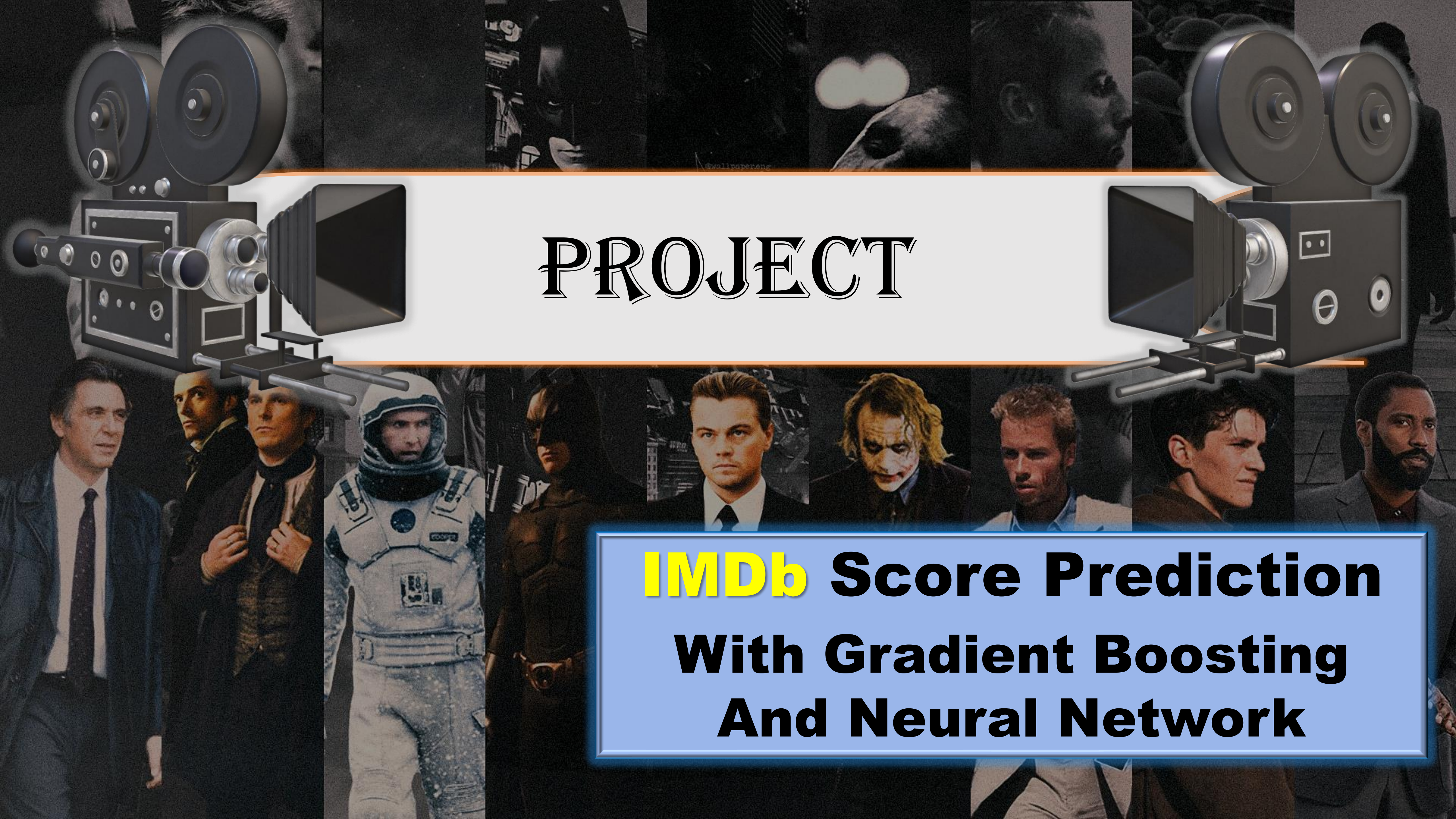


PROJECT

IMDb Score Prediction With Gradient Boosting And Neural Network

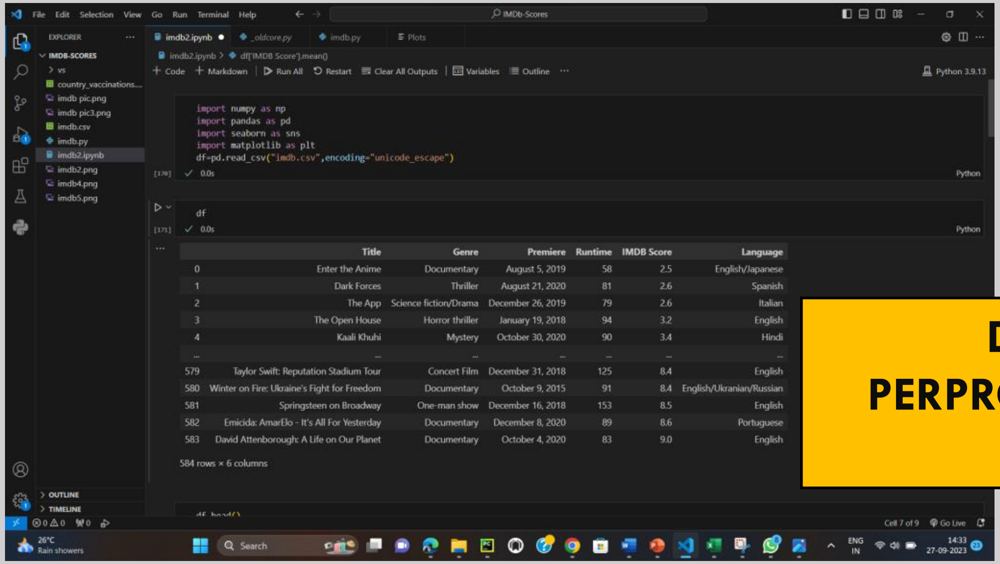
Develop a machine learning model to predict the IMDb Scores of the movies available on Films Based in their genre, premiere date, runtime and language . The model aims to accurately finds the popularity of the movies to the assist users in discovering highly rated films that align with their preferences

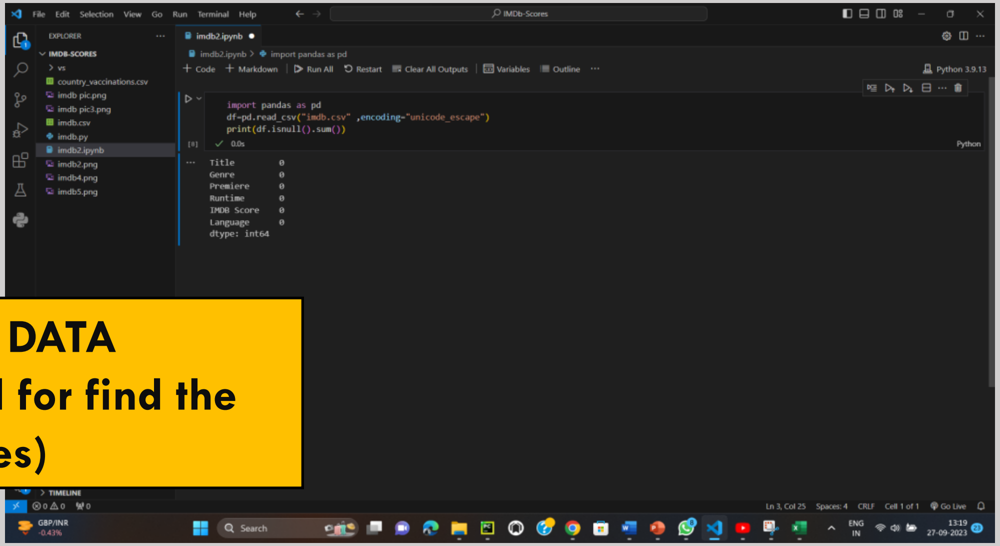
Design the project based on :

* Data Source
* Data Preprocessing
* Feature Engineering
* Model Selection
* Model Training
* Evaluation

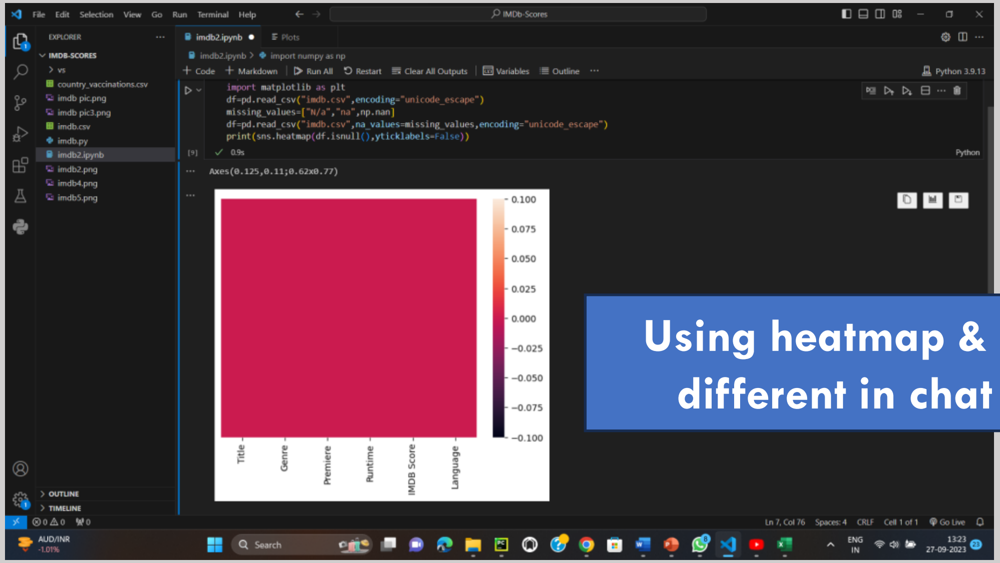
Main algorithms & ML are :

