Unified Advertising and Analytics Platform

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Appendix -I

In the rapidly evolving landscape of digital advertising and data analytics, organization face increasing complexity in selecting, implementing, and maintaining the right algorithms across diverse use cases- from predicting ad performance to detecting fraud, personalizing recommendations, and optimizing bidding strategies. With over 200+ algorithms available which span machine learning, deep learning, optimization, natural language processing, and more; teams often struggle with consistency, transparency, and cross-functional alignment.

This Algorithm Reference Table serves as a centralized knowledge repository that bridges the gap between data science, engineering, product and business teams. it ensures the following

- Standardized Understanding: Every algorithm is clearly names, categorized by the functional group, and described in the context of real-world advertising and analytics applications.
- Informed Decision-Making: By outlining input data requirements and expected outputs with realistic examples, the table enables to assess feasibility, integrate models correctly, and align on data pipelines.
- Accelerated Development: Engineers and ML practitioners can quickly identify suitable algorithms for tasks like CTR prediction, audience segmentation, or attribution modeling. Thus, reducing redundant research and speeding up prototyping.
- Improved Collaboration: Product managers, analysts, and stakeholders gain insight into how models work and what they require, fostering better requirements gathering and system design.
- Governance and Scalability: As platforms grow, this reference supports model governance, versioning, and auditing. Thus, ensuring consistent application of algorithms across campaigns, channels, and markets.

To summarize, this reference table transforms algorithmic complexity into actionable clarity, empowering organization to build more intelligent, transparent, and effective advertising and analytics systems at scale.

Table 1: Unified Advertising and Analytics Platform: Algorithm Reference Table

Id	Functional Group	Algorithm Name	Use-case in Platform	Input Data(with Sample)	Output Data (with sample)
1	Click-Through Rate Prediction	Logistic Regression	Baseline modeling of ad click probability	{"user_age": 32, "device": "mobile", "ad_category": "fashion", "hour": 14}	0.42(probability of click)
2	Click-Through Rate Prediction	Factorization Machines (FM)	Modeling pairwise feature interactions in sparse advertising data	[1, 0, 1, ...](sparse one-hot encoded vector)	0.61(predicted CTR)
3	Click-Through Rate Prediction	Field-aware Factorization Machines (FFM)	Capturing field-level feature interactions (e.g., user × ad × context)	[(user, age, 32), (ad, category, fashion), (context, hour, 14)]	0.58(click probability)

4	Click-Through Rate Prediction	Wide & Deep Learning	Balancing memorization of rules and generalization via deep learning	wide: [user_id_123, ad_id_456], deep: [CTR_hist=0.3, time_on_site=120s]	0.73(CTR prediction)
5	Click-Through Rate Prediction	Deep Factorization Machine (DeepFM)	End-to-end CTR model combining factorization and deep network	Same as Wide & Deep	0.71(click likelihood)
6	Click-Through Rate Prediction	Compressed Interaction Network Extended (xDeepFM)	Modeling both vector-wise and bit-wise feature interactions	Embedded feature tensors	0.69(CTR score)
7	Click-Through Rate Prediction	Deep & Cross Network (DCN)	Learning explicit cross-feature interactions for ad relevance	[user_embedding, ad_embedding, context_features]	0.67(conversion prediction)
8	Click-Through Rate Prediction	Neural Factorization Machines (NFM)	Bi-linear interaction layer followed by deep network	Feature interaction tensor	0.64(CTR score)
9	Click-Through Rate Prediction	Attentional Factorization Machines (AFM)	Attention-weighted feature interactions for improved relevance	Feature pairs with attention weights	(weights: [0.8, 0.2]), score: 0.66
10	Click-Through Rate Prediction	Deep Interest Network (DIN)	Modeling user interest using attention over historical behavior	clicked_ads: [A1, A2, A3], target_ad: A4	Attention-weighted interest → 0.70
11	Click-Through Rate Prediction	Deep Interest Evolution Network (DIEN)	Modeling the evolution of user interests over time using RNN	Sequence of clicked ads over time	Dynamic interest state → 0.68
12	Click-Through Rate Prediction	Behavior Sequence Transformer (BST)	Transformer-based modeling of user behavior sequences	[Ad1, Ad2, ..., AdN](tokenized)	Contextual embedding → 0.72
13	Click-Through Rate Prediction	Feature Importance and Bilinear feature Interaction NETwork (FiBiNET)	Dynamic modeling of feature importance and interactions	User, ad, context embeddings	Feature importance + 0.65
14	Click-Through Rate Prediction	Automatic Feature Interaction (AutoInt)	Using self-attention to automatically discover feature crosses	Feature embeddings	Interaction patterns + 0.63
15	Click-Through Rate Prediction	Tabular Network (TabNet)	Sequential attention mechanism for tabular advertising data	[age=30, income=70k, device=mobile, ...]	Attention masks + 0.60
16	Recommendation	Collaborative Filtering (User-based)	Recommending ads based on behavior of similar users	user_item_matrix: U1 → [A1(1), A2(0), A3(1)]	Recommended: A4 , A5
17	Recommendation	Collaborative Filtering (Item-based)	Recommending ads similar to those previously engaged with	item_similarity: A1 ↔ A4 (0.92)	Suggested: A4

