Context-Aware Online Traffic Prediction

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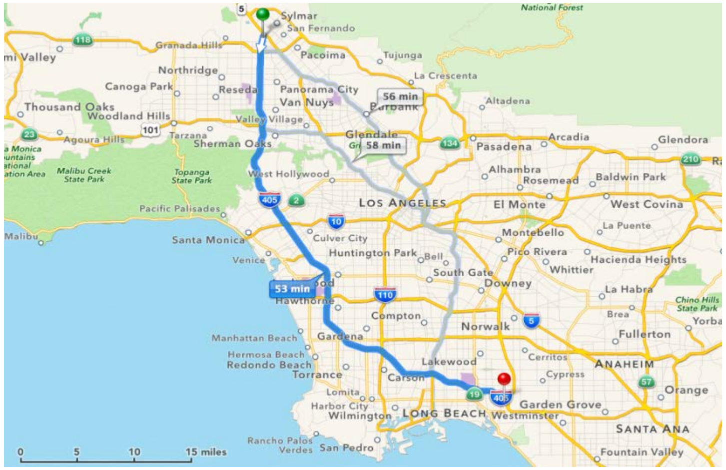
J. Xu, D. Deng, U. Demiryurek, C. Shahabi and M. van der Schaar, "Mining the Situation: Spatiotemporal Traffic Prediction with Big Data," *IEEE Journal of Selected Topics in Signal Processing (JSTSP) - Special Issue on Signal Processing for Big Data,* 2015.
J. Xu, D. Deng, U. Demiryurek, C. Shahabi, and M. van der Schaar, "Context-Aware Online Spatiotemporal Traffic Prediction," accepted and to appear in *ICDM Workshop on Spatial and Spatio-Temporal Data Mining, 2014*

Online Traffic Prediction

- Traffic congestion - time and energy wasted
  - 4.2 billion vehicle-hours of delay
  - 2.8 billion gallons in wasted fuel
  - $87.2 billion in lost productivity (0.7% GDP)

- Use Big Data to enable intelligent transportation
  - Road sensor instrumentations
  - Auxiliary commodity sensors (CCTV cameras, GPS)

Traffic congestion on I-405



2000 sensors along 50 miles of I-405

Importance of Traffic Prediction

- Drivers: avoid congested areas
  - E.g. through intelligent navigation systems
- Policy makers: decide traffic regulations
  - E.g. replace a carpool lane with a toll lane
- Urban planners: design better pathways
  - E.g. adding new lanes, carpool lanes
- Civil engineers: plan construction zones
  - E.g. predict how short-term construction impacts traffic

Requirements and challenges

- **Google Maps**
  - Suggests current routes based on current traffic condition
  - Traffic is changing