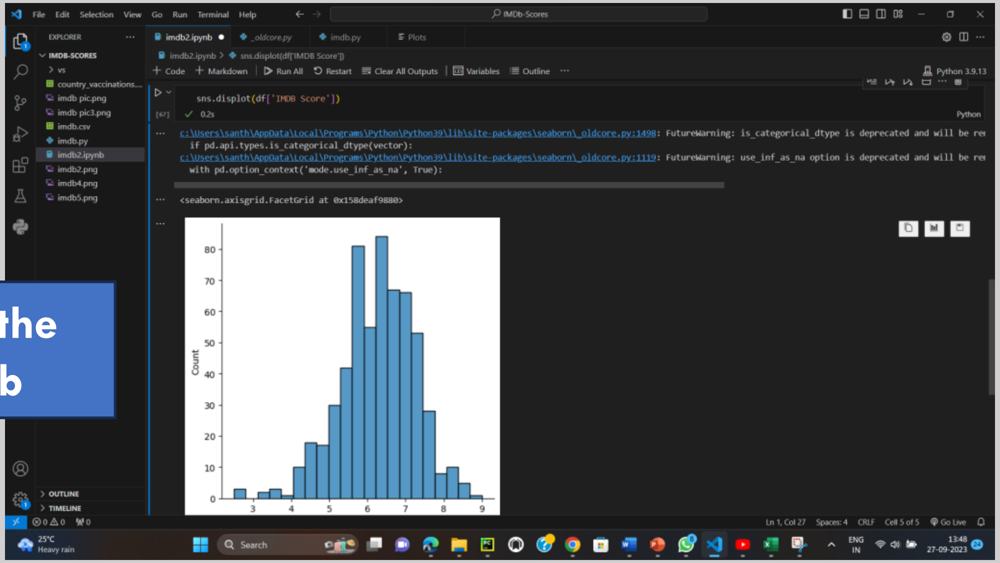
linear Regression ,Random Forest Regression to Predict IMDb Scores .Train the selected model using preprocessing data Regression metrics like MAE ,MSE,R-squared,Gradient Boosting and Neural Network.





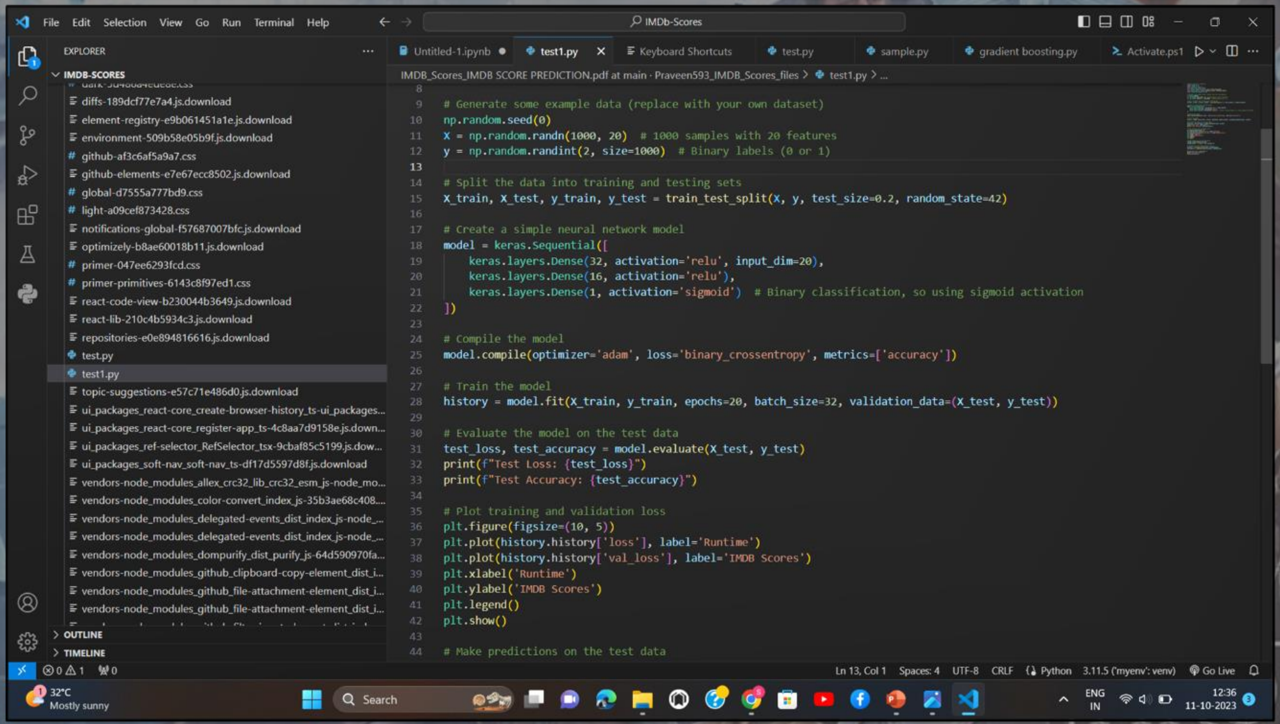
DATA SOURCE & DATA PERPROCESSING (used for find the missing values)



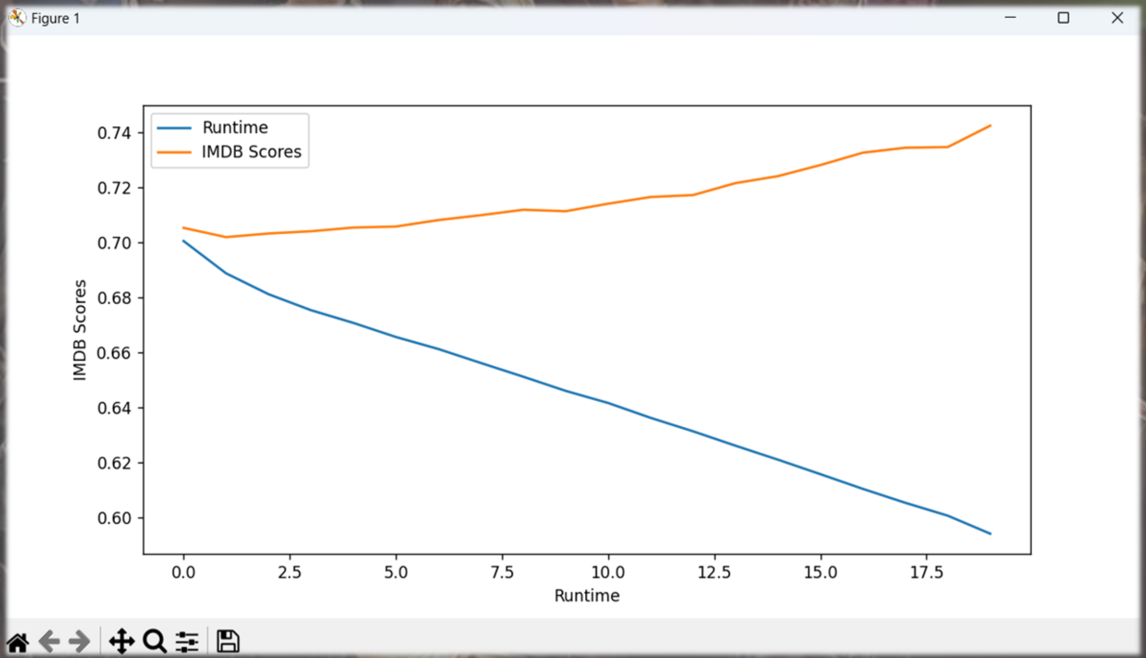


Using heatmap & displot can find the different in chat and predict IMDb

NEURAL NETWORKING



- Neural Networking is an ensemble learning technique that combines the predictions of several weak learners to create a strong predictive model.
- Neural Networking,with its iterative learning approach, stands as a powerful tool for predictive modeling, providing accurate results across diverse dataset



- **Hyperparameter Tuning:** Proper tuning of hyperparameters is crucial for optimal performance.
- **Potential for Overfitting:** Care must be taken to avoid overfitting, especially if the weak learners are too complex.

Key Components For Gradient Boosting

- **Weak Learners**: Typically shallow decision trees are used.
- **Boosting**: Models are built sequentially, and each subsequent model corrects errors made by the previous ones.

Use Cases For Gradient Boosting

- **Commonly Applied**: Used in various domains, including finance, healthcare, and Kaggle competitions.