18	Recommendation	Matrix Factorization using Singular Value Decomposition (SVD)	Latent factor modeling of user-ad preferences	Sparse interaction matrix	user_vec=[0.5, -0.3], item_vec=[0.4, 0.7]
19	Recommendation	Non-negative Matrix Factorization (NMF)	Interpretable latent factor decomposition with non-negative constraints	Click count matrix	Non-negative factors → recommendations
20	Recommendation	Alternating Least Squares (ALS)	Efficient matrix factorization for implicit feedback data	(user_id, item_id, implicit_feedback)	User/item embeddings
21	Recommendation	Neural Collaborative Filtering (NCF)	Deep learning-based user-item matching	[user_embedding, item_embedding]	Preference score: 0.81
22	Recommendation	Wide & Deep Learning for Recommendations	Hybrid recommendation system combining memorization and generalization	Behavioral + contextual features	Ranked ad list
23	Recommendation	Deep Knowledge-Aware Network (DKN)	Integrating knowledge graphs into recommendation logic	News text + KG entities	Relevance score: 0.77
24	Recommendation	Multi-Layer Perceptron (MLP)	Non-linear modeling of user-ad matching	Concatenated user-ad embeddings	Engagement score: 0.74
25	Recommendation	Restricted Boltzmann Machines (RBM)	Probabilistic modeling of user preferences	Binary interaction vector	Reconstruction → recommendations
26	Recommendation	Variational Autoencoders (VAE)	Generative modeling for diverse recommendations	User behavior vector	Reconstructed preferences → A3, A6
27	Recommendation	Neural Matrix Factorization	Combining matrix factorization with deep neural networks	User and item embeddings	Predicted rating: 4.2/5
28	Recommendation	Graph Convolutional Networks (GCN)	Leveraging user-item graph structure for recommendations	(user1)-[click]->(ad2)edges	Node embeddings
29	Recommendation	PinSage	Graph convolutional network for billion-scale recommendations	Billion-node graph	Ad embeddings → recommendations
30	Recommendation	Light Graph Convolutional Network (LightGCN)	Simplified and efficient GCN for recommendations	User-item interaction graph	Recommendation scores
31	Recommendation	Session-based Recommendations using Gated Recurrent Units (GRU4Rec)	Predicting next ad in an anonymous session	[A1, A2](current session)	Predicted next: A3
32	Recommendation	Next Item Recommendation using Self-Attentive Sequential Modeling (SASRec)	Transformer-based sequential recommendation	Behavior sequence tokens	Next ad ID: A5