Forecast future traffic based on current traffic

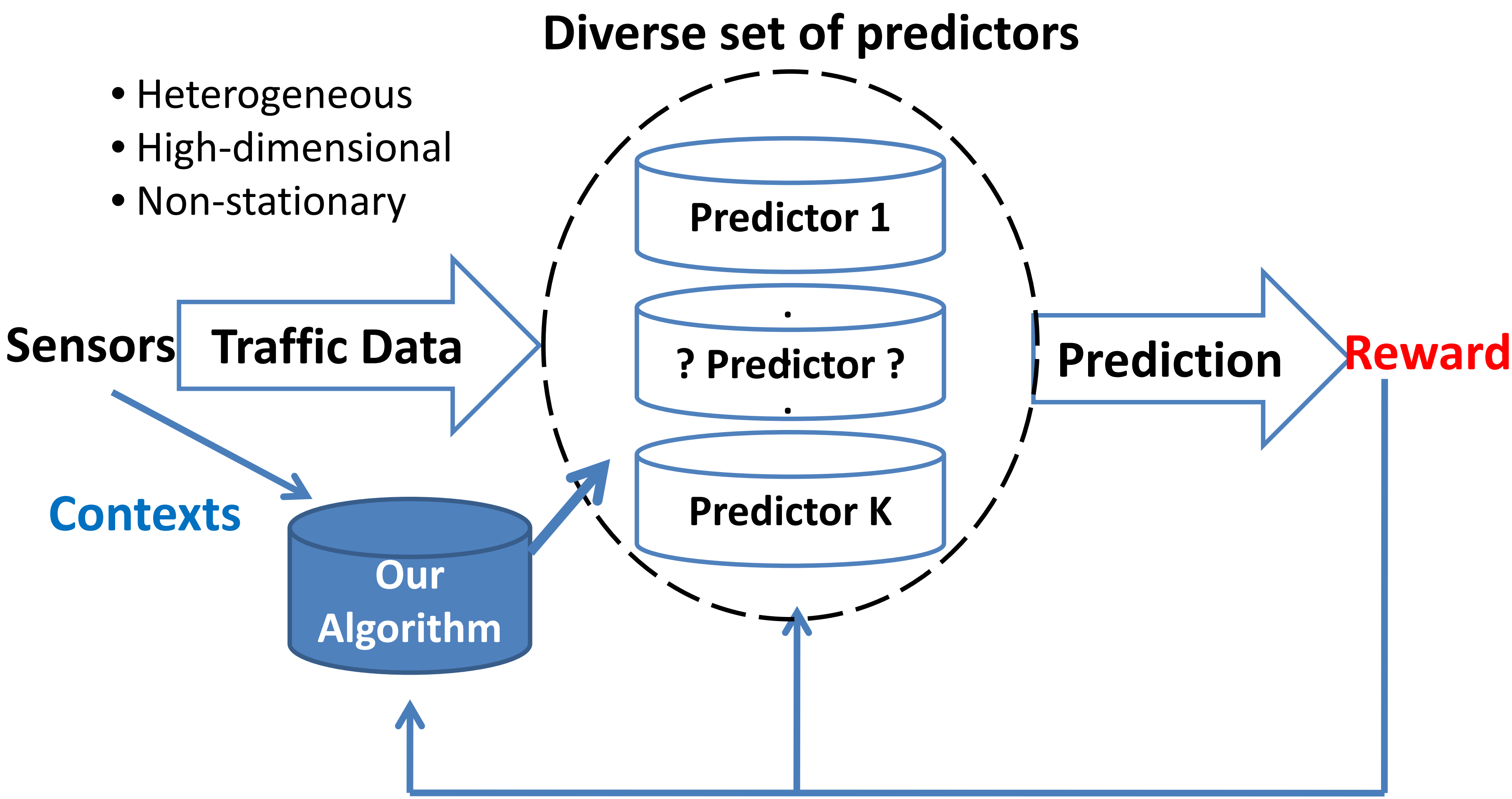
Predict accident-prone areas

- **Existing works on traffic prediction**
  - Time series anal, Naïve Bayes, Decision Tree, Nearest Neighbor etc.
  - Work well only in their envisioned situations
    - Typical conditions, rush hours, presence of accidents

- **Central challenges**
  - Many situations
  - Traffic situations are never identical
  - Traffic situations may be similar, but similarity must be discovered
  - High performance