Key Components For Neural Network

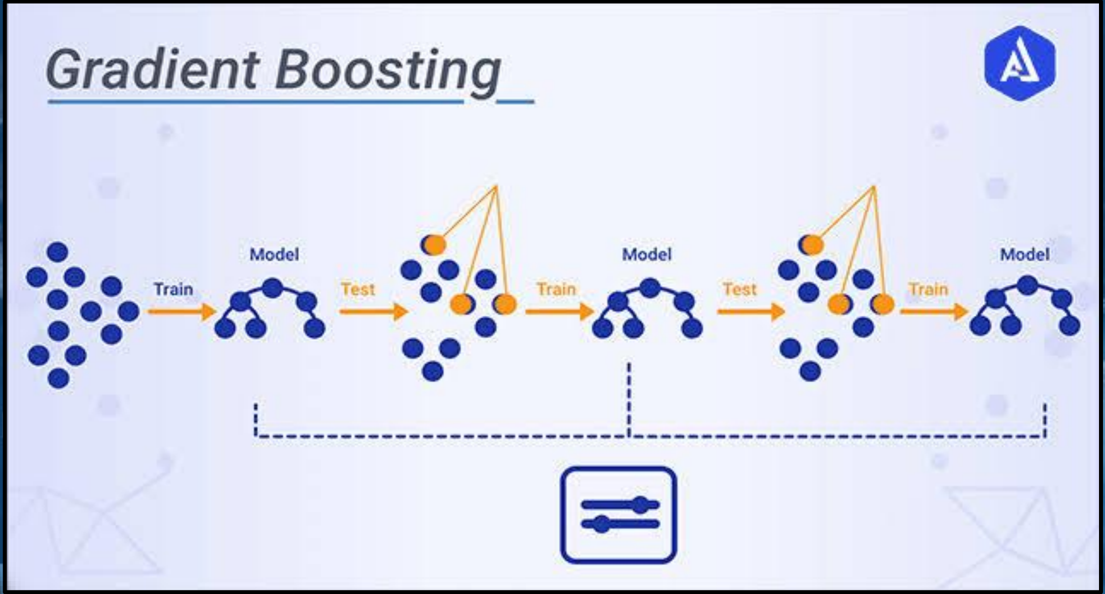
- **Neurons**: Basic computational units that process information.
- **Layers**: Organized in input, hidden, and output layers.
- **Activation Functions**: Determine the strength of connections between neurons.

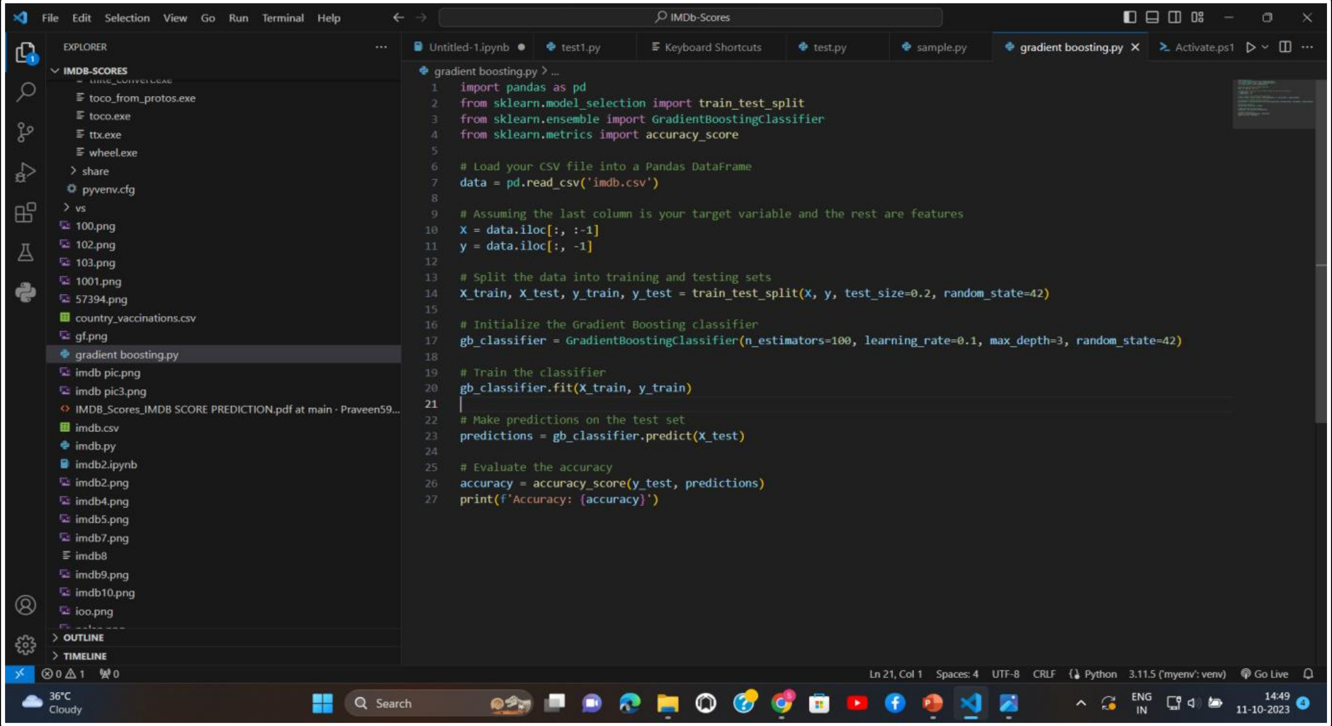
Use Cases For Gradient Boosting

- **Image and Speech Recognition**: Neural Networks excel in tasks like image and speech recognition.

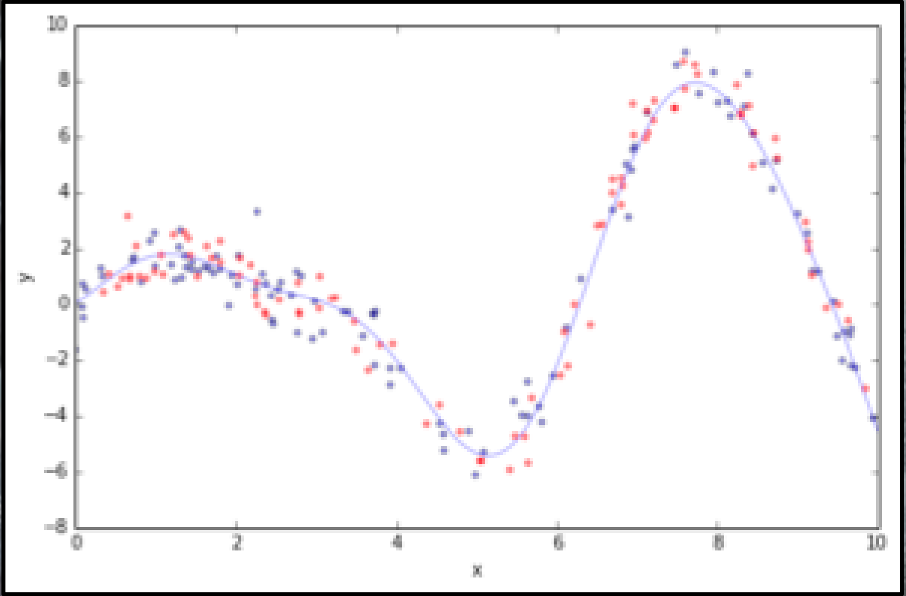
GRADIENT BOOSTING

- Gradient Boosting is an ensemble learning technique that combines the predictions of several weak learners to create a strong predictive model.
- Gradient Boosting, with its iterative learning approach, stands as a powerful tool for predictive modeling, providing accurate results across diverse datasets.

