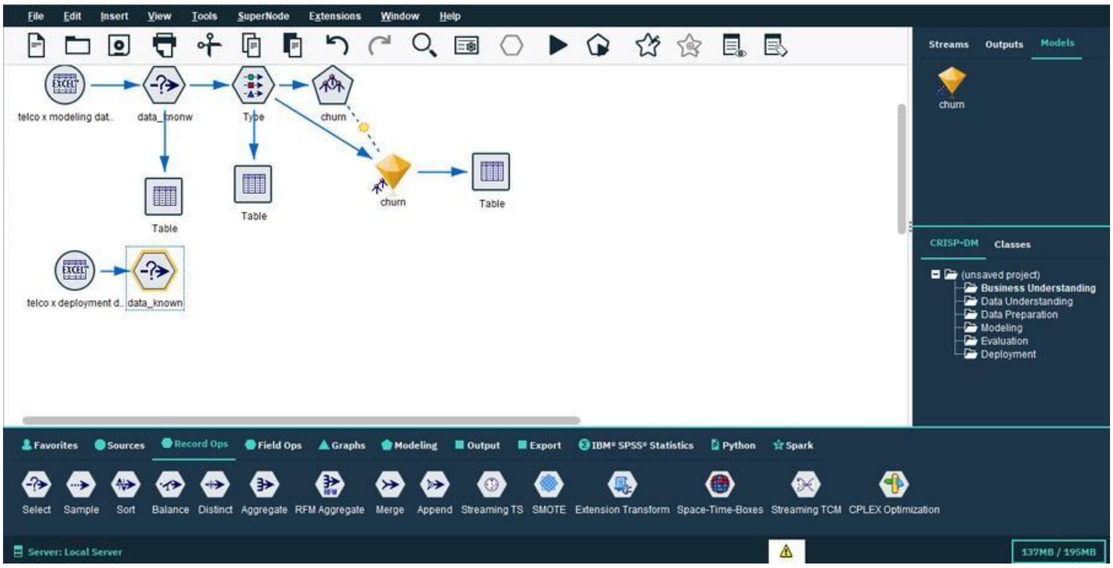
Step 8: Import Deployment Data

- Add another **Excel Node** to the canvas.
- Import the **deployment dataset** (new telecom data for testing).