Handle diverse traffic situations

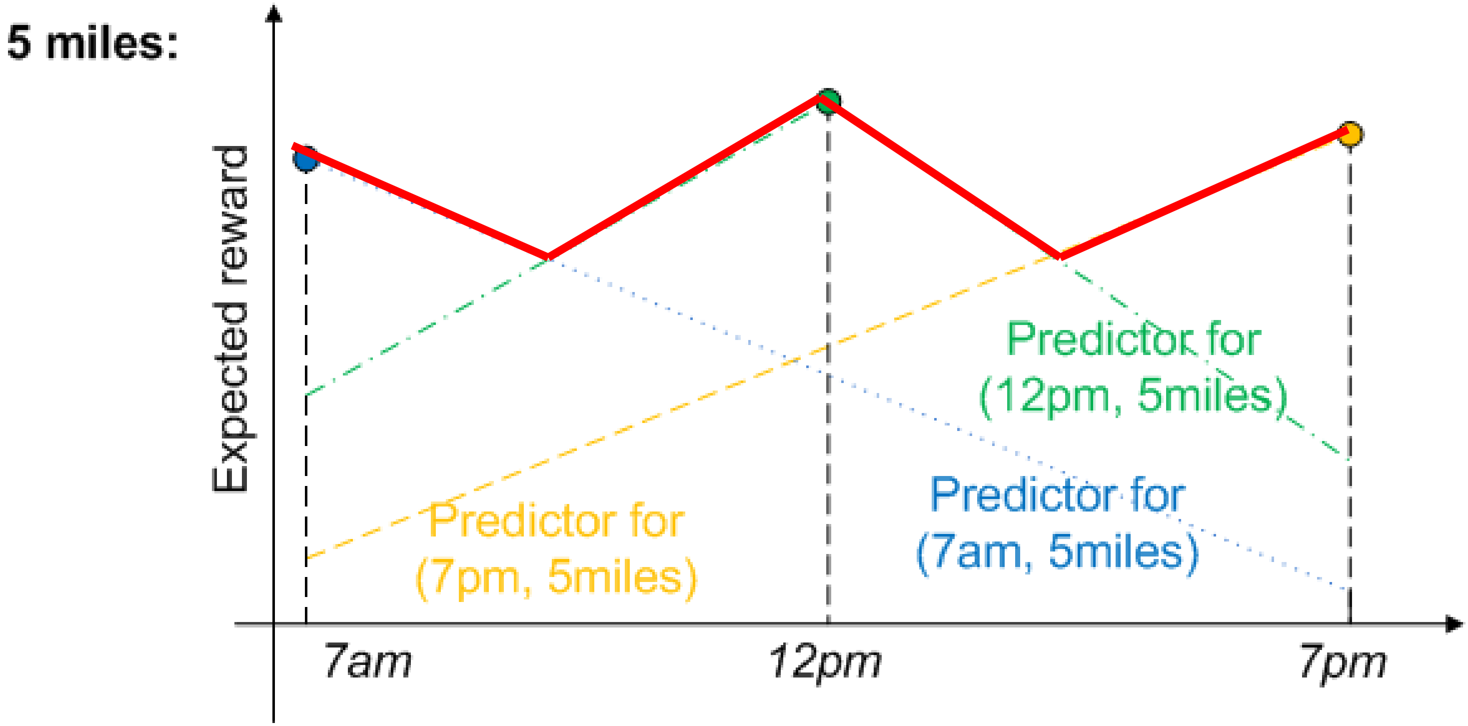
Our Approach for Traffic Prediction



Context – a D-dimensional vector: time of day, location, weather condition, traffic direction, road type, intersection, accident, etc.

