Exploratory Data Analysis (EDA)

1. Data Cleaning

- Handle missing values (fill with mean/median for numerical, "Unknown" for categorical).
- Remove duplicates and standardize data types.

2. Univariate Analysis

- **Numerical:** Histograms, Boxplots (identify distributions & outliers).
- Categorical: Bar Charts, Pie Charts (analyze ad types, demographics, device usage).

3. Bivariate & Multivariate Analysis

- Correlation Heatmap Identify relationships (e.g., Ad Spend vs. Revenue).
- Scatter & Box Plots Analyze CPC, CTR, and ROI trends.
- **Pivot Tables** Compare campaign performance across features.

4. Outlier Detection

- **Boxplots & Z-Score** Spot anomalies in revenue, clicks, CPC.
- Winsorization Cap extreme values to prevent skewed insights.

5. Time-Series Analysis

- Trend & Seasonality Analysis Identify peak engagement times.
- Rolling Averages Smoothen daily variations.

6. KPI Evaluation

- What features impact Click-Through Rate (CTR) the most?
- How does Ad Spend correlate with Revenue & Conversions?
- Are there **underperforming campaigns** with low engagement?
- Which locations, devices, or demographics perform best?
- Are there seasonal trends in ad performance?

Data Preprocessing

1. Handling Missing Values

- Fill numerical values using mean/median.
- Fill categorical values with mode or "Unknown".
- Drop columns if missing data >40%.

2. Standardization & Normalization

- Standardization (Z-score): For models sensitive to scale (e.g., regression, SVM).
- Normalization (Min-Max Scaling): For distance-based models (e.g., KNN, neural networks).

3. Encoding Categorical Variables

- One-Hot Encoding: For non-ordinal categories (device type, location).
- Label Encoding: For ordinal categories (ad ranking levels).

4. Handling Time-Series Data

- Convert timestamps to datetime format.
- Extract hour, day, week, month, season for trend analysis.
- Create lag features & moving averages for forecasting.

1. Feature Extraction (Deriving New Features)

We create additional features that provide better insights into **ad performance & user behavior**.

Engagement Metrics:

- CTR (Click-Through Rate) = (Clicks / Impressions) × 100 → Measures ad effectiveness.
- Bounce Rate = (Users leaving without action / Total users) × 100 → Identifies poor-performing ads.
- Avg. Session Duration → Helps in understanding user retention.

Financial Performance Metrics:

- ROI (Return on Investment) = (Revenue Ad Cost) / Ad Cost → Evaluates profitability.
- **CPC (Cost per Click)** = Total Ad Spend / Clicks → Helps in budget optimization.
- CAC (Customer Acquisition Cost) = Total Ad Spend / Number of Conversions.

User Behavior & Demographics:

- Engagement Time (Peak Hours, Day of Week, Seasonality) → Identifies the best times for ads.
- Location-based Conversion Rate → Helps in targeted marketing strategies.
- **Device-Based CTR** → Determines which devices perform better.

✓ Campaign Effectiveness:

- Ad Fatigue Score (CTR decay over time) → Detects if an ad is losing impact.
- Repeat User Ratio = Returning Users / Total Users → Helps in loyalty assessment.

2. Feature Selection (Choosing the Best Features)

To avoid **redundancy & improve model accuracy**, we select the most relevant features.

- Correlation Analysis:
 - Check relationships between features (remove highly correlated features).
- Variance Inflation Factor (VIF):
 - If VIF > 5, the feature may be redundant (like Total Ad Spend vs. CPC).
- Dimensionality Reduction (If Needed):
 - Apply PCA (Principal Component Analysis) if too many features cause overfitting.

1. Click-Through Rate (CTR) Prediction

Goal: Estimate how likely users are to click on an ad.

Best Model: XGBoost / LightGBM

- Handles categorical + numerical data well.
- Works great for structured ad campaign data.

2. Conversion Rate Prediction

Goal: Predict how many users will take the desired action (purchase, signup).

Best Model: Logistic Regression / Random Forest

- Logistic Regression works well if data is linear.
- Random Forest captures complex **non-linear relationships** (e.g., how age, location, device affect conversions).

