



Sales Forecasting and Optimization

DEPI Graduation Project



Meet our team

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Data Description

The dataset contains 9,800 rows and 18 columns describing customer details, order information, product categories, and financial transactions. Key variables include:

- Customer demographics (Segment, City, State, Region)
- Product details (Category, Sub-Category, Product Name)
- Order information (Order Date, Ship Date, Ship Mode)
- Target variable: Sales amount (in USD)





Sample Data

| Row ID | Order ID | Order Date | Ship Date | Ship Mode | Customer ID | Customer Name | Segment | Country | City |
|--------|------------------|------------|------------|----------------|-------------|-----------------|-----------|---------------|-----------------|
| | 1 CA-2017-15215 | 8/11/2017 | 11/11/2017 | Second Class | CG-12520 | Claire Gute | Consumer | United States | Henderson |
| | CA-2017-15215 | 8/11/2017 | 11/11/2017 | Second Class | CG-12520 | Claire Gute | Consumer | United States | Henderson |
|] ; | CA-2017-13868 | 12/6/2017 | 16/06/2017 | Second Class | DV-13045 | Darrin Van Huff | Corporate | United States | Los Angeles |
| | 4 US-2016-10896 | 11/10/2016 | 18/10/2016 | Standard Class | SO-20335 | Sean O'Donnell | Consumer | United States | Fort Lauderdale |
| | US-2016-10896 | 11/10/2016 | 18/10/2016 | Standard Class | SO-20335 | Sean O'Donnell | Consumer | United States | Fort Lauderdale |
| (| CA-2015-115812 | 9/6/2015 | 14/06/2015 | Standard Class | BH-11710 | Brosina Hoffman | Consumer | United States | Los Angeles |
| | 7 CA-2015-115812 | 9/6/2015 | 14/06/2015 | Standard Class | BH-11710 | Brosina Hoffman | Consumer | United States | Los Angeles |
| | CA-2015-11581 | 9/6/2015 | 14/06/2015 | Standard Class | BH-11710 | Brosina Hoffman | Consumer | United States | Los Angeles |
| | CA-2015-11581 | 9/6/2015 | 14/06/2015 | Standard Class | BH-11710 | Brosina Hoffman | Consumer | United States | Los Angeles |
| 10 | CA-2015-11581 | 9/6/2015 | 14/06/2015 | Standard Class | BH-11710 | Brosina Hoffman | Consumer | United States | Los Anaeles |

| State | Postal Cod | Region | Product ID | Category | Sub-Category | Product Name | Sales |
|------------|------------|--------|-----------------|-----------------|--------------|---------------------------------------|----------|
| Kentucky | 42420 | South | FUR-BO-10001798 | Furniture | Bookcases | Bush Somerset Collection Bookcase | 261.96 |
| Kentucky | 42420 | South | FUR-CH-10000454 | Furniture | Chairs | Hon Deluxe Fabric Upholstered Stacki | 731.94 |
| California | 90036 | West | OFF-LA-10000240 | Office Supplies | Labels | Self-Adhesive Address Labels for Type | 14.62 |
| Florida | 33311 | South | FUR-TA-10000577 | Furniture | Tables | Bretford CR4500 Series Slim Rectange | 957.5775 |
| Florida | 33311 | South | OFF-ST-10000760 | Office Supplies | Storage | Eldon Fold 'N Roll Cart System | 22.368 |
| California | 90032 | West | FUR-FU-10001487 | Furniture | Furnishings | Eldon Expressions Wood and Plastic | 48.86 |
| California | 90032 | West | OFF-AR-10002833 | Office Supplies | Art | Newell 322 | 7.28 |
| California | 90032 | West | TEC-PH-10002275 | Technology | Phones | Mitel 5320 IP Phone VoIP phone | 907.152 |
| California | 90032 | West | OFF-BI-10003910 | Office Supplies | Binders | DXL Angle-View Binders with Locking | 18.504 |
| California | 90032 | West | OFF-AP-10002892 | Office Supplies | Appliances | Belkin F5C206VTEL 6 Outlet Surge | 114.9 |