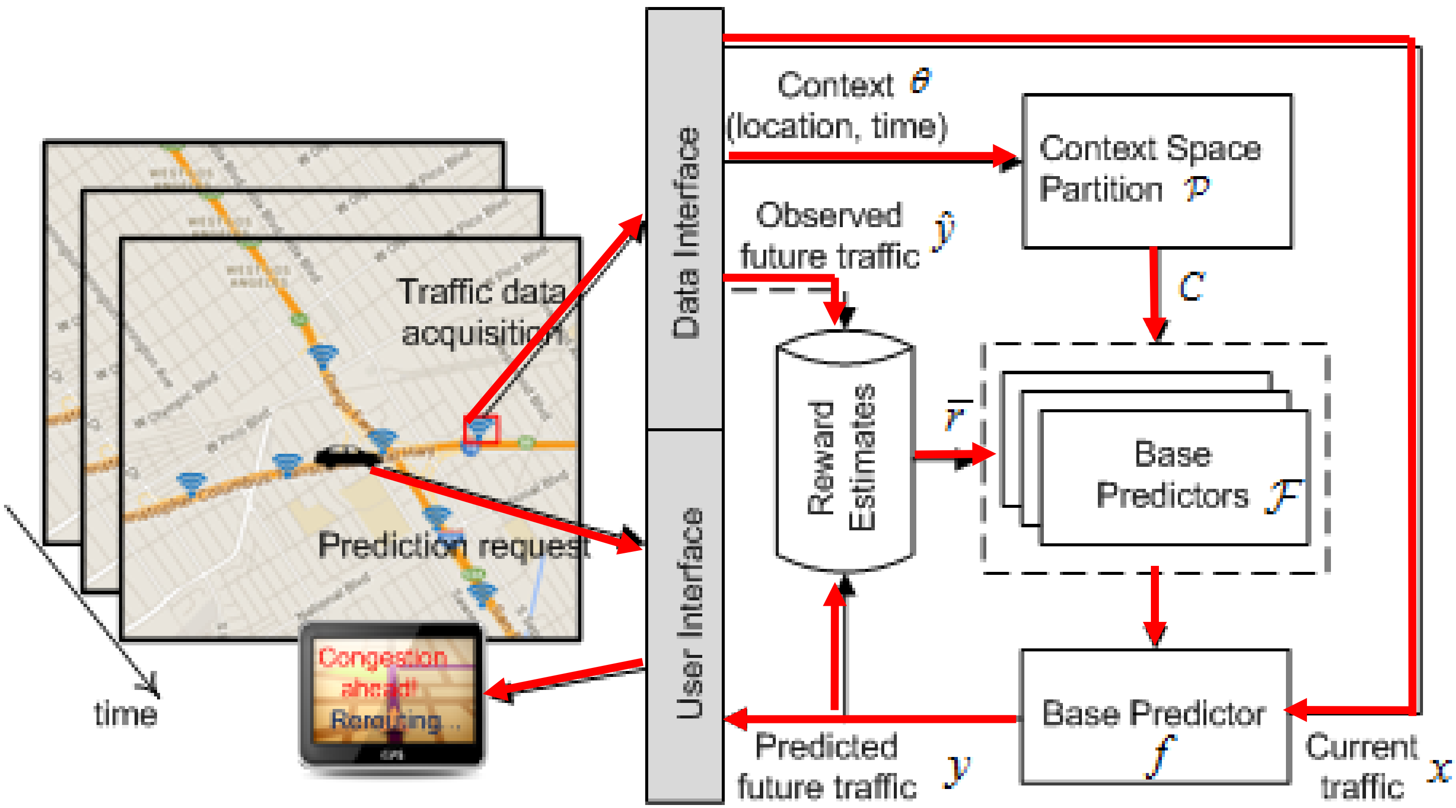
Our Approach for Traffic Prediction

– Predictor performance is <u>unknown</u> in different situations!
– Learn which predictor or combination of predictors to use.

