# Urban Transfer Learning: A Comprehensive Market and Technical Analysis of Cross-Domain Urban Intelligence

## Executive Summary

The modernization of global urban infrastructure continues to accelerate, driven by the imperative to create "Smart Cities" capable of optimizing complex systems ranging from transportation grids and energy distribution networks to public health monitoring and environmental protection. However, the deployment of Artificial Intelligence (AI) in urban environments faces a critical bottleneck: the "Urban Data Divide." While mature smart cities such as Beijing, New York, and London possess petabytes of historical data spanning decades of sensor readings, emerging cities—particularly in the developing world or newly planned zones—suffer from acute data scarcity. This scarcity renders traditional, data-hungry Deep Learning models ineffective, creating a "cold start" problem that threatens to stall global smart city adoption.

To bridge this gap, academia and industry have coalesced around a sophisticated paradigm known as **Urban Transfer Learning (UTL)**. UTL is a methodology designed to extract domain-invariant knowledge—universal laws of human mobility, traffic physics, and environmental dynamics—from data-rich "source" cities and transfer this intelligence to data-poor "target" cities. This report provides an exhaustive analysis of the UTL landscape, detailing the evolution from simple parameter fine-tuning to advanced Spatio-Temporal Graph Neural Networks (ST-GNNs), Adversarial Domain Adaptation, and Federated Transfer Learning (FTL).

The analysis reveals a bifurcated market. On the theoretical front, research has moved toward "structure-aware" transfer, utilizing graph-based techniques to account for the topological differences between road networks (e.g., grid vs. radial layouts) to mitigate "Negative Transfer." On the industrial front, giants such as DiDi Chuxing, Uber, JD iCity, Google, and Baidu have operationalized these techniques into proprietary platforms like "Michelangelo" and "Urban Computing Brains," allowing them to launch optimized services in new markets with near-zero historical data.

Furthermore, the report identifies a pivotal shift on the horizon: the transition from task-specific transfer learning to **Urban Foundation Models (UFMs)**. Driven by the Generative AI revolution, these large-scale, pre-trained models promise a future where urban intelligence is generalized rather than transferred, potentially solving the scalability crisis of current smart city deployments.

## 1. Introduction: The Urban Data Paradox

### 1.1 The Smart City Promise and the Data Scarcity Reality

The concept of the "Smart City" is predicated on the continuous feedback loop of sensing, analyzing, and acting. In an ideal scenario, a city is carpeted with sensors—inductive loop detectors for traffic, LiDAR for topography, electrochemical sensors for air quality, and ubiquitous GPS probes for human mobility. These data streams feed into Deep Learning models that predict traffic congestion, optimize energy usage, and manage public safety in real-time.

However, the reality of global urbanization is characterized by extreme heterogeneity in digital maturity.

* **Data-Rich "Source" Domains:** Tier-1 cities (e.g., Shanghai, New York City) have mature infrastructure. For instance, New York City has years of taxi trajectory data and comprehensive air quality monitoring stations. Beijing’s traffic monitoring systems capture flow rates at thousands of intersections every minute.1
* **Data-Scarce "Target" Domains:** Conversely, the vast majority of cities, especially in developing regions or newly constructed "new areas" (e.g., China’s Xiong’an New Area), lack this historical depth. They may have limited sensor coverage, short data accumulation periods (e.g., only a few months), or lack labeled data entirely (e.g., raw GPS points without "congestion" labels).3

This disparity creates a fundamental failure mode for standard Machine Learning (ML). Traditional ML algorithms operate under the **i.i.d. assumption**: that training and testing data are independent and identically distributed. When a model trained on the dense, grid-like streets of Manhattan is applied to the winding, organic layout of Rome or a new city with sparse data, the distribution shift leads to catastrophic performance degradation. The model fails to generalize because it has overfit to the specific spatial topology and temporal patterns of the source city.

### 1.2 Defining the Paradigm: Urban Transfer Learning

**Urban Transfer Learning (UTL)** emerges as the necessary solution to this "Cold Start" problem. It is defined as the process of leveraging knowledge from a source domain $ D\_S $ (a mature city with abundant data) to improve the learning of a predictive function in a target domain $ D\_T $ (a new or data-scarce city) where $ D\_S \neq D\_T $ or the learning tasks $ T\_S \neq T\_T $.4

The objective is not merely to copy data but to extract **invariant patterns**.