Data Dictionary

| Column Name | Description | Datatype |
|---------------|--|----------|
| Row ID | Unique numeric identifier for each row in the dataset | int64 |
| Order ID | Unique identifier for each order. | object |
| Order Date | The date when the order was placed. | object |
| Ship Date | The date when the order was shipped. | object |
| Ship Mode | Shipping method used (e.g., Second Class, Standard Class). | object |
| Customer ID | Unique identifier for each customer. | object |
| Customer Name | Name of the customer who placed the order. | object |
| Segment | Customer segment (e.g., Consumer, Corporate, Home Office). | object |
| Country | Country of the customer. | object |



Data Dictionary

| Column Name | Description | Datatype |
|--------------|--|----------|
| City | City of the customer. | object |
| State | State of the customer. | object |
| Postal Code | Postal/ZIP code (may contain missing values). | float64 |
| Region | Geographic region of the customer (e.g., West, South). | object |
| Product ID | Unique identifier for each product. | object |
| Category | Unique identifier for each customer. | object |
| Sub-Category | Sub-category of the product (e.g., Chairs, Labels). | object |
| Product Name | Name of the product. | object |
| Sales | Target — Sale amount (in USD) for the product line. | float64 |
| 8 0 | | |

Data Exploration

We began by examining the dataset structure:

- Checked basic statistics (mean, min, max values)
- Identified data types and missing values
- Analyzed unique values in categorical columns
- Visualized distributions of key variables

Key findings:

- The dataset had minimal missing values (only in Postal Code column)
- Significant outliers were present in the Sales variable
- High cardinality in Product Name and City columns

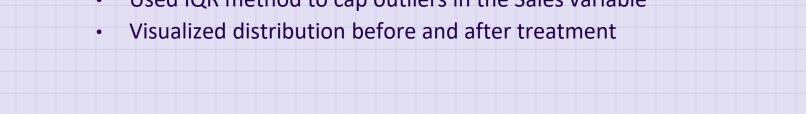


Handling Missing Values

Dropped rows with missing Postal Codes (only 11 rows affected)

Outlier Treatment

Used IQR method to cap outliers in the Sales variable







Encoding Categorical Variables

- Applied Label Encoding to all categorical columns including:
 - Ship Mode (4 categories)
 - Segment (3 categories)
 - Region (4 categories)
 - Product Category/Sub-category
 - Geographic locations (City, State)





Feature Engineering

- Date Features:
 - Extracted Year, Month, Day, and Weekday from Order Date
 - Calculated Shipping Duration (days between order and shipment)
- Text Processing:
 - Standardized Product Names by converting to lowercase and removing punctuation





Feature Selection

We dropped unnecessary columns that wouldn't contribute to modeling:

- Row ID, Customer ID, Product ID (unique identifiers)
- Customer Name (personal information)
- Order ID (transaction identifier)
- Ship Date (redundant since we have shipping duration)

Correlation

 We calculated the correlation matrix to understand the linear relationships between numerical features and the target variable (Sales).







02



View the Dashboard from here







\$2.26M

Total Sales

Year
2015 2016 2017 2018



| Customer_Name | City | Region Sur |
|----------------|---------------|------------|
| Aaron Bergman | Arlington | Central |
| Aaron Bergman | Oklahoma City | Central |
| Aaron Bergman | Seattle | West |
| Aaron Hawkins | Gulfport | South |
| Aaron Hawkins | Los Angeles | West |
| Aaron Hawkins | New York City | East |
| Aaron Hawkins | Philadelphia | East |
| Aaron Hawkins | San Francisco | West |
| Aaron Hawkins | Troy | East |
| Aaron Smayling | Arlington | South |