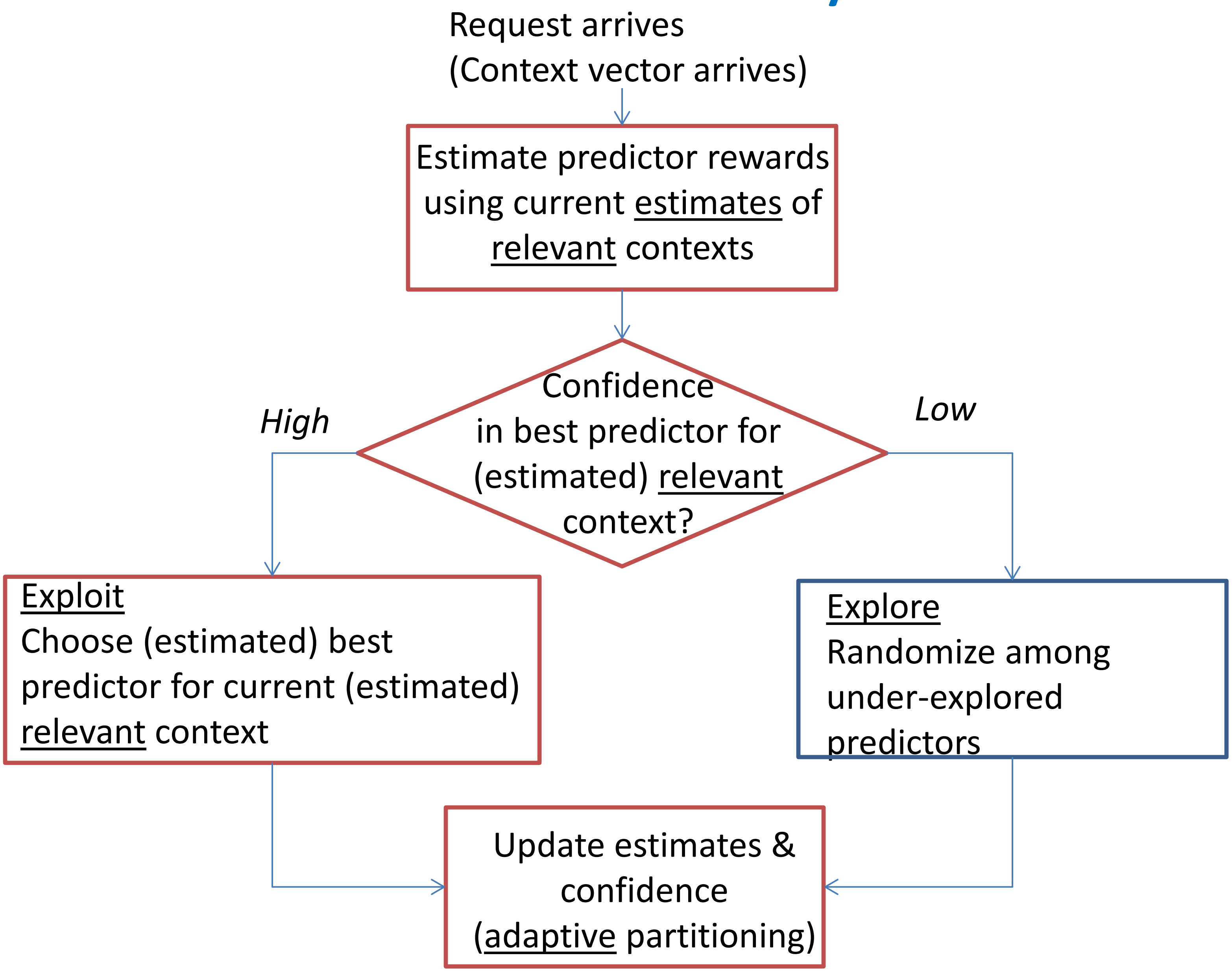


- Contexts organize information and are key to learning effectively ☺
- However, context space can be very large ☹
  - We discover what contexts are *<u>relevant</u>* for each prediction

Envisioned Traffic Prediction System



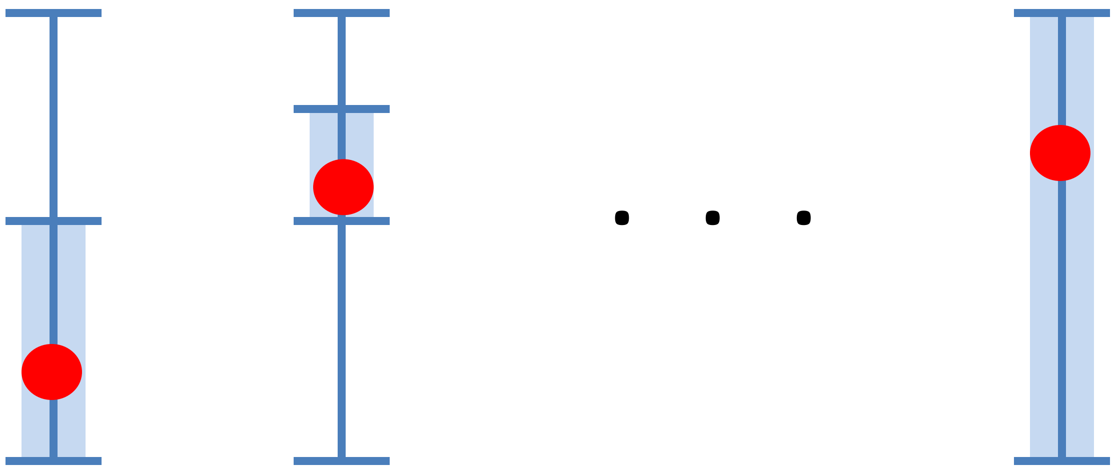
Context-Aware Discovery and Decision



Adaptive Partitioning

Current partitioning at time t

Arrival & context at time t



-> Choose a Predictor (explore/exploit)

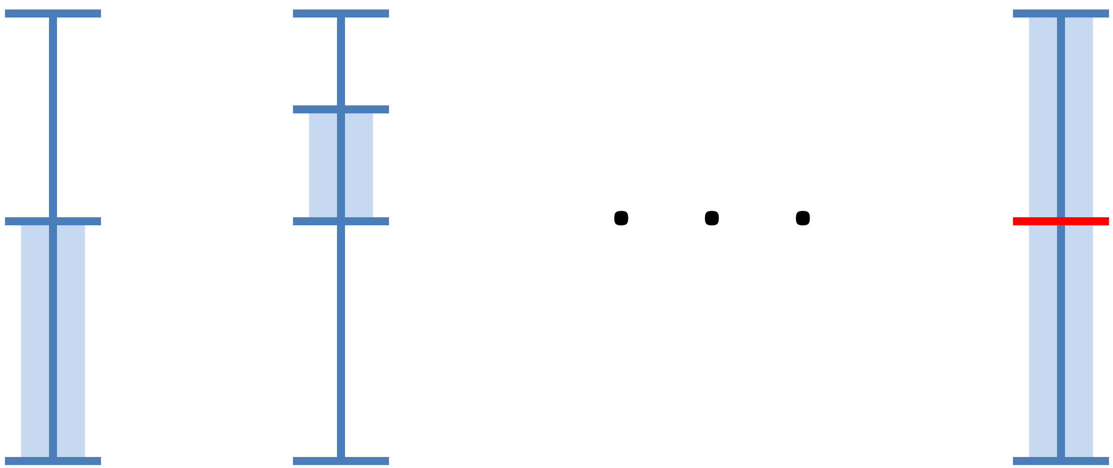
-> Observe Reward

Adaptive Partitioning – Updating

For each context is information above noise level?

No → No adaptation (partition remains the same)

Yes → Adaptation (subdivide one bin in partition)