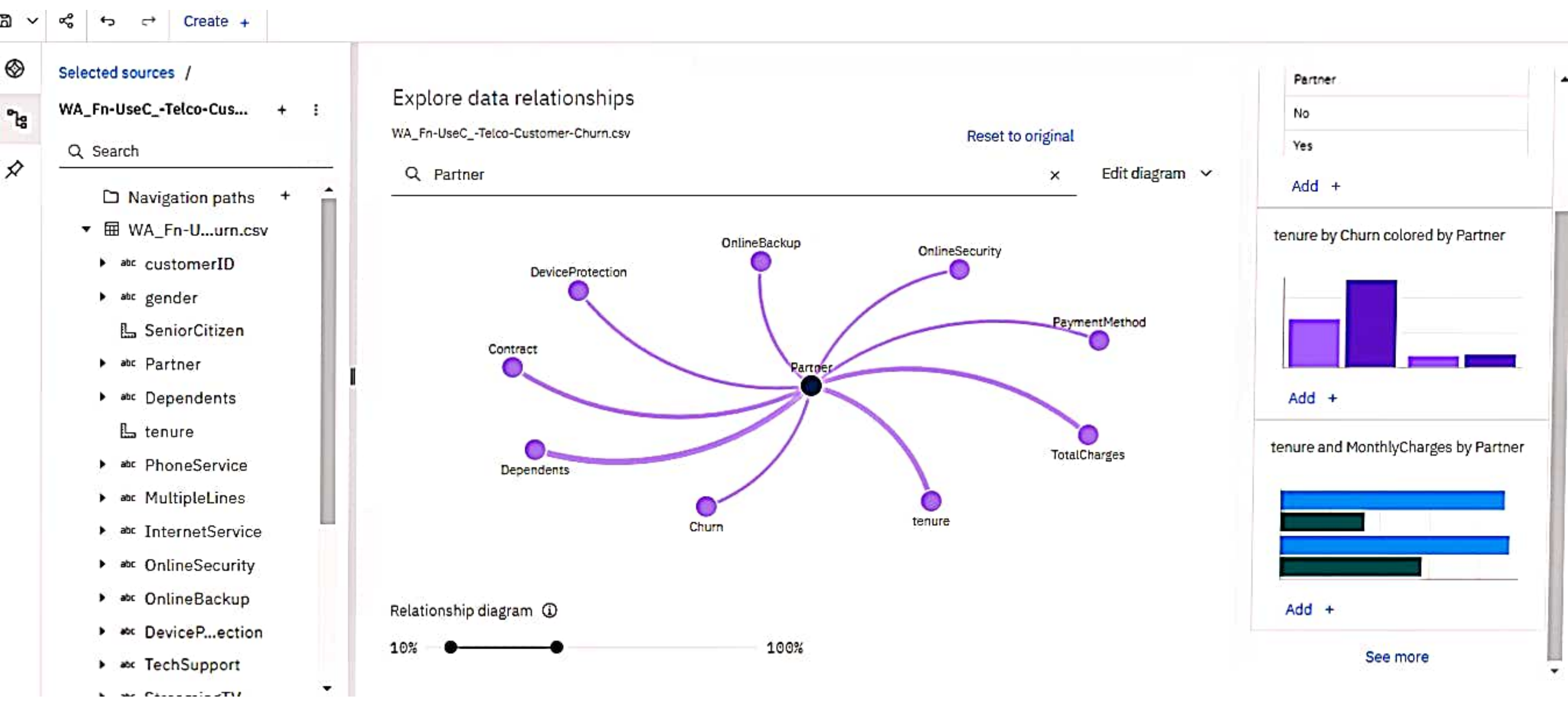


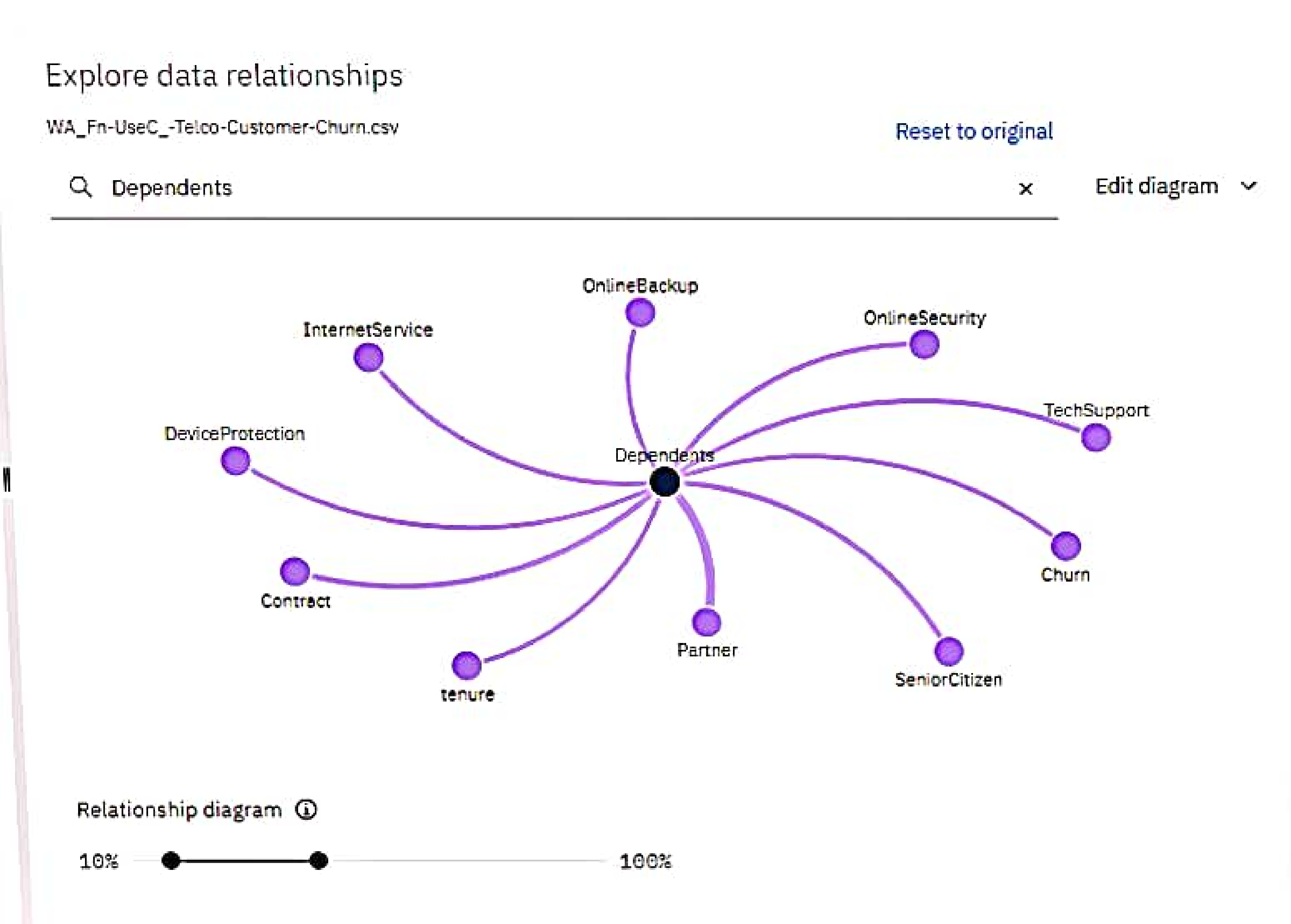


```python
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.metrics import accuracy_score

# Load your CSV file into a Pandas DataFrame
data = pd.read_csv('imdb.csv')

# Assuming the last column is your target variable and the rest are features
X = data.iloc[:, :-1]
y = data.iloc[:, -1]

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Initialize the Gradient Boosting classifier
gb_classifier = GradientBoostingClassifier(n_estimators=100, learning_rate=0.1, max_depth=3, random_state=42)

# Train the classifier
gb_classifier.fit(X_train, y_train)

# Make predictions on the test set
predictions = gb_classifier.predict(X_test)

# Evaluate the accuracy
accuracy = accuracy_score(y_test, predictions)
print(f'Accuracy: {accuracy}')
```



THANK YOU


Create +
Selected sources /
WA_Fn-UseC_-Telco-Cus...
Search
Navigation paths
WA_Fn-U...urn.csv
customerID
gender
SeniorCitizen
Partner
Dependents
tenure
PhoneService
MultipleLines
InternetService
OnlineSecurity
OnlineBackup
DeviceP...ection
TechSupport
Explore data relationships
WA_Fn-UseC_-Telco-Customer-Churn.csv
Reset to original
Partner
Edit diagram
OnlineBackup
OnlineSecurity
DeviceProtection
PaymentMethod
Contract
Partner
TotalCharges
Dependents
Churn
tenure
Relationship diagram
10%
100%
Partner
No
Yes
Add +
tenure by Churn colored by Partner
Add +
tenure and MonthlyCharges by Partner
Add +
See more