4922

Total Orders

Region

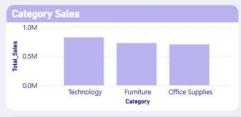
Central East South West

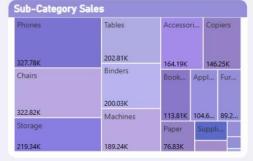


459.48

Avg_Order_Value









\$35.66K

Total_Sales





| Customer_Name | City | Region | Sum |
|--------------------|---------------|--------|-----|
| Aaron Hawkins | New York City | East | |
| Aaron Hawkins | Troy | East | |
| Aaron Smayling | New York City | East | |
| Adam Shillingsburg | New York City | East | |
| Aimee Bixby | Yonkers | East | |
| Alan Dominguez | Philadelphia | East | |
| Alex Avila | New York City | East | |
| Allen Goldenen | New York City | East | |
| Andrew Roberts | Columbus | East | |
| Andrew Roberts | Philadelphia | Fast | |







179.18

Avg_Order_Value









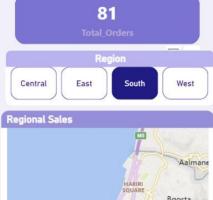
\$44.52K

Total_Sales





| Customer_Name | City | Region Sur |
|-------------------|--------------|------------|
| Aaron Smayling | Jacksonville | South |
| Adrian Hane | Louisville | South |
| Anna Gayman | Jacksonville | South |
| Anne McFarland | Salem | South |
| Barry Franzݶsisch | Jacksonville | South |
| Barry Gonzalez | Monroe | South |
| Bart Watters | Greensboro | South |
| Beth Fritzler | Miami | South |
| Bradley Drucker | Columbus | South |
| Brian Dahlen | Miami | South |