* *Temporal Invariants:* Commuting patterns often follow similar diurnal cycles (morning/evening peaks) regardless of the city.
* *Spatial Invariants:* Commercial districts tend to attract inflow during the day and outflow at night; residential areas exhibit the inverse.
* *Physical Invariants:* The fundamental relationship between traffic density and flow speed (the fundamental diagram of traffic flow) remains consistent due to physics, even if the road geometry changes.5

By encoding these invariants, UTL allows models to "hallucinate" missing data or "warm start" predictions in the target city, significantly accelerating the deployment of smart city applications.

### 1.3 Scope and Structure of Analysis

This report dissects the UTL ecosystem through multiple lenses:

* **Theoretical Frameworks:** Examining the mathematical underpinnings of domain adaptation, from instance weighting to adversarial feature alignment.
* **Algorithmic Architectures:** Detailing the specific neural network structures (CNNs, RNNs, GNNs) used to encode urban dynamics.
* **Industry Implementation:** analyzing how companies like DiDi, Uber, and Google leverage UTL for competitive advantage.
* **Critical Challenges:** Addressing Negative Transfer, Privacy, and Data Heterogeneity.
* **Future Trajectories:** Exploring the rise of Foundation Models and Digital Twins.

## 2. Theoretical Frameworks and Methodological Paradigms

The implementation of UTL is not a monolithic process but a spectrum of methodologies tailored to the specific nature of the data and the severity of the scarcity. The literature broadly categorizes UTL approaches into a three-step framework: **Source Domain Identification**, **Source-Target Domain Linking**, and **Target Domain Refining**.4

### 2.1 The General Process Framework

#### 2.1.1 Source Domain Identification

The first step is critical: selecting the right "teacher." Not all data-rich cities are suitable sources for every target. Transferring traffic patterns from a coastal tourist city (e.g., Miami) to an inland industrial hub (e.g., Detroit) may introduce bias. Techniques involve calculating similarity metrics based on static city attributes (population density, road network topology, GDP) or dynamic signatures (mobility rhythms) to select the optimal source.4

#### 2.1.2 Source-Target Domain Linking

Once a source is identified, the system must establish a bridge. This is the core technical challenge, as direct feature matching is often impossible due to differing spatial granularities (e.g., $1km \times 1km$ grids vs. census tracts) or sensor modalities. Linking strategies include:

* **Region Matching:** Identifying semantic counterparts (e.g., matching the "Times Square" of City A to the "Central Business District" of City B).7
* **Common Subspace Learning:** Projecting the diverse data from both cities into a shared, lower-dimensional latent space where their distributions are aligned.2

#### 2.1.3 Target Domain Refining

The transferred model is rarely perfect out-of-the-box. Refining involves "Fine-Tuning" the model using the limited ground-truth data available in the target city. This step adjusts the high-level weights of the neural network to accommodate local idiosyncrasies (e.g., specific road closures or local holidays) while retaining the broad structural knowledge learned from the source.8

### 2.2 Taxonomy of Transfer Approaches

#### 2.2.1 Instance-Based Transfer

This method assumes that certain *parts* of the source data are directly relevant to the target. It involves re-weighting source samples to match the target distribution. For example, to predict traffic during a storm in a new city, the algorithm might assign high weights to historical data from stormy days in the source city and zero weight to sunny days. While conceptually simple, this is computationally expensive in urban contexts due to the massive volume of spatio-temporal data and is often insufficient for addressing deep structural differences.9

#### 2.2.2 Feature-Based Transfer (Representation Learning)

This is the dominant paradigm in modern UTL. It aims to learn a "common feature representation" that is invariant across domains.

* **FLORAL (Flexible Multi-modal Transfer):** Proposed by Microsoft Research, FLORAL addresses the challenge where the source and target cities have different *sets* of data modalities. It utilizes a dictionary learning approach to learn correlations between modalities (e.g., Traffic, POIs, Weather) in the source city. It then transfers these correlations to the target city, allowing the target to infer missing modalities (e.g., inferring air quality from traffic data alone).2
* **Adversarial Domain Adaptation:** Inspired by GANs, this method uses a "Domain Discriminator" network that tries to guess which city a feature vector comes from. The "Feature Generator" network tries to fool the discriminator. When the discriminator can no longer distinguish between the source and target features, the representation is considered "domain-invariant".10

#### 2.2.3 Parameter-Based Transfer

This involves pre-training a deep neural network on the source domain and transferring the weights to the target domain.