Explore data relationships
WA_Fn-UseC_-Telco-Customer-Churn.csv
Reset to original
Dependents
Edit diagram
OnlineBackup
InternetService
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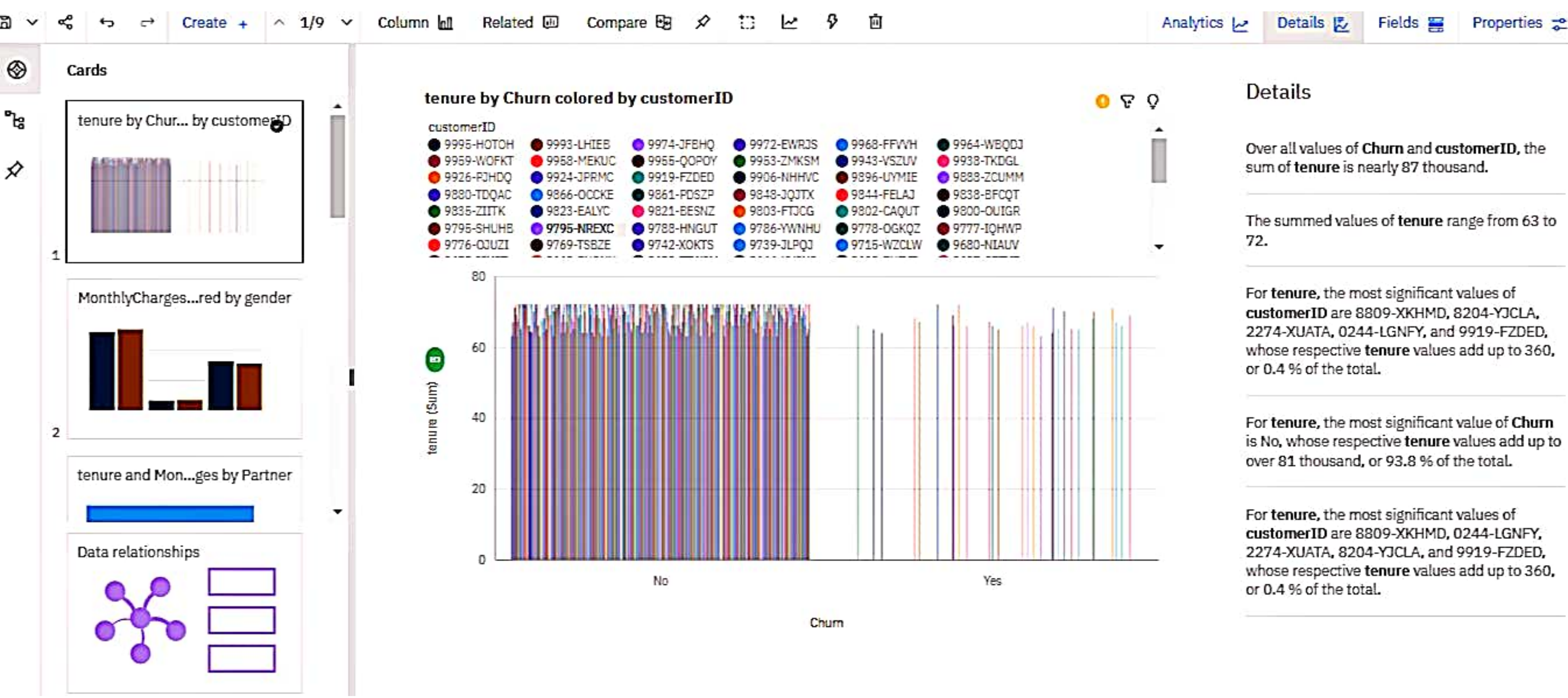
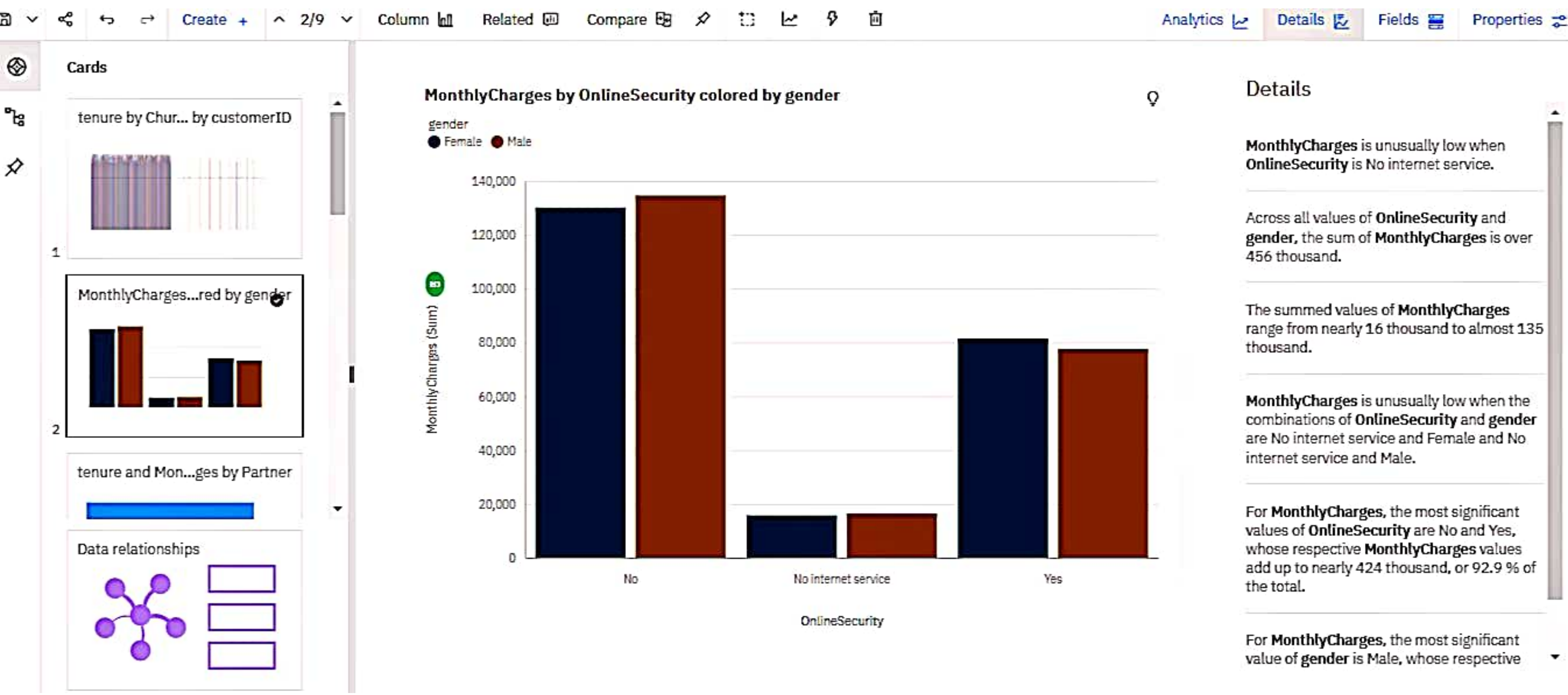
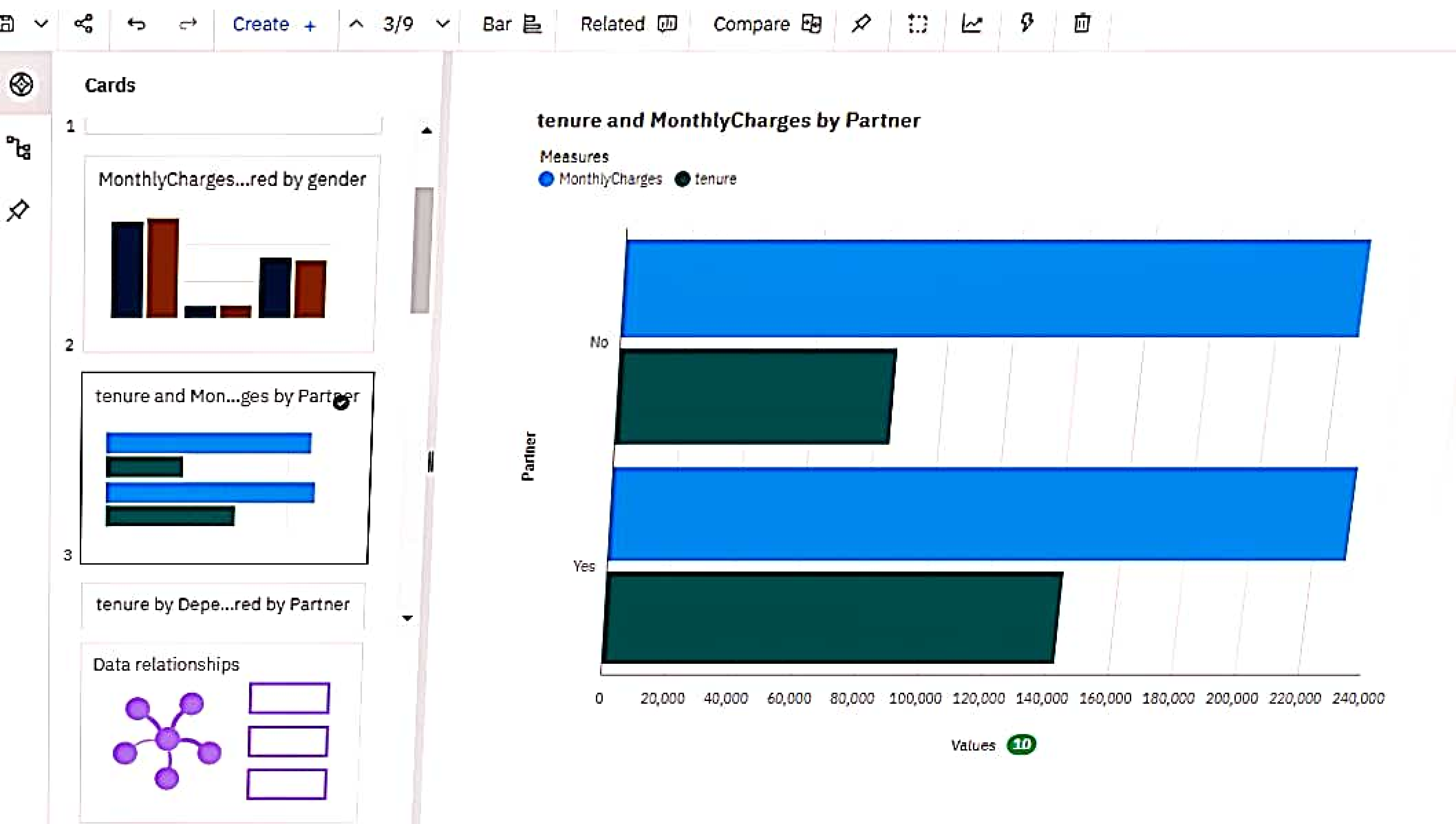
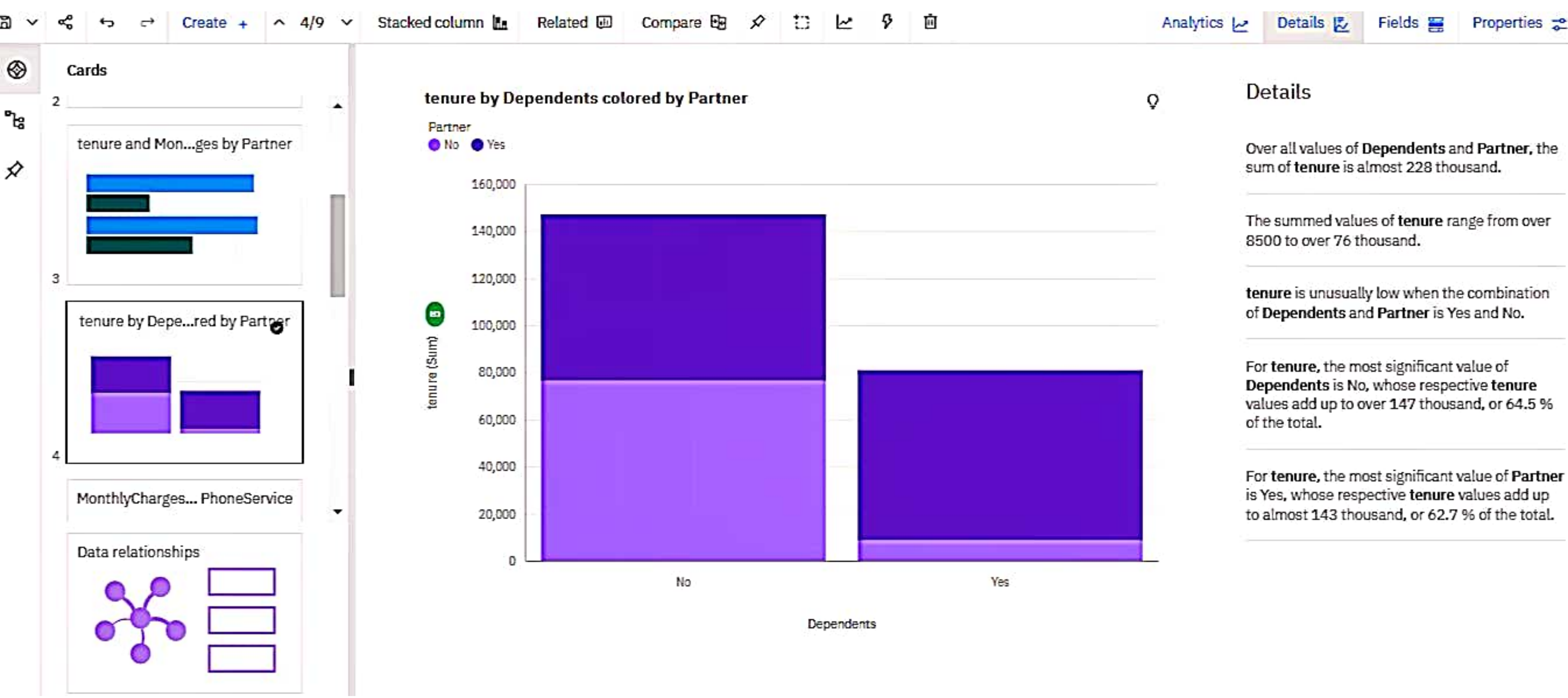
TechSupport
DeviceProtection
Dependents
Churn
Contract
Partner
SeniorCitizen
tenure
Relationship diagram
10%
100%