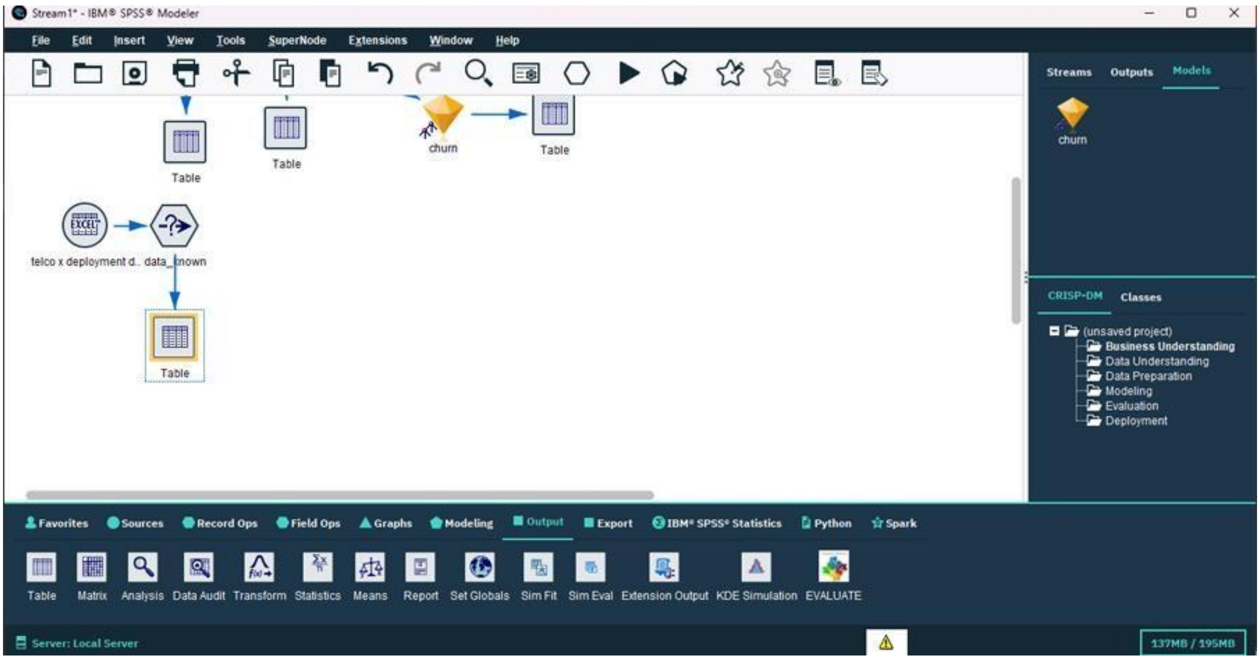
Step-9: Filter Deployment Data

- Add a **Select Node** and connect it to the new **Excel Node**.
- Use the same condition: data_known = "yes".
- This keeps only valid deployment records.



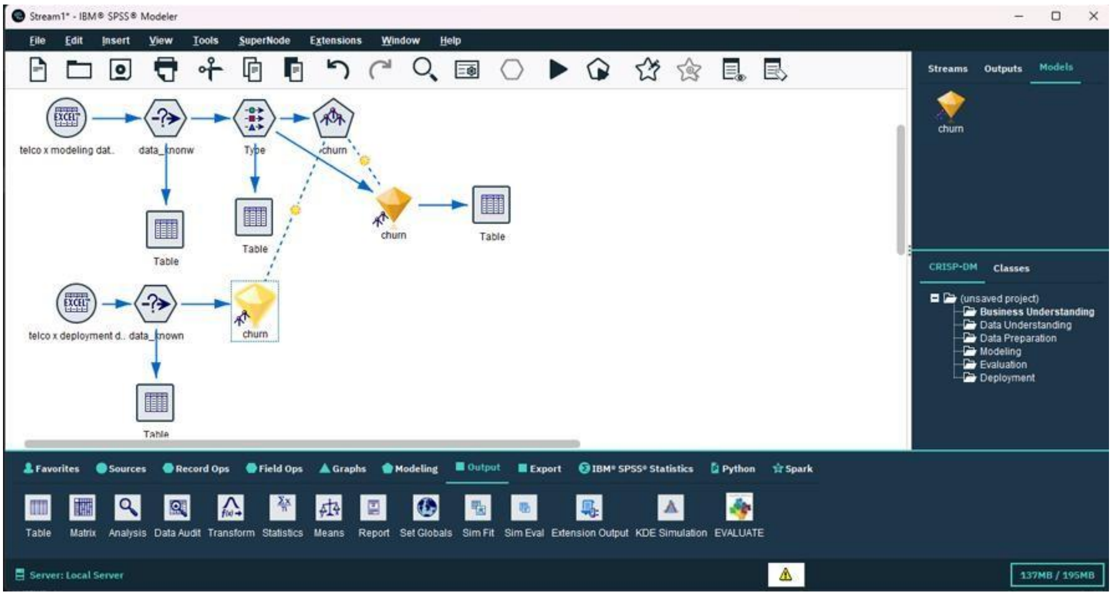
Step 10: View Deployment Data

- Connect a **Table Node** to the **Select Node**.
- Click **Run** to view the filtered deployment data.