33	Recommendation	Multi-Armed Bandit for Recommendations	Balancing exploration and exploitation in ad selection	Click feedback on variants	Best-performing ad: A2
34	Recommendation	Contextual Bandits	Personalizing recommendations using real-time context	context: {time=20, location=NYC}	Recommended: A7
35	Recommendation	Reinforcement Learning for Recommendations	Optimizing long-term user engagement or lifetime value	(state, action, reward)	Policy: show A3
36	Search	Best Matching 25 (BM25)	Keyword-based retrieval of relevant ads or content	query: "running shoes", ad_text: "Buy lightweight running shoes"	Relevance score: 3.8
37	Search	Term Frequency-Inverse Document Frequency (TF-IDF)	Measuring keyword relevance in documents	doc1: "shoes sale", doc2: "discount shoes"	TF-IDF vector → similarity: 0.75
38	Search	PageRank	Ranking publishers or domains by authority	(page_A → page_B), (page_B → page_C)	PageRank: 0.15
39	Search	Hyperlink-Induced Topic Search (HITS)	Identifying authoritative and hub pages in a network	Web link graph	Authority: 0.21, Hub: 0.18
40	Search	Latent Semantic Indexing (LSI)	Semantic matching of queries and documents	Term-document matrix	Concept vectors → similarity
41	Search	Latent Dirichlet Allocation (LDA)	Discovering latent topics in text or user behavior	"user reads sports, tech, fashion"	Topic dist: {sports: 0.6, tech: 0.3}
42	Search	Word2Vec for Search	Generating semantic word embeddings	"shoe" → [0.82, -0.31, ...]	Similar words: sneaker, trainer
43	Search	Bidirectional Encoder Representations from Transformers for Search (BERT for Search)	Contextual understanding of search queries and ad copy	"iPhone charger fast"	Contextual embedding → match fast_charger
44	Search	Elasticsearch Scoring Algorithms	Fast retrieval and ranking of indexed documents	Indexed JSON documents	Ranked list: [ad3, ad1, ad7]
45	Search	Approximate Nearest Neighbor (ANN) Search	Fast similarity search in high-dimensional embedding space	Query embedding [0.8, -0.2, ...]	Top-5 similar ads
46	Bidding	Real-Time Bidding (RTB)	Participating in per-impression auctions programmatically	impression: {user_id=U1, site=blog.com}	Bid: $1.20
47	Bidding	Second Price Auction	Auction where winner pays second-highest bid	Bids: [A: $1.50, B: $1.20]	Winner pays: $1.21
48	Bidding	Vickrey-Clarke-Groves (VCG) Auction	Truthful auction mechanism maximizing social welfare	Bids + externality estimates	Payment: $1.10

49	Bidding	First Price Auction	Auction where winner pays their own bid	Bids: [A: $1.40, B: $1.30]	Winner pays: $1.40
50	Bidding	Dynamic Bidding	Adjusting bids in real-time based on predicted performance	predicted_CVR = 0.05	Bid: $2.10
51	Bidding	Budget Optimization using Online Packing	Allocating spend across campaigns under constraints	daily_budget=$1000, spent=$300	Allocate $150 to Campaign A
52	Bidding	Linear Programming for Budget Allocation	Optimizing budget distribution across channels	ROAS_A=4.0, ROAS_B=2.5	Budget split: 70% A, 30% B
53	Bidding	Multi-Armed Bandit Bidding	Testing and optimizing bid strategies over time	strategy_A_win_rate=0.3	Best: Strategy C
54	Bidding	Thompson Sampling for Bidding	Bayesian probabilistic bidding strategy	Posterior: mean=1.2, std=0.1	Bid: $1.25
55	Bidding	Reinforcement Learning Bidding	Learning optimal long-term bidding policies	(state: high_competition)	Action: bid $1.80
56	Optimization	Gradient Descent	Iterative optimization of model parameters	loss_gradient = 0.45	Updated weights
57	Optimization	Stochastic Gradient Descent (SGD)	Online parameter updates using mini-batches	Mini-batch gradient	Weight delta
58	Optimization	Adaptive Moment Estimation (Adam) Optimizer	Adaptive learning rate with momentum	Gradients + momentum	Parameter update
59	Optimization	Adaptive Gradient Algorithm (Adagrad)	Per-parameter adaptive learning rates	Historical gradients	Per-parameter step size
60	Optimization	Root Mean Square Propagation (RMSprop)	Adaptive learning rate stabilizing training	Squared gradients	Adaptive rate
61	Optimization	Limited-memory Broyden–Fletcher–Goldfarb–Shanno (L-BFGS)	Quasi-Newton optimization for fast convergence	Gradient history	Fast convergence
62	Optimization	Coordinate Descent	Optimizing one parameter at a time	Feature gradients	Parameter updates
63	Optimization	Genetic Algorithms	Evolutionary optimization of complex systems	[solution1, solution2]	Evolved best solution
64	Optimization	Particle Swarm Optimization	Heuristic global optimization	Candidate positions	Near-optimal config
65	Optimization	Simulated Annealing	Probabilistic technique for global optimization	Current cost: 120	New config: cost 110
66	Clustering & Segmentation	K-Means Clustering	Partitioning users into K distinct segments	[age=30, spend=50, frequency=3]	Cluster label: 2