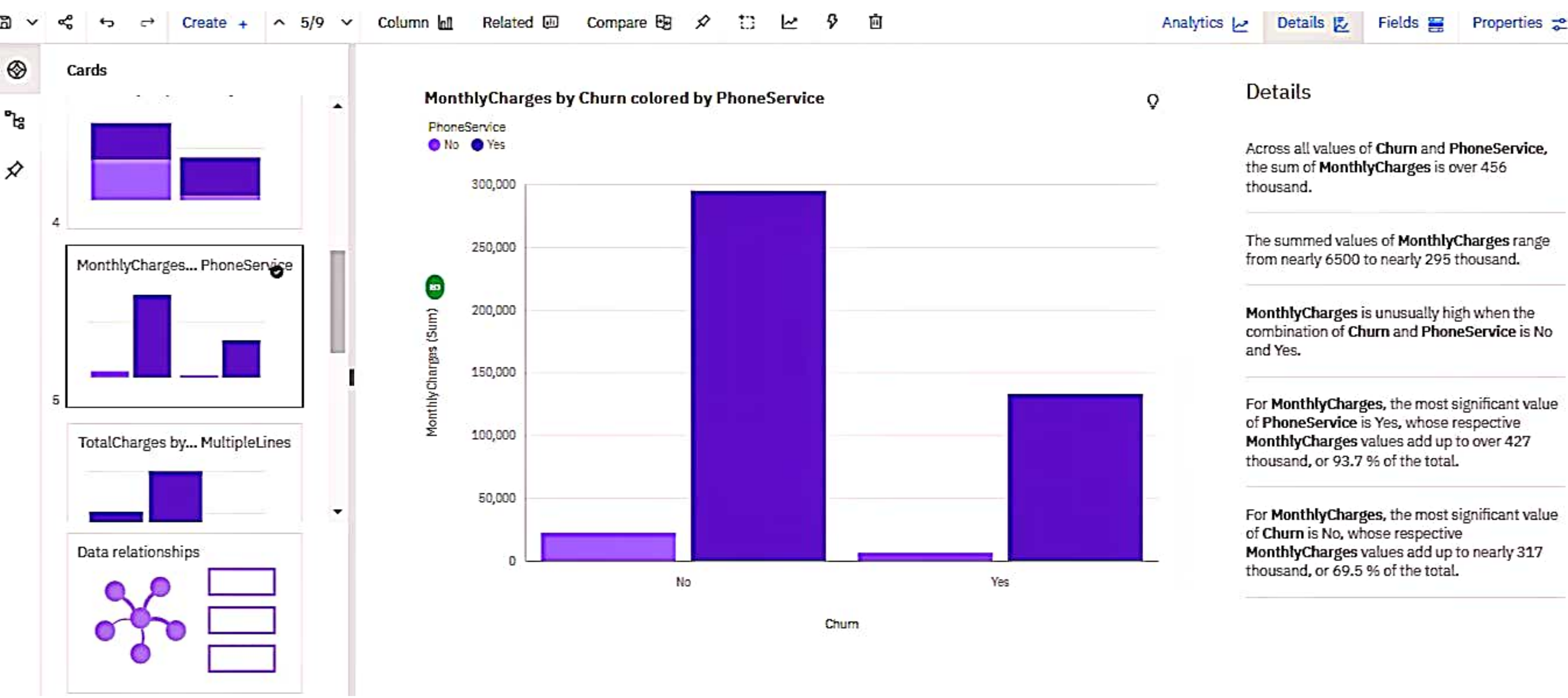

Create
1/9
Column
Related
Compare
Analytics
Details
Fields
Properties
Cards
tenure by Chur... by customerID
MonthlyCharges...red by gender
tenure and Mon...ges by Partner
Data relationships
tenure by Churn colored by customerID
customerID
80
60
40
20
0
tenure (Sum)
No
Yes
Churn
Details
Over all values of Churn and customerID, the sum of tenure is nearly 87 thousand.
The summed values of tenure range from 63 to 72.
For tenure, the most significant values of customerID are 8809-XKHMD, 8204-YJCLA, 2274-XUATA, 0244-LGNFY, and 9919-FZDED, whose respective tenure values add up to 360, or 0.4 % of the total.
For tenure, the most significant value of Churn is No, whose respective tenure values add up to over 81 thousand, or 93.8 % of the total.
For tenure, the most significant values of customerID are 8809-XKHMD, 0244-LGNFY, 2274-XUATA, 8204-YJCLA, and 9919-FZDED, whose respective tenure values add up to 360, or 0.4 % of the total.