Avg_Order_Value

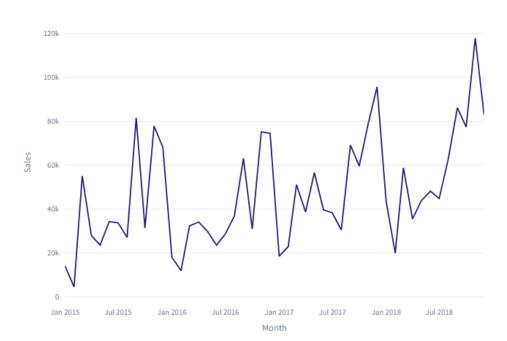






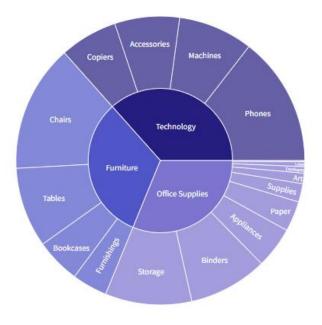




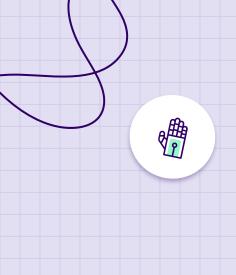




Sales by Category & Sub-Category







03

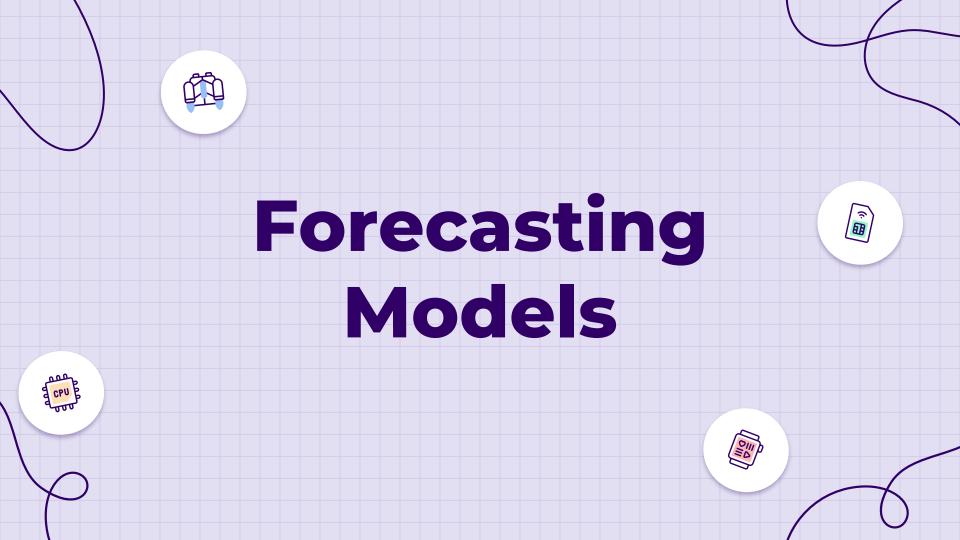


Prediction

View the Prediction form from here







Objective:

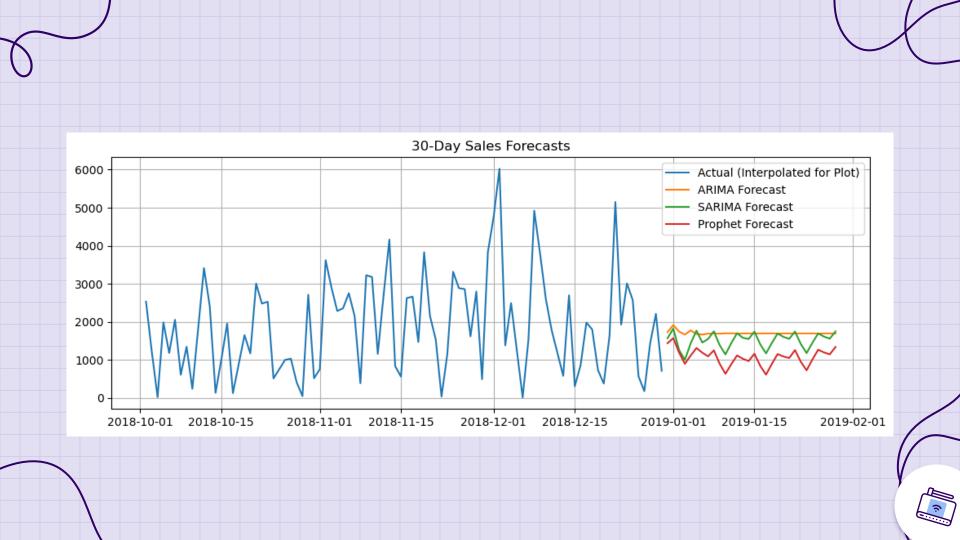
 Predict future sales using three different models: ARIMA, SARIMA and Prophet.

Steps:

- Data Preparation:
 - Group sales by date (Order Date).
 - Handle missing values with interpolation.
- Models Used:
 - ARIMA (5,1,2): Captures trends and basic patterns.
 - \circ SARIMA (1,1,1)(1,1,1,7): Adds weekly seasonality.
 - Prophet: Automatically detects trends and seasonality.
- Forecast Horizon: 30 days ahead.







Ensemble Boosting Models

d CPU B

Objective:

 Predict sales using ensemble boosting models (XGBoost, LightGBM, CatBoost) and optimize performance via hyperparameter tuning.

Steps:

- Data Preparation:
 - Split into features (X) and target (y = Sales).
 - Train-test split (80-20) with scaling (StandardScaler).
- Models Used:
 - XGBoost: High flexibility, handles complex patterns.
 - LightGBM: Faster training, good for large datasets.
 - CatBoost: Robust to categorical features, minimal preprocessing.
- Evaluation Metrics:
 - MSE (Mean Squared Error): Lower = Better.
 - R² Score: Closer to 1 = Better fit.