67	Clustering & Segmentation	Hierarchical Clustering	Building nested clusters of users	Distance matrix	Dendrogram
68	Clustering & Segmentation	Density-Based Spatial Clustering of Applications with Noise (DBSCAN)	Detecting dense clusters and outliers	Feature vectors	Labels: [0, 0, -1, 1]
69	Clustering & Segmentation	Gaussian Mixture Models (GMM)	Soft probabilistic clustering	[income=60k, age=35]	Prob: {seg1: 0.7, seg2: 0.3}
70	Clustering & Segmentation	Spectral Clustering	Clustering based on graph Laplacian	Similarity matrix	Cluster assignments
71	Clustering & Segmentation	Affinity Propagation	Clustering by identifying exemplars	Similarity scores	Exemplars: U3, U7
72	Clustering & Segmentation	Mean Shift Clustering	Finding dense regions in feature space	Feature space	Mode locations
73	Clustering & Segmentation	Balanced Iterative Reducing and Clustering using Hierarchies (BIRCH)	Scalable clustering for large datasets	Data points	Incremental tree
74	Clustering & Segmentation	Ordering Points To Identify the Clustering Structure (OPTICS)	Density-based clustering with variable density	Reachability plot	Cluster ordering
75	Clustering & Segmentation	Fuzzy C-Means	Soft clustering with partial membership	Feature vector	Membership: [0.6, 0.4]
76	Anomaly Detection	Isolation Forest	Detecting anomalies by isolating data points	[click_rate=100/min, IP_count=50]	Anomaly score: 0.92
77	Anomaly Detection	One-Class Support Vector Machine (One-Class SVM)	Learning boundary of normal data	Normal traffic samples	-1(outlier)
78	Anomaly Detection	Local Outlier Factor (LOF)	Measuring local density deviation	Neighbor distances	LOF: 2.1
79	Anomaly Detection	Autoencoders for Anomaly Detection	Detecting anomalies via reconstruction error	Input: [0.1, 0.8, ...]	Error: 0.45→ anomaly
80	Anomaly Detection	Statistical Process Control	Monitoring KPIs for process stability	CTR: [0.04, 0.03, 0.12]	Alert: out of control
81	Natural Language Processing	Named Entity Recognition (NER)	Extracting named entities from text	"Buy iPhone 15 from Apple"	Entities: {iPhone 15, Apple}
82	Natural Language Processing	Sentiment Analysis	Determining emotional tone of text	"Great ad, loved it!"	Sentiment: positiv e (0.9)
83	Natural Language Processing	Topic Modeling using Latent Dirichlet Allocation (LDA)	Discovering themes in text	"user reads sports articles"	Topic: sports (0.8)

84	Natural Language Processing	Text Classification	Assigning categories to text	"This ad promotes fitness"	Category: health
85	Natural Language Processing	Intent Recognition	Inferring user intent from input	"Where to buy sneakers?"	Intent: purchase
86	Graph Algorithms	PageRank	Measuring node importance in a graph	Link graph	Score: 0.18
87	Graph Algorithms	Personalized PageRank	Ranking nodes from a user's perspective	Seed node: user_U1	Ranked nodes
88	Graph Algorithms	Random Walk with Restart	Simulating user navigation on a graph	Start node, graph	Visit probabilities
89	Graph Algorithms	Community Detection using Louvain Method	Detecting densely connected groups	Social graph	Community labels
90	Graph Algorithms	Graph Neural Networks (GNN)	Learning representations from graph-structured data	Graph + node features	Embeddings
91	Advanced Machine Learning	eXtreme Gradient Boosting (XGBoost)	High-performance gradient boosting	[feature1=0.5, feature2=1.2]	Prediction: 0.76
92	Advanced Machine Learning	Light Gradient Boosting Machine (LightGBM)	Fast and memory-efficient boosting	Large tabular data	Score: 0.74
93	Advanced Machine Learning	Categorical Boosting (CatBoost)	Gradient boosting with native categorical support	category="mobile"	Prediction: 0.70
94	Advanced Machine Learning	Random Forest	Ensemble of decision trees	Feature vector	Class prob: [0.7, 0.3]
95	Advanced Machine Learning	Support Vector Machines (SVM)	Maximum-margin classification	Text TF-IDF vector	Label: spam
96	Advanced Machine Learning	Naive Bayes	Probabilistic classifier based on Bayes' theorem	Word counts	P(click)=0.6
97	Advanced Machine Learning	Decision Trees	Tree-based interpretable models	[age>25, income>50k]	Rule path → click