* **RegionTrans:** A seminal model that combines parameter transfer with region matching. It pre-trains a Convolutional Neural Network (CNN) on the source city's spatio-temporal heatmap. However, instead of applying the model globally, it selectively transfers weights between matched regions, ensuring that the local spatial context is respected.7
* **Meta-Learning (MetaST):** Moving beyond simple weight transfer, MetaST uses meta-learning to find an optimal *initialization* for the network. It trains on tasks from multiple cities to find a set of initial parameters that are "highly adaptable"—meaning they can be fine-tuned to a new city with very few gradient descent steps. This effectively targets the "Few-Shot" learning scenario common in new smart city deployments.12

#### 2.2.4 Relational and Graph-Based Transfer

Urban environments are networks, not grids. Relational transfer focuses on transferring the *structure* of interactions.

* **Spatial Homogeneity-Aware Transfer (SHTL):** This framework posits that transfer is only valid if the underlying road network topologies are similar. It uses link prediction to map the connectivity patterns of road networks. It calculates a "Spatial Homogeneity" score (using the F1 score of link prediction) and only permits transfer between regions with high topological similarity, thereby preventing negative transfer caused by structural mismatches.8

## 3. Deep Dive: Algorithmic Architectures and Mechanisms

The efficacy of UTL relies on the underlying neural architectures that encode the complex spatio-temporal dynamics of cities.

### 3.1 Spatio-Temporal Graph Neural Networks (ST-GNNs)

Early urban computing models treated cities as images (using CNNs on grid maps). However, road networks are non-Euclidean graphs. ST-GNNs have become the state-of-the-art for urban modeling.

* **Graph Convolution:** Captures spatial dependencies by aggregating information from connected nodes (intersections) rather than spatially adjacent pixels.
* **Transfer Mechanism:** In UTL, the graph structure (Adjacency Matrix $A$) differs between cities. Therefore, standard GNNs cannot be directly transferred. Solutions include **ST-DAAN (Deep Attentive Adaptation Network)**, which incorporates a global attention mechanism to capture broader spatial dependencies that are independent of the specific graph topology. It also employs a domain adaptation layer that minimizes the **Maximum Mean Discrepancy (MMD)** between the source and target feature distributions, forcing the GNN to learn topology-invariant traffic rules.14

### 3.2 The RegionTrans Architecture

**RegionTrans** represents a benchmark in the field, specifically addressing the "Spatio-Temporal Discrepancy."

1. **Decomposition:** It divides both source and target cities into grid-based regions.
2. **Matching Function:** It employs a matching algorithm to pair regions. This is not merely geographic; it uses **Pearson Correlation Coefficient** on short-term data (e.g., matching a region with an early-morning peak in City A to a similar region in City B) or latent feature similarity.15
3. **Optimization:** The training objective minimizes the prediction error in the target region while regularizing the model parameters to remain close to the parameters of the matched source region. This "constrained fine-tuning" prevents the model from overfitting to the sparse target data.7

### 3.3 Prompt Learning and Pre-training (PromptST)

Adapting the "Prompting" paradigm from Natural Language Processing (NLP), **PromptST** represents the cutting edge. Instead of retraining the model, it freezes a pre-trained spatio-temporal model and learns a lightweight "prompt" (a set of learnable vectors prepended to the input). This prompt guides the pre-trained model to adapt its behavior to the target city's context. This approach drastically reduces the computational cost of adaptation, as only the small prompt parameters are updated, not the entire massive network.12

## 4. Industry Landscape and Implementation Case Studies

The commercial application of UTL is dominated by technology giants that possess the "Source Data"—the massive historical logs of user mobility.

### 4.1 Ride-Hailing and Mobility: DiDi Chuxing and Uber

#### 4.1.1 DiDi Chuxing: The "Gaia" Ecosystem and Dispatch Optimization

DiDi Chuxing, one of the world's largest mobility platforms, faces the challenge of rapidly expanding into new cities where it has zero historical data.

* **Order Dispatching:** DiDi frames dispatching as a semi-Markov Decision Process (SMDP) solved via Deep Reinforcement Learning (DRL). A key challenge is that training a DRL agent from scratch takes weeks of trial-and-error (interaction data).
* **Transfer Strategy:** DiDi employs transfer learning to initialize the Value Function ($V$) and Policy Network ($\pi$) of the agent in a new city using the learned policies from a mature city (e.g., Beijing). This allows the agent to make near-optimal dispatch decisions from Day 1.
* **Gaia Open Dataset:** To fuel research, DiDi released the "Gaia" dataset, providing high-resolution trajectory data from cities like Xi'an and Chengdu. This dataset has become the de facto standard for benchmarking academic UTL algorithms.16

#### 4.1.2 Uber: Michelangelo and POET

Uber's AI platform, **Michelangelo**, facilitates the lifecycle of ML models at scale.