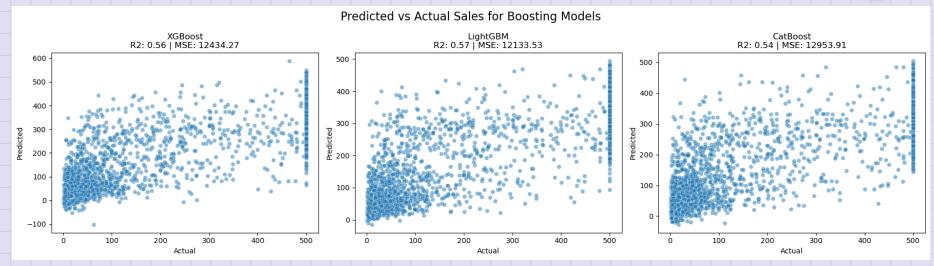


Model Performance & Tuning

- Initial Results (R² Scores):
 - XGBoost = 0.56.
 - LightGBM = 0.57.
 - CatBoost = 0.54.
- Hyperparameter Tuning:
 - Used RandomizedSearchCV to optimize:
 - n_estimators, learning_rate, max_depth (XGBoost).
 - num_leaves (LightGBM).
 - depth (CatBoost).
- Tuning Impact (R² Scores):
 - XGBoost = 0.571.
 - LightGBM = 0.570.
 - CatBoost = 0.528.









Objective:

 Predict future sales using ensemble (Random Forest) and single-tree (Decision Tree) approaches.

Models Used:

- Decision Tree:
 - Simple splits (max_depth=5, random_state=42).
 - Prone to overfitting but interpretable.
- Random Forest:
 - Ensemble of 100 trees (n_estimators=100).
 - Robust to overfitting, handles non-linearity.

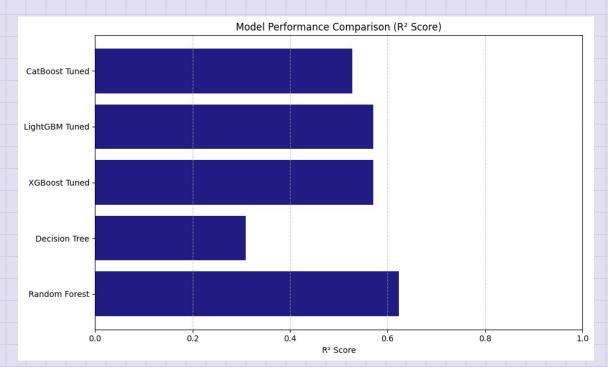
Performance (R² Scores):

- Decision Tree = 0.31.
- Random Forest = 0.62.

Best Model:

Random Forest was chosen as the final model based on performance.











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Chosen Model:

- After evaluation, Random Forest was selected for deployment due to its:
 - ✓ Lowest MSE (best R² score)
 - √ Fast prediction speed
 - √ Handling of complex patterns

Deployment Steps:

- 1. Save Model: Used joblib to serialize and save the trained model.
- 2. Build Web App: Created an interactive Streamlit application.

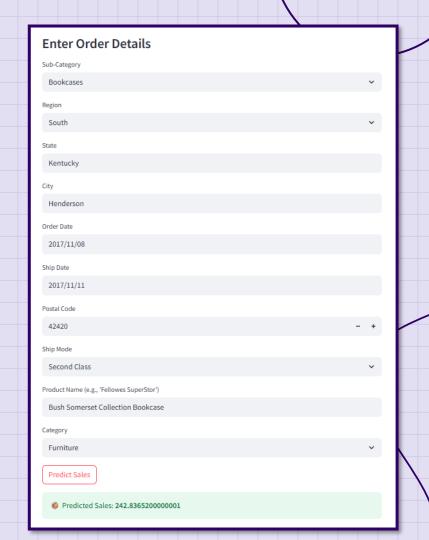






User-Friendly Interface:

- Input Order Details: Users can enter features (e.g., category, order date, region).
- Real-Time Prediction: Instantly displays predicted Sales value.







Business Impact

• **Better Decision-Making:** Improves planning across inventory, marketing, and operations using accurate sales forecasts.



- Revenue Growth: Increases sales by aligning stock and promotions with customer demand.
- Reduced Operational Costs: Lowers costs by avoiding overstocking, stockouts, and inefficient logistics.
- Improved Customer Satisfaction: Ensures product availability, leading to a better customer experience and higher loyalty.

Thanks!

Do you have any questions?

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