98	Advanced Machine Learning	Ensemble Methods	Combining multiple models for robustness	Model outputs	Averaged prediction
99	Advanced Machine Learning	Transfer Learning	Applying knowledge from one domain to another	Pretrained BERT + ad data	Fine-tuned model
100	Advanced Machine Learning	Federated Learning	Training models across decentralized devices	Local gradients	Aggregated update
101	Additional Deep Learning Architectures	Transformer Networks	Attention-based sequence modeling	[Ad1, Ad2, Ad3]	Contextual embeddings
102	Additional Deep Learning Architectures	Bidirectional Encoder Representations from Transformers (BERT)	Deep contextual language model	"Click here for deal"	Embedding: [0.2, -0.4, ...]
103	Additional Deep Learning Architectures	Generative Pre-trained Transformer-style Models (GPT-style Models)	Text generation for creatives	Prompt: "Write a headline"	"Get 50% Off Today!"
104	Additional Deep Learning Architectures	Recurrent Neural Networks (RNN)	Modeling sequential data	[click, view, exit]	Hidden state
105	Additional Deep Learning Architectures	Long Short-Term Memory (LSTM)	RNN variant for long-term dependencies	Behavior sequence	Prediction: convert
106	Additional Deep Learning Architectures	Gated Recurrent Units (GRU)	Lightweight RNN architecture	Sequential data	Output: 0.68
107	Additional Deep Learning Architectures	Convolutional Neural Networks (CNN)	Image feature extraction	Image pixels (224x224)	Feature map
108	Additional Deep Learning Architectures	Residual Network (ResNet)	Deep CNN with skip connections	Ad image	Class: electronics
109	Additional Deep Learning Architectures	Densely Connected Convolutional Network (DenseNet)	Dense feature reuse in CNNs	Image	Embedding vector

110	Additional Deep Learning Architectures	Attention Mechanisms	Focusing on relevant inputs	Sequence of embeddings	Weighted context
111	Additional Deep Learning Architectures	Self-Attention	Internal attention within sequences	Token embeddings	Context-aware output
112	Additional Deep Learning Architectures	Multi-Head Attention	Multiple parallel attention heads	Embedded sequence	Rich representation
113	Additional Deep Learning Architectures	Capsule Networks	Preserving spatial hierarchies in images	Image	Pose + activation
114	Additional Deep Learning Architectures	Autoencoders	Unsupervised learning via reconstruction	Input vector	Reconstructed output
115	Additional Deep Learning Architectures	Variational Autoencoders (VAE)	Generative modeling with latent variables	Latent vector	Generated sample
116	Reinforcement Learning Algorithms	Q-Learning	Model-free reinforcement learning	(state, action, reward)	Q-table update
117	Reinforcement Learning Algorithms	Deep Q-Network (DQN)	Deep neural network for Q-learning	State embedding	Action: bid_high
118	Reinforcement Learning Algorithms	Actor-Critic Methods	Combining policy and value networks	State, reward	Policy update
119	Reinforcement Learning Algorithms	Advantage Actor-Critic (A2C)	Synchronous policy gradient method	Environment feedback	Gradient update
120	Reinforcement Learning Algorithms	Asynchronous Advantage Actor-Critic (A3C)	Parallelized A2C with multiple agents	Multiple environments	Faster learning
121	Reinforcement Learning Algorithms	Proximal Policy Optimization (PPO)	Stable policy optimization algorithm	Trajectories, advantages	Improved policy