3. Cost per Click (CPC) Optimization

Goal: Predict how much an advertiser will pay per click.

Best Model: Gradient Boosting (CatBoost, XGBoost)

- Handles pricing data variations well.
- Good for feature importance analysis (e.g., impact of ad type, audience demographics).

4. Return on Investment (ROI) Forecasting

Goal: Estimate campaign profitability.

Best Model: Linear Regression / ARIMA

- Linear Regression is effective for short-term ROI analysis.
- ARIMA works well for long-term trend forecasting (predicting future ROI based on past data).

5. Ad Spend Optimization

Goal: Predict the ideal budget allocation for max conversions.

Best Model: SARIMAX (for time-series) / Reinforcement Learning (RL-based budget allocation)

- SARIMAX accounts for seasonality & ad performance over time.
- Reinforcement Learning (Multi-Armed Bandit) dynamically adjusts budgets based on live performance.

6. Ad Fatigue Detection (When an ad loses effectiveness)

Goal: Identify when engagement drops over time.

Best Model: LSTM / Transformer Models

- LSTM (Long Short-Term Memory) captures how CTR changes over time.
- Transformers handle large-scale ad datasets (multi-campaign tracking).

1. Click-Through Rate (CTR) Prediction

- Metric: ROC-AUC Score (how well the model distinguishes between clicked & non-clicked ads)
- Secondary Metrics: Precision, Recall, F1-Score

2. Conversion Rate Prediction

- Metric: Precision & Recall (especially important if conversions are rare)
- F1-Score for balancing false positives & false negatives

3. Cost per Click (CPC) Optimization

 Metric: Mean Absolute Error (MAE) / Root Mean Squared Error (RMSE) (to measure pricing accuracy)

4. Return on Investment (ROI) Forecasting

- Metric: Mean Squared Error (MSE) (for predicting financial performance)
- R² Score (to check how well the model explains variance in ROI)

5. Ad Spend Optimization

- Metric: Mean Absolute Percentage Error (MAPE) (for predicting optimal spend)
- Hit Ratio (percentage of times the model correctly predicts budget allocation)

6. Ad Fatigue Detection

- Metric: Time-to-Failure (TTF) Prediction Accuracy (when engagement starts declining)
- F1-Score (to detect early signs of ad fatigue)

Validation Techniques

- ✓ Train-Test Split (80-20) General case
- ✓ Time-Based Validation For time-dependent ad data
- ✓ Cross-Validation (K-Fold / Time-Series Split) Ensures model stability

1. Model Serialization (Saving the Trained Model)

- Formats:
 - Pickle (.pkl) For traditional ML models.
 - **HDF5** (.h5) For deep learning models (TensorFlow/Keras).
 - ONNX (.onnx) For cross-framework compatibility.
- Storage Options:
 - Local Storage For initial testing.
 - Cloud Storage (AWS S3, Google Cloud Storage, Azure Blob) For scalability.

2. Containerization (Ensuring Portability)

- Docker Packages the model with all dependencies.
- Docker Compose Manages multiple services like APIs & databases.
- Kubernetes For scalable deployment across multiple instances.

3. Model Deployment (Making It Accessible)

API Deployment:

- FastAPI / Flask To expose the model via an API.
- TorchServe / TensorFlow Serving For efficient deep learning model hosting.

Cloud Deployment:

- AWS (Elastic Beanstalk, Lambda, SageMaker, EKS)
- GCP (Vertex AI, Cloud Run, Kubernetes Engine)
- Azure (ML Studio, AKS, Functions)

Edge Deployment:

TensorFlow Lite / ONNX Runtime – For mobile & IoT devices.

4. Monitoring & Logging

- Grafana + Prometheus To track model performance in production.
- MLflow For experiment tracking & model registry.
- Elastic Stack (ELK: Elasticsearch, Logstash, Kibana) For logging & visualization.

5. Version Control & Continuous Integration

- GitHub / GitLab For code & model versioning.
- DVC (Data Version Control) To track changes in datasets & models.
- CI/CD Pipelines (Jenkins, GitHub Actions, GitLab CI/CD) For automated deployment.