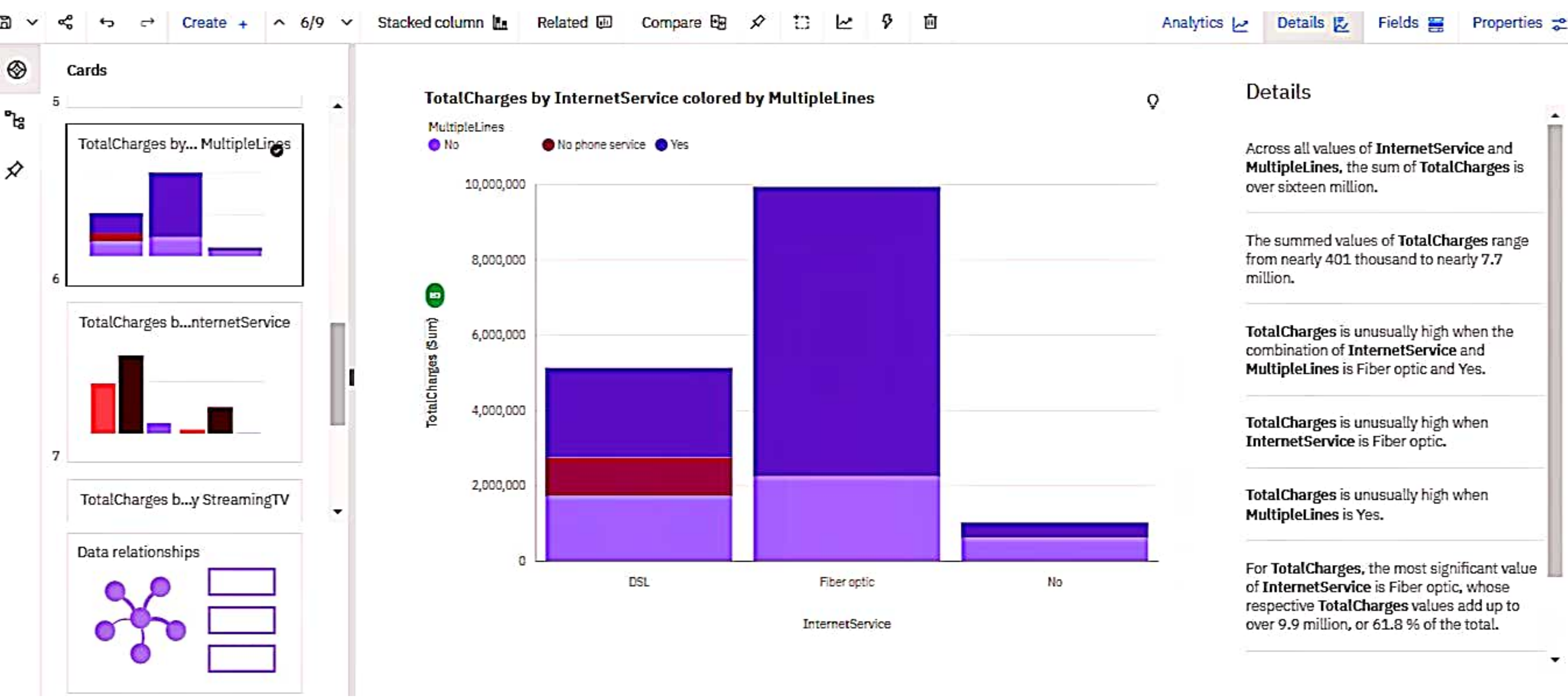

Create
2/9
Column
Related
Compare
Analytics
Details
Fields
Properties
Cards
tenure by Chur... by customerID
1
MonthlyCharges...red by gender
2
tenure and Mon...ges by Partner
Data relationships
MonthlyCharges by OnlineSecurity colored by gender
gender
Female
Male
140,000
120,000
100,000
80,000
60,000
40,000
20,000
0
MonthlyCharges (Sum)
No
No internet service
Yes
OnlineSecurity
Details
MonthlyCharges is unusually low when OnlineSecurity is No internet service.
Across all values of OnlineSecurity and gender, the sum of MonthlyCharges is over 456 thousand.
The summed values of MonthlyCharges range from nearly 16 thousand to almost 135 thousand.
MonthlyCharges is unusually low when the combinations of OnlineSecurity and gender are No internet service and Female and No internet service and Male.
For MonthlyCharges, the most significant values of OnlineSecurity are No and Yes, whose respective MonthlyCharges values add up to nearly 424 thousand, or 92.9 % of the total.
For MonthlyCharges, the most significant value of gender is Male, whose respective

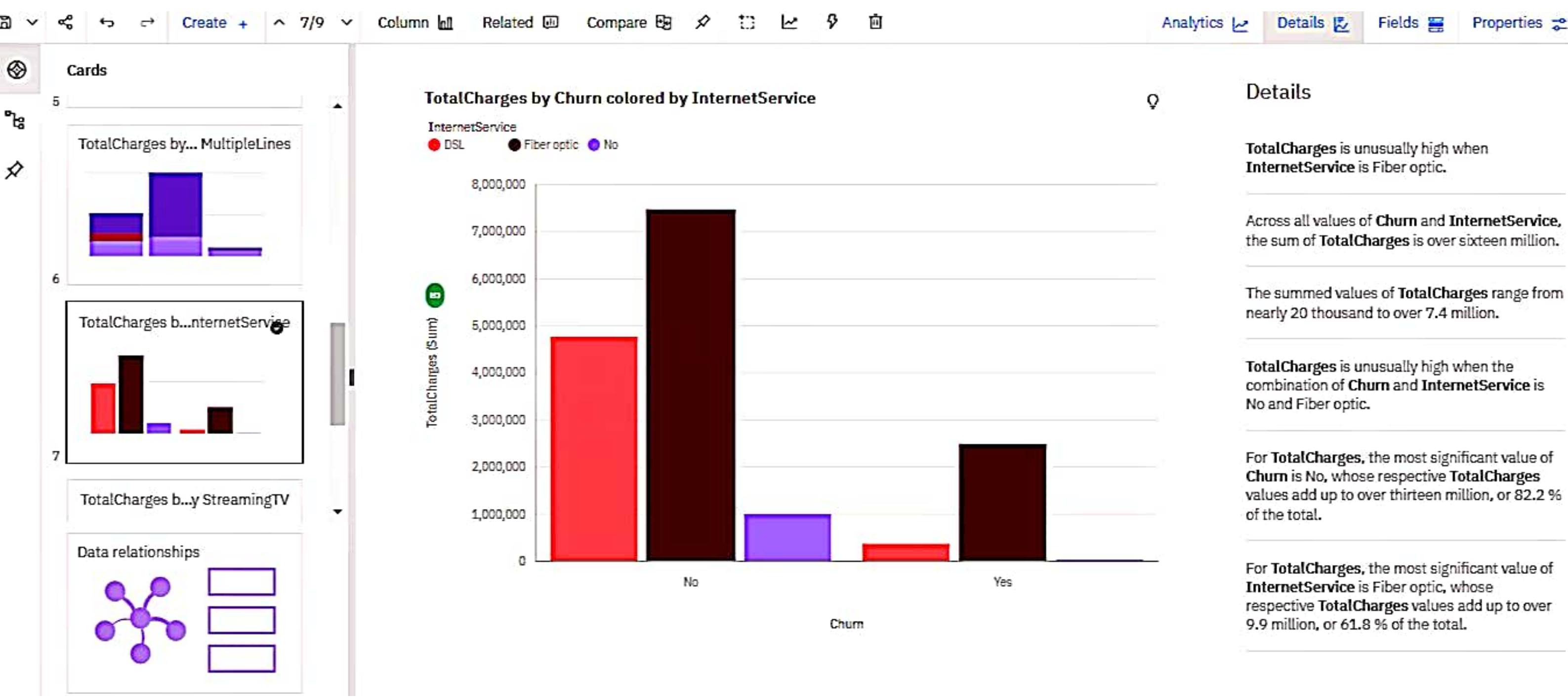


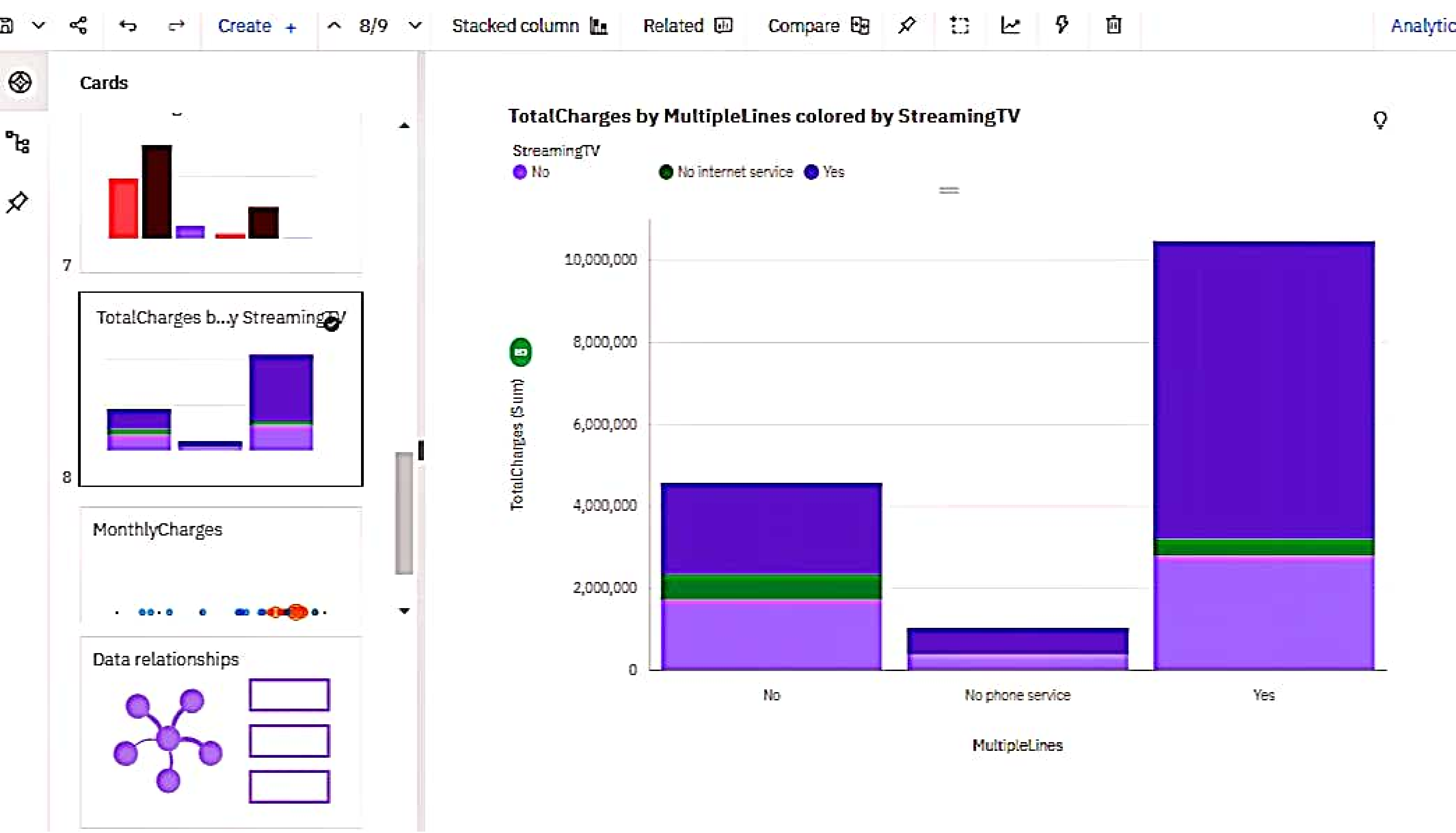
Create +
3/9
Bar
Related
Compare
Cards
MonthlyCharges...red by gender
tenure and Mon...ges by Partner
tenure by Depe...red by Partner
Data relationships
tenure and MonthlyCharges by Partner
Measures
MonthlyCharges
tenure
No
Yes
Partner
0
20,000
40,000
60,000
80,000
100,000
120,000
140,000
160,000
180,000
200,000
220,000
240,000
Values
10