122	Reinforcement Learning Algorithms	Deep Deterministic Policy Gradient (DDPG)	Actor-critic for continuous control	State: spend=80%	Action: bid=$1.60
123	Reinforcement Learning Algorithms	Twin Delayed Deep Deterministic Policy Gradient (TD3)	Improved DDPG with delayed updates	State-action pairs	Stable bid policy
124	Reinforcement Learning Algorithms	Soft Actor-Critic (SAC)	Maximum entropy reinforcement learning	Environment	Exploratory policy
125	Reinforcement Learning Algorithms	Multi-Agent Reinforcement Learning (MARL)	Modeling multiple competing agents	Multi-agent states	Competitive policy
126	Time Series & Sequential Algorithms	AutoRegressive Integrated Moving Average (ARIMA)	Forecasting time-series KPIs	[spend_day1=100, ...]	Predict: spend_day 8=120
127	Time Series & Sequential Algorithms	Prophet	Robust forecasting with trend and seasonality	Daily impressions	Forecast with trend
128	Time Series & Sequential Algorithms	Exponential Smoothing	Simple time-series forecasting	[CTR: 0.04, 0.05, 0.03]	Predicted: 0.042
129	Time Series & Sequential Algorithms	Seasonal Decomposition of Time Series	Breaking down trend, seasonality, residual	Monthly data	Three components
130	Time Series & Sequential Algorithms	Long Short-Term Memory (LSTM) for Time Series	Predicting future metrics from sequences	Sequential CTR	Forecast: 0.048
131	Time Series & Sequential Algorithms	Temporal Convolutional Networks (TCN)	Causal convolutions for sequence modeling	Time-series input	Future prediction
132	Time Series & Sequential Algorithms	State Space Models	Modeling latent system dynamics	Observations	Hidden state estimate
133	Time Series & Sequential Algorithms	Kalman Filters	Estimating true state from noisy data	Noisy metric stream	Estimated true value

134	Time Series & Sequential Algorithms	Hidden Markov Models (HMM)	Inferring hidden states from observations	Click sequence	Most likely state path
135	Time Series & Sequential Algorithms	Dynamic Time Warping (DTW)	Measuring similarity between sequences	[A,B,C] vs [A,C,D]	Distance: 1.8
136	Dimensionality Reduction	Principal Component Analysis (PCA)	Reducing feature dimensions	High-dim feature vector	2D projection
137	Dimensionality Reduction	t-Distributed Stochastic Neighbor Embedding (t-SNE)	Visualizing high-dimensional data	Feature matrix	2D plot coordinates
138	Dimensionality Reduction	Uniform Manifold Approximation and Projection (UMAP)	Preserving global and local structure	Embeddings	Low-dim map
139	Dimensionality Reduction	Independent Component Analysis (ICA)	Separating mixed signals	Mixed audio-like data	Independent components
140	Dimensionality Reduction	Linear Discriminant Analysis (LDA)	Supervised dimensionality reduction	Labeled features	Discriminative axes
141	Dimensionality Reduction	Canonical Correlation Analysis (CCA)	Finding correlations between sets	User & ad features	Correlated dimensions
142	Dimensionality Reduction	Multidimensional Scaling (MDS)	Visualizing similarity as spatial layout	Distance matrix	Spatial layout
143	Dimensionality Reduction	Random Projection	Fast dimensionality reduction	High-dim vector	Compressed vector
144	Dimensionality Reduction	Feature Selection Algorithms	Selecting most relevant features	Dataset with labels	Selected: [age, income]
145	Dimensionality Reduction	Recursive Feature Elimination	Iteratively removing weak features	Model performance	Final feature set
146	Bandit Algorithms	Epsilon-Greedy	Simple exploration-exploitation strategy	Reward history	Action: explore (ε=0.1)
147	Bandit Algorithms	Upper Confidence Bound (UCB)	Optimistic exploration based on confidence	Reward stats	Action with highest UCB
148	Bandit Algorithms	Thompson Sampling	Bayesian probabilistic exploration	Beta distribution	Sampled action
149	Bandit Algorithms	Linear Upper Confidence Bound (LinUCB)	Contextual bandit with linear rewards	Context + reward	Best action
150	Bandit Algorithms	Contextual Bandits	Decision-making based on context	Context features	Recommended ad