* **Feature Stores and Transfer:** Michelangelo utilizes a centralized feature store where features engineered for one market (e.g., "average traffic speed at 5 PM") can be reused across models for different cities.
* **POET (Paired Open-Ended Trailblazer):** While primarily a research project, POET demonstrates Uber's focus on "Diversity-Driven" learning. It generates a diverse set of simulated environments (representing different urban topologies and traffic conditions) to train agents that are robust to environmental shifts. This simulation-to-reality transfer is crucial for their autonomous driving and fleet management systems.18

### 4.2 Urban Governance and Infrastructure: Baidu, Google, JD

#### 4.2.1 Google: Project Green Light and Congestion Functions

Google leverages its ubiquitous Google Maps data to perform UTL without installing new hardware.

* **Project Green Light:** This initiative uses AI to optimize traffic signal timing. By modeling traffic flow dynamics from millions of android devices (Source Data), Google infers the optimal signal patterns for specific intersections (Target) and provides recommendations to city engineers. The "transfer" here is the application of general traffic flow models to specific, un-instrumented intersections.20
* **Congestion Functions:** Google Research has developed methods to learn "segment-level congestion functions" (relationship between volume and speed). By transferring these functions from data-rich cities like Los Angeles, they can accurately estimate congestion in cities like Munich or Dubai where ground-truth volume data is sparse.5

#### 4.2.2 Baidu: From Autonomous Driving to Smart Cities

Baidu utilizes its **Apollo** autonomous driving fleet and **Baidu Maps** user data.

* **V2X Transfer:** Knowledge learned from the high-fidelity sensors of autonomous vehicles is transferred to road-side infrastructure units (RSUs) to improve traffic perception in smart cities.
* **Crowd Safety:** Following the 2014 Shanghai Stampede, Baidu developed crowd prediction models. Using UTL, they transfer crowd anomaly patterns learned from major transport hubs to predict dangerous densities in other public spaces, providing early warnings to authorities.4
* **Building Height Estimation:** Baidu uses street-view imagery to estimate building heights for 3D city modeling. A model trained on cities with LIDAR ground truth is transferred to cities where only street-view images are available, utilizing domain adaptation to handle differences in architectural styles.23

#### 4.2.3 JD iCity: The "City Operating System"

JD Technology (JD.com) focuses on the "Urban Computing" layer for government clients.

* **Federated Learning for Governance:** JD iCity addresses the problem of data silos *within* a city (e.g., the transport department won't share data with the environmental department). They deploy Federated Learning systems that allow models to be trained across these silos (transferring gradients, not data), enabling holistic urban management.24

### 4.3 Microsoft Research: The Pioneers

Microsoft Research Asia (MSRA), particularly under the leadership of Dr. Yu Zheng (now at JD), pioneered the field.

* **Urban Air:** They demonstrated the first successful cross-city transfer for air quality, using **FLORAL** to infer pollution levels in cities without stations by transferring the "Meteorology-Traffic-AirQuality" correlation structure from Beijing.2
* **Noise Prediction:** Similar techniques were applied to noise pollution, inferring city-wide noise maps from sparse user-collected samples.2

## 5. Advanced Applications: Beyond Traffic Prediction

While transportation is the beachhead market, UTL is expanding into diverse urban verticals.

### 5.1 Environmental Intelligence

* **Air Quality Inference:** In developing nations, reference-grade air quality stations are prohibitively expensive. UTL allows for the deployment of "Virtual Stations." By transferring the complex non-linear relationships between low-cost proxies (traffic density, weather, POI density) and pollutant levels learned in a sensor-rich city, accurate air quality maps can be generated for sensor-poor cities.2
* **Noise Modeling:** Similar to air quality, noise pollution follows land-use patterns. UTL transfers acoustic models from mapped cities to unmapped ones, aiding in urban planning and health impact assessments.28

### 5.2 Commercial Intelligence and Site Selection

* **CityTransfer:** For retail chains (e.g., Starbucks, McDonald's), entering a new city involves high risk in site selection. **CityTransfer** is a specialized UTL application that recommends optimal store locations. It learns the "latent success factors" (e.g., the optimal mix of residential density, competitor distance, and transit accessibility) from established markets and transfers this logic to the new city, adjusting for local purchasing power and density baselines.4