Create +
4/9
Stacked column
Related
Compare
Analytics
Details
Fields
Properties
Cards
2
tenure and Mon...ges by Partner
3
tenure by Depe...red by Partner
4
MonthlyCharges... PhoneService
Data relationships
tenure by Dependents colored by Partner
Partner
No
Yes
160,000
140,000
120,000
100,000
80,000
60,000
40,000
20,000
0
tenure (Sum)
No
Yes
Dependents
Details
Over all values of Dependents and Partner, the sum of tenure is almost 228 thousand.
The summed values of tenure range from over 8500 to over 76 thousand.
tenure is unusually low when the combination of Dependents and Partner is Yes and No.
For tenure, the most significant value of Dependents is No, whose respective tenure values add up to over 147 thousand, or 64.5 % of the total.
For tenure, the most significant value of Partner is Yes, whose respective tenure values add up to almost 143 thousand, or 62.7 % of the total.

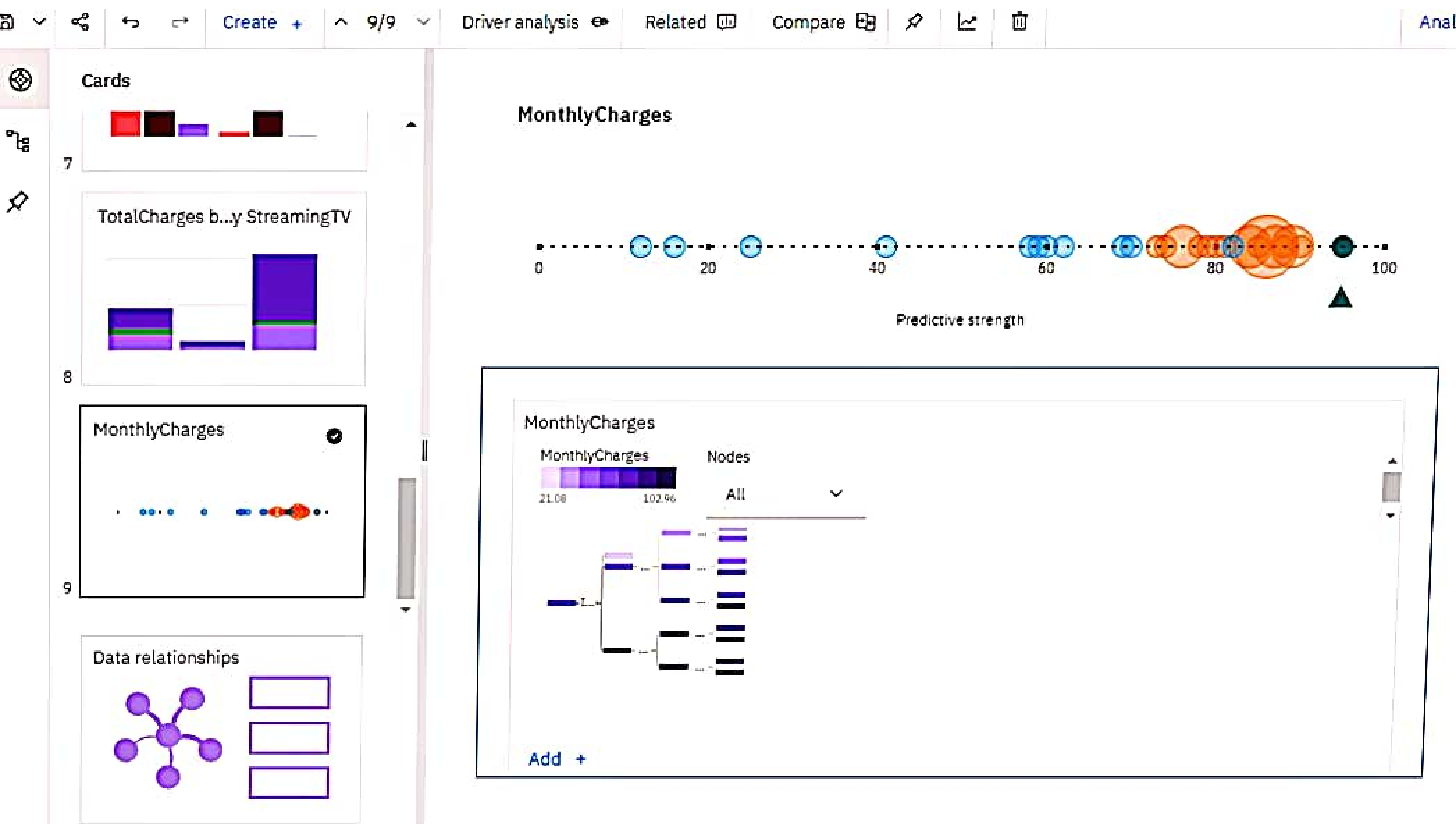

Create
5/9
Column
Related
Compare
Analytics
Details
Fields
Properties
Cards
4
MonthlyCharges... PhoneService
5
TotalCharges by... MultipleLines
Data relationships
MonthlyCharges by Churn colored by PhoneService
PhoneService
No
Yes
300,000
250,000
200,000
150,000
100,000
50,000
0
MonthlyCharges (Sum)
No
Yes
Churn
Details
Across all values of Churn and PhoneService, the sum of MonthlyCharges is over 456 thousand.
The summed values of MonthlyCharges range from nearly 6500 to nearly 295 thousand.
MonthlyCharges is unusually high when the combination of Churn and PhoneService is No and Yes.
For MonthlyCharges, the most significant value of PhoneService is Yes, whose respective MonthlyCharges values add up to over 427 thousand, or 93.7 % of the total.
For MonthlyCharges, the most significant value of Churn is No, whose respective MonthlyCharges values add up to nearly 317 thousand, or 69.5 % of the total.


Create
6/9
Stacked column
Related
Compare
Analytics
Details
Fields
Properties
Cards
TotalCharges by... MultipleLines
TotalCharges b...nternetService
TotalCharges b...y StreamingTV
Data relationships
TotalCharges by InternetService colored by MultipleLines
MultipleLines
No
No phone service
Yes
10,000,000
8,000,000
6,000,000
4,000,000
2,000,000
0
TotalCharges (Sum)
DSL
Fiber optic
No
InternetService
Details
Across all values of InternetService and MultipleLines, the sum of TotalCharges is over sixteen million.
The summed values of TotalCharges range from nearly 401 thousand to nearly 7.7 million.
TotalCharges is unusually high when the combination of InternetService and MultipleLines is Fiber optic and Yes.
TotalCharges is unusually high when InternetService is Fiber optic.
TotalCharges is unusually high when MultipleLines is Yes.
For TotalCharges, the most significant value of InternetService is Fiber optic, whose respective TotalCharges values add up to over 9.9 million, or 61.8 % of the total.


Create +
7/9
Column
Related
Compare
Analytics
Details
Fields
Properties
Cards
TotalCharges by... MultipleLines
TotalCharges b...nternetService
TotalCharges b...y StreamingTV
Data relationships
TotalCharges by Churn colored by InternetService
InternetService
DSL
Fiber optic
No
8,000,000
7,000,000
6,000,000
5,000,000
4,000,000
3,000,000
2,000,000
1,000,000
0
TotalCharges (Sum)
No
Yes
Churn
Details
TotalCharges is unusually high when InternetService is Fiber optic.
Across all values of Churn and InternetService, the sum of TotalCharges is over sixteen million.
The summed values of TotalCharges range from nearly 20 thousand to over 7.4 million.
TotalCharges is unusually high when the combination of Churn and InternetService is No and Fiber optic.
For TotalCharges, the most significant value of Churn is No, whose respective TotalCharges values add up to over thirteen million, or 82.2 % of the total.
For TotalCharges, the most significant value of InternetService is Fiber optic, whose respective TotalCharges values add up to over 9.9 million, or 61.8 % of the total.



Create +
8/9
Stacked column
Related
Compare
Analytic
Cards
7
TotalCharges b...y StreamingTV
8
MonthlyCharges
Data relationships
TotalCharges by MultipleLines colored by StreamingTV
StreamingTV
No
No internet service
Yes
10,000,000
8,000,000
6,000,000
4,000,000
2,000,000
0
TotalCharges (Sum)
No
No phone service
Yes
MultipleLines



Create +
9/9
Driver analysis
Related
Compare
Anal
Cards
7
TotalCharges b...y StreamingTV
8
MonthlyCharges
9
Data relationships
MonthlyCharges
0
20
40
60
80
100
Predictive strength
MonthlyCharges
MonthlyCharges
21.08
102.96
Nodes
All
Add +