151	Bandit Algorithms	Multi-Armed Bandits	Optimizing single decisions under uncertainty	Arm rewards	Best arm
152	Bandit Algorithms	Dueling Bandits	Comparing two options directly	Preference feedback	Winner: A
153	Bandit Algorithms	Combinatorial Bandits	Selecting combinations of arms	Joint rewards	Best combo
154	Bandit Algorithms	Bayesian Bandits	Incorporating prior beliefs	Prior + data	Posterior decision
155	Bandit Algorithms	Adversarial Bandits	Handling worst-case environments	Reward sequence	Robust action
156	Attribution Modeling	Last Click Attribution	Assigning full credit to last touchpoint	Journey: [A→B→C]	C: 100% credit
157	Attribution Modeling	First Click Attribution	Assigning full credit to first touchpoint	Same journey	A: 100% credit
158	Attribution Modeling	Linear Attribution	Equal credit across all touchpoints	3 touches	Each: 33.3%
159	Attribution Modeling	Time Decay Attribution	Weighting recent touches more heavily	Timestamped path	Recent: higher weight
160	Attribution Modeling	Position-Based Attribution	40-20-40 rule (first/middle/last)	3-touch path	First: 40%, Last: 40%
161	Attribution Modeling	Data-Driven Attribution	Machine learning-based credit assignment	Full journey data	Fair allocation
162	Attribution Modeling	Shapley Value Attribution	Game-theoretic fair credit allocation	All subsets	Marginal contribution
163	Attribution Modeling	Markov Chain Attribution	Modeling customer journey as state transitions	Transition matrix	Removal impact
164	Attribution Modeling	Removal Effect Attribution	Measuring impact of removing a channel	Simulate removal	Drop: 15% conversions
165	Attribution Modeling	Algorithmic Attribution	Combining multiple attribution models	Multiple inputs	Holistic credit
166	Fraud Detection	Isolation Forest	Detecting bot traffic and fraudulent impressions	[bot_score=0.95, speed=200/sec]	Anomaly: True
167	Fraud Detection	One-Class Support Vector Machine (One-Class SVM)	Learning normal traffic patterns	Normal samples	-1(outlier)
168	Fraud Detection	Local Outlier Factor (LOF)	Detecting local density anomalies	Neighbor analysis	LOF > 1 → outlier

169	Fraud Detection	Elliptic Envelope	Robust covariance estimation for outlier detection	Multivariate features	Outlier flag
170	Fraud Detection	Mahalanobis Distance	Measuring multivariate distance from center	Feature vector, mean, covariance	Distance: 4.2
171	Fraud Detection	Benford's Law Analysis	Detecting fabricated numerical data	Spend logs	Digit deviation
172	Fraud Detection	Statistical Anomaly Detection	Threshold-based outlier detection	CTR history	Alert if > 3σ
173	Fraud Detection	Ensemble Fraud Detection	Combining multiple fraud models	Model outputs	Final fraud score
174	Fraud Detection	Graph-based Fraud Detection	Detecting coordinated fake accounts	User interaction graph	Suspicious group
175	Fraud Detection	Behavioral Biometrics	Analyzing human interaction patterns	Mouse movement, taps	Classification: hum an
176	Optimization & Operations Research	Linear Programming	Optimizing linear objectives under constraints	Constraints, objectives	Optimal spend plan
177	Optimization & Operations Research	Integer Programming	Solving optimization with integer variables	Binary variables	Campaign selection
178	Optimization & Operations Research	Mixed-Integer Programming	Combining continuous and discrete decisions	Mixed variables	Optimal config
179	Optimization & Operations Research	Quadratic Programming	Optimizing quadratic objectives	Quadratic objective	Balanced spend
180	Optimization & Operations Research	Convex Optimization	Finding global optimum in convex problems	Convex function	Global solution
181	Optimization & Operations Research	Genetic Algorithms	Evolutionary search for optimal solutions	Population	Best setup
182	Optimization & Operations Research	Particle Swarm Optimization	Swarm-based heuristic optimization	Particles	Near-optimal