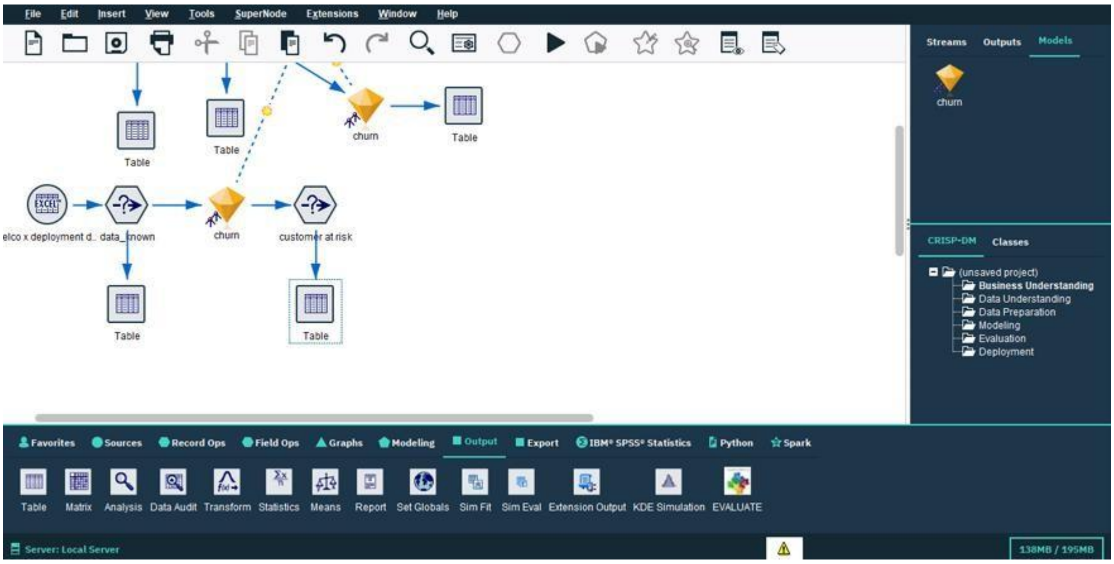
Step 11: Apply Existing Churn Model

- Right-click the **Churn Nugget**, choose **Copy Node**, and paste it on the canvas.
- Connect it to the **Select Node** of deployment data.
- This applies the existing churn model to new data.



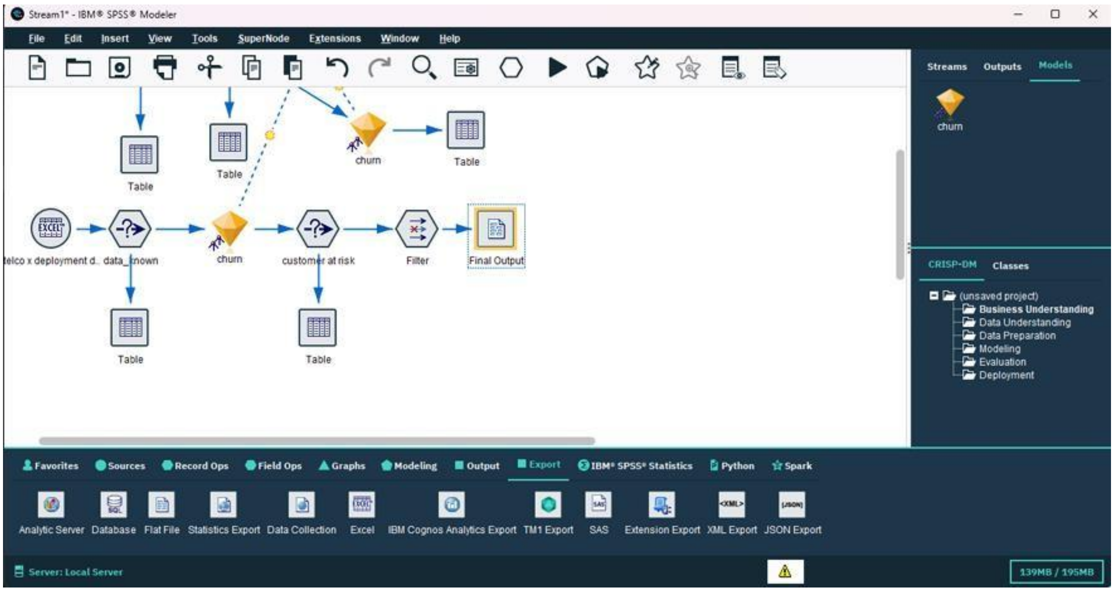
Step 12: Identify Customers Likely to Churn

- Add another **Select Node**.
- Set condition:
  - $R-churn = "Churned"
  - $RC-churn > 0.94
- Connect a **Table Node** to view customers likely to churn.