### 5.3 Public Safety and Crisis Response

* **Pandemic Mobility Modeling:** During the COVID-19 pandemic, historical mobility data became irrelevant due to lockdowns. UTL allowed researchers to transfer "Lockdown Mobility Models" from regions that were hit early (e.g., Wuhan, Italy) to regions entering the early phases of the outbreak. This allowed for better prediction of virus spread and the effectiveness of containment measures in the absence of local precedent.29

## 6. The Privacy Frontier: Federated Transfer Learning

A critical barrier to UTL is data privacy. Cities are distinct legal jurisdictions, and transferring raw data (e.g., citizen trajectories) across borders often violates regulations like GDPR or local data sovereignty laws.

### 6.1 The Need for Federated Architectures

**Federated Learning (FL)** allows model training without centralizing data. In the context of UTL, this evolves into **Federated Transfer Learning (FTL)**.

* **Horizontal FTL:** When the source and target cities have the same feature space (e.g., both have loop detectors) but different user samples.
* **Vertical FTL:** When the two domains share user samples (e.g., the same users appearing in a telecom dataset and a ride-hailing dataset) but have different feature spaces.

### 6.2 Cross-City Federated Transfer Learning (CcFTL)

**CcFTL** is a specific framework designed for urban region profiling. It enables a target city to learn region embeddings (e.g., characterizing a region as "commercial" or "residential") by leveraging a source city's model.

* **Mechanism:** It uses **Homomorphic Encryption** to share model updates (gradients) securely. The source city sends encrypted knowledge to the target, which integrates it into its local training loop.
* **Application:** This has been applied to predict mobile traffic usage and profiling urban functions, demonstrating that privacy-preserving transfer can achieve performance comparable to centralized training.25

### 6.3 Security Risks: Poisoning and Robustness

While FTL protects privacy, it introduces security risks.

* **Poisoning Attacks:** A malicious actor (or a compromised edge device in a city) could inject "poisoned" data into the local training process to corrupt the global transferred model.
* **Defenses:** Research focuses on "Byzantine-robust" aggregation algorithms that can detect and discard statistical outliers in the gradient updates, ensuring the transferred knowledge remains pure.32

## 7. Critical Challenges and Mitigation Strategies

### 7.1 The Specter of Negative Transfer

**Negative Transfer** occurs when the transferred knowledge hurts the target domain's performance. In urban contexts, this is often due to **Topological Mismatch**.

* **Scenario:** Transferring a traffic prediction model from Washington D.C. (a planned city with a grid/diagonal layout) to Beijing (a ring-road based layout) can lead to errors because the spatial propagation of congestion differs fundamentally.
* **Mitigation (SHTL):** The **Spatial Homogeneity-Aware Transfer Learning (SHTL)** framework addresses this. It calculates a structural similarity score between the road networks of the source and target. If the "spatial homogeneity" is low, the transfer is blocked or the weight of the source knowledge is down-regulated. This ensures that transfer only happens between structurally compatible cities.8

### 7.2 Data Heterogeneity

Cities utilize diverse hardware. One may use magnetic loops (counting axles), another cameras (counting shapes), and another floating car data (GPS).

* **Challenge:** The feature spaces $ X\_S $ and $ X\_T $ are different.
* **Mitigation:** **Heterogeneous Domain Adaptation** techniques, such as **FLORAL**, learn a mapping dictionary to translate features. Additionally, modern Foundation Models are increasingly "modality-agnostic," learning to encode diverse inputs into a unified embedding space.2

## 8. Future Directions: Foundation Models and Digital Twins

The field is currently undergoing a paradigm shift from "Model Transfer" to "General Intelligence."

### 8.1 Urban Foundation Models (UFMs)

Just as GPT-4 serves as a foundation for text, **Urban Foundation Models (UFMs)** are emerging. These are massive, transformer-based models pre-trained on petabytes of multi-modal data from thousands of cities.

* **The Shift:** Instead of "transferring" a model from City A to City B, a UFM is "prompted" with the context of City B.
* **Zero-Shot/Few-Shot Capabilities:** UFMs like **UniST** and **PromptST** demonstrate the ability to perform accurate predictions in a new city with little to no fine-tuning, simply by understanding the universal language of spatio-temporal dynamics. This represents the "holy grail" of UTL—a truly generalizable urban brain.12

### 8.2 Generative AI and Synthetic Data

Generative AI is transforming UTL by enabling the creation of **Synthetic Source Domains**.