183	Optimization & Operations Research	Ant Colony Optimization	Pathfinding inspired by ant behavior	Graph	Optimal path
184	Optimization & Operations Research	Simulated Annealing	Probabilistic global optimization	Current solution	Improved config
185	Optimization & Operations Research	Tabu Search	Metaheuristic avoiding revisited solutions	Memory of moves	Better solution
186	Advanced Recommendation Techniques	Neural Graph Collaborative Filtering (NGCF)	GCN-based recommendation system	User-item graph	Recommendation score
187	Advanced Recommendation Techniques	Multi-Task Learning for Recommendations	Sharing knowledge across tasks	Multiple labels	Joint predictions
188	Advanced Recommendation Techniques	Cross-Domain Recommendations	Transferring preferences across domains	Source domain data	Target recs
189	Advanced Recommendation Techniques	Knowledge Graph Embeddings	Representing entities and relations	KG triples (head, rel, tail)	Entity embeddings
190	Advanced Recommendation Techniques	Entity Embeddings	Converting categories to dense vectors	Categorical IDs	Dense embeddings
191	Advanced Recommendation Techniques	Multi-View Learning	Learning from multiple data sources	Web, app, CRM data	Unified user profile
192	Advanced Recommendation Techniques	Adversarial Training for Recommendations	Improving model robustness	Perturbed inputs	Robust model
193	Advanced Recommendation Techniques	Contrastive Learning	Learning representations via contrast	Positive/negative pairs	Discriminative embeddings
194	Advanced Recommendation Techniques	Self-Supervised Learning	Learning without labeled data	Raw behavior logs	Pretrained model

195	Advanced Recommendation Techniques	Meta-Learning for Recommendations	Fast adaptation to new users/items	Few-shot data	Rapid personalization
196	Computer Vision Algorithms	You Only Look Once (YOLO)	Real-time object detection in images	Ad image	Bounding box + label
197	Computer Vision Algorithms	Image Classification using ResNet or VGG	Classifying visual content	Image pixels	Label: electronics
198	Computer Vision Algorithms	Image Segmentation	Identifying pixel-level object regions	Image	Pixel mask
199	Computer Vision Algorithms	Optical Character Recognition (OCR)	Extracting text from images	Image with text	"Sale: 50% Off"
200	Computer Vision Algorithms	Visual Similarity Search	Finding visually similar creatives	Image embedding	Similar ads: [A3, A7]
201	Computer Vision Algorithms	Siamese Networks	Measuring similarity between two images	Image pair	Similarity: 0.88
202	Computer Vision Algorithms	Triplet Loss Networks	Learning embeddings via triplets	Anchor, positive, negative	Distance: 0.3
203	Computer Vision Algorithms	Style Transfer	Transferring artistic style between images	Style + content image	Styled output image
204	Computer Vision Algorithms	Image Generation using Generative Adversarial Networks (GANs)	Generating synthetic ad creatives	Noise vector	Synthetic image
205	Computer Vision Algorithms	Visual Attention Models	Predicting where users look in an image	Image + model	Heatmap of attention
206	Additional Specialized Algorithms	Monte Carlo Methods	Simulating probabilistic outcomes	Probabilistic model	Expected ROAS: 3.2
207	Additional Specialized Algorithms	Markov Chain Monte Carlo (MCMC)	Sampling from complex posterior distributions	Prior + data	Posterior samples
208	Additional Specialized Algorithms	Bayesian Networks	Probabilistic graphical models	Conditional probability tables	Inference result
209	Additional Specialized Algorithms	Gaussian Processes	Non-parametric Bayesian regression	Training data	Mean ± Variance

210	Additional Specialized Algorithms	Survival Analysis	Modeling time-to-event (e.g., churn)	Time, event flag	Hazard function
211	Additional Specialized Algorithms	A/B Testing Algorithms	Comparing two variants statistically	Control vs treatment	p-value: 0.03, lift: +12%
212	Additional Specialized Algorithms	Multi-Variate Testing	Testing multiple variables simultaneously	Factorial design	Best combo: A+B+D
213	Additional Specialized Algorithms	Sequential Testing	Early stopping in experiments	Interim results	Stop: significant
214	Additional Specialized Algorithms	Causal Inference Algorithms	Estimating causal effects from data	Observational data	ATE: +0.08
215	Additional Specialized Algorithms	Counterfactual Estimation	Predicting outcomes under interventions	Observed data	Outcome if no ad: 0.1
216	Additional Specialized Algorithms	Uplift Modeling	Identifying persuadable users	Treatment response	Uplift: +0.15
217	Additional Specialized Algorithms	Incremental Response Modeling	Measuring true ad-induced lift	Campaign data	Lift: +20%
218	Additional Specialized Algorithms	Churn Prediction Algorithms	Predicting user attrition	Behavior features	Churn prob: 0.78
219	Additional Specialized Algorithms	Lifetime Value Modeling	Predicting future user revenue	History: spend, frequency	LTV: $120
220	Additional Specialized Algorithms	Cohort Analysis Algorithms	Analyzing user groups over time	Signup date, behavior	Retention: D7=45%