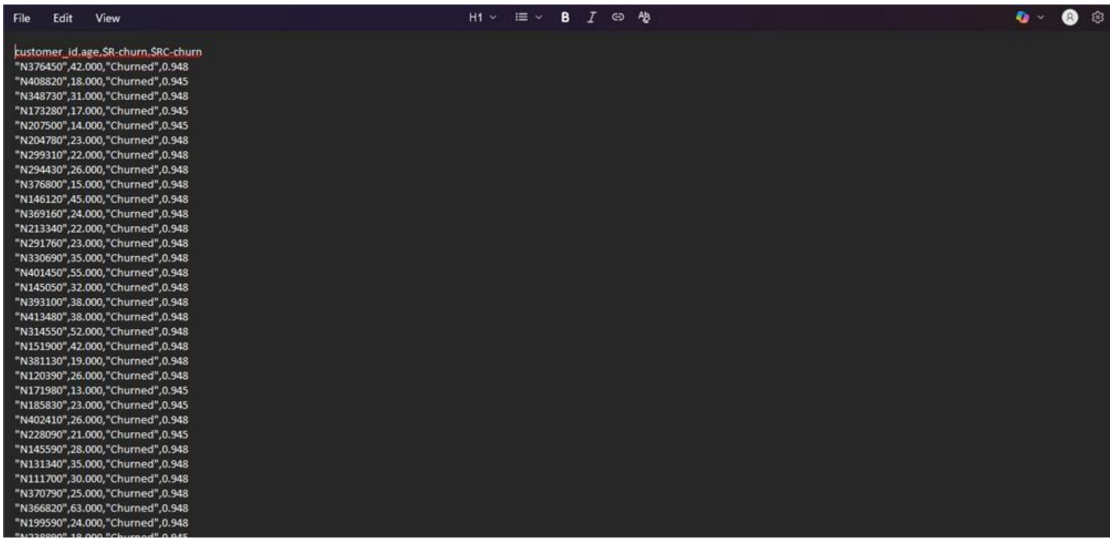
Step 13: Filter Fields and Prepare Output File

- From **Field palette**, add a **Filter Node**.
- Connect it to the **Select Node**.
- Choose the required fields for final output.
- From **Export palette**, drag a **Flat File Node**.
- Connect it to the **Filter Node** and set file path and format.



Step 14: Export Final Data

- Click **Run** on the **Flat File Node**.
- The final file is saved at the specified location.
- You can open it in **Notepad, Word, or Excel** to view the final list of predicted churn customers.



```
customer_id,age,$R-churn,$RC-churn
"N376450",42.000,"Churned",0.948
"N408820",18.000,"Churned",0.945
"N348730",31.000,"Churned",0.948
"N173280",17.000,"Churned",0.945
"N207500",14.000,"Churned",0.945
"N204780",23.000,"Churned",0.948
"N299310",22.000,"Churned",0.948
"N294430",26.000,"Churned",0.948
"N376800",15.000,"Churned",0.948
"N146120",45.000,"Churned",0.948
"N369160",24.000,"Churned",0.948
"N213340",22.000,"Churned",0.948
"N291760",23.000,"Churned",0.948
"N330690",35.000,"Churned",0.948
"N401450",55.000,"Churned",0.948
"N145050",32.000,"Churned",0.948
"N393100",38.000,"Churned",0.948
"N413480",38.000,"Churned",0.948
"N314550",52.000,"Churned",0.948
"N151900",42.000,"Churned",0.948
"N381130",19.000,"Churned",0.948
"N120390",26.000,"Churned",0.948
"N171980",13.000,"Churned",0.945
"N185830",23.000,"Churned",0.945
"N402410",26.000,"Churned",0.948
"N228090",21.000,"Churned",0.945
"N145590",28.000,"Churned",0.948
"N131340",35.000,"Churned",0.948
"N111700",30.000,"Churned",0.948
"N370790",25.000,"Churned",0.948
"N366820",63.000,"Churned",0.948
"N199590",24.000,"Churned",0.948
```

Final Outcome:

- The **customer churn prediction model** was successfully built and tested.
- Identified customers most likely to leave the service.
- Exported final filtered data for reporting and business use.