* **Scenario:** If no suitable source city exists for a specific target scenario (e.g., a rare disaster), a Generative AI model can *create* a synthetic city simulation that exhibits those conditions. The target model is then trained on this synthetic data.
* **Digital Twins:** This feeds into the development of Urban Digital Twins (e.g., the EU's **NexTCity** project). These twins serve as the ultimate "Source Domain," allowing for infinite simulation and training before models are deployed in the physical world.36

## 9. Conclusion

Urban Transfer Learning has evolved from a niche academic technique into the operational backbone of the global smart city market. It provides the only viable mathematical framework to address the "Cold Start" problem that plagues developing urbanization.

The trajectory of UTL is clear:

1. **From Instance to Structure:** Methodologies have moved from simple data weighting to complex, graph-based adversarial adaptation that respects the topological uniqueness of cities.
2. **From Centralized to Federated:** Privacy concerns are driving the adoption of encrypted, federated transfer protocols, allowing cities to collaborate without sharing secrets.
3. **From Transfer to Generalization:** The rise of Urban Foundation Models suggests a future where the need for explicit "transfer" diminishes. Instead, generalized AI agents, pre-trained on the collective urban experience of the world, will be deployed to new cities, adapting instantly via prompt engineering.

For city planners and technology providers, the message is pivotal: Data scarcity is no longer an excuse for a lack of intelligence. Through the strategic application of Urban Transfer Learning, the collective wisdom of the world's mature smart cities can be harnessed to accelerate the development of the next generation of urban environments.

### **Table 1: Comparative Analysis of Key Urban Transfer Learning Algorithms**

| **Algorithm** | **Core Mechanism** | **Primary Application** | **Key Innovation** | **Source** |
| --- | --- | --- | --- | --- |
| **RegionTrans** | Parameter Fine-Tuning + Region Matching | Crowd Flow Prediction | Matches "Source" and "Target" regions using temporal/latent correlation to optimize transfer. | 7 |
| **ST-DAAN** | Domain Adaptation + Attention | Traffic/Crowd Flow | Uses MMD (Maximum Mean Discrepancy) to align feature distributions; Global Attention for spatial dependency. | 14 |
| **FLORAL** | Feature Representation Learning | Air Quality Prediction | Learns a shared dictionary for multi-modal data (POI + Traffic + Weather) to handle missing modalities. | 2 |
| **MetaST** | Meta-Learning | Spatio-Temporal Prediction | Learns a "universal initialization" parameter set that adapts quickly to new cities (Few-Shot Learning). | 12 |
| **CityTransfer** | Collaborative Filtering / Matrix Factorization | Chain Store Site Selection | Transfers "location success" latent features to recommend sites in new cities. | 4 |
| **SHTL** | Graph/Topology Analysis | Urban Flow Prediction | Incorporates "Spatial Homogeneity" to prevent negative transfer by checking road network similarity. | 8 |
| **CcFTL** | Federated Learning | Region Profiling | Enables cross-city transfer without sharing raw data (Privacy-Preserving) using homomorphic encryption. | 25 |
| **PromptST** | Prompt Tuning | General Spatio-Temporal Tasks | Adapts pre-trained models via lightweight learnable prompts, reducing computational cost. | 12 |

### **Table 2: Industry Implementations of Urban Transfer Learning**

| **Company** | **Platform/Project** | **Application** | **Technology Stack** | **Source** |
| --- | --- | --- | --- | --- |
| **DiDi Chuxing** | Dispatching System | Ride-hailing Demand | Deep Reinforcement Learning (DRL), Semi-Markov Decision Processes (SMDP). | 17 |
| **Uber** | Michelangelo / POET | ETA, Pricing, Safety | Feature Stores, Diversity-driven Learning, PyTorch/TensorFlow. | 18 |
| **Google** | Project Green Light | Traffic Signal Control | AI modeling of traffic flow from Maps data; "Congestion Functions". | 20 |
| **Baidu** | Apollo / Baidu Maps | V2X, Crowd Safety | Autonomous Driving Data transfer to infrastructure; Big Data analytics; AutoDL. | 4 |
| **JD Technology** | JD iCity | Logistics, Governance | Federated Learning, Spatio-Temporal Data Mining, Urban Operating System. | 24 |
| **Microsoft Research** | Urban Computing | Air Quality, Noise | FLORAL, Multi-modal data fusion, Cloud-based Urban Computing. | 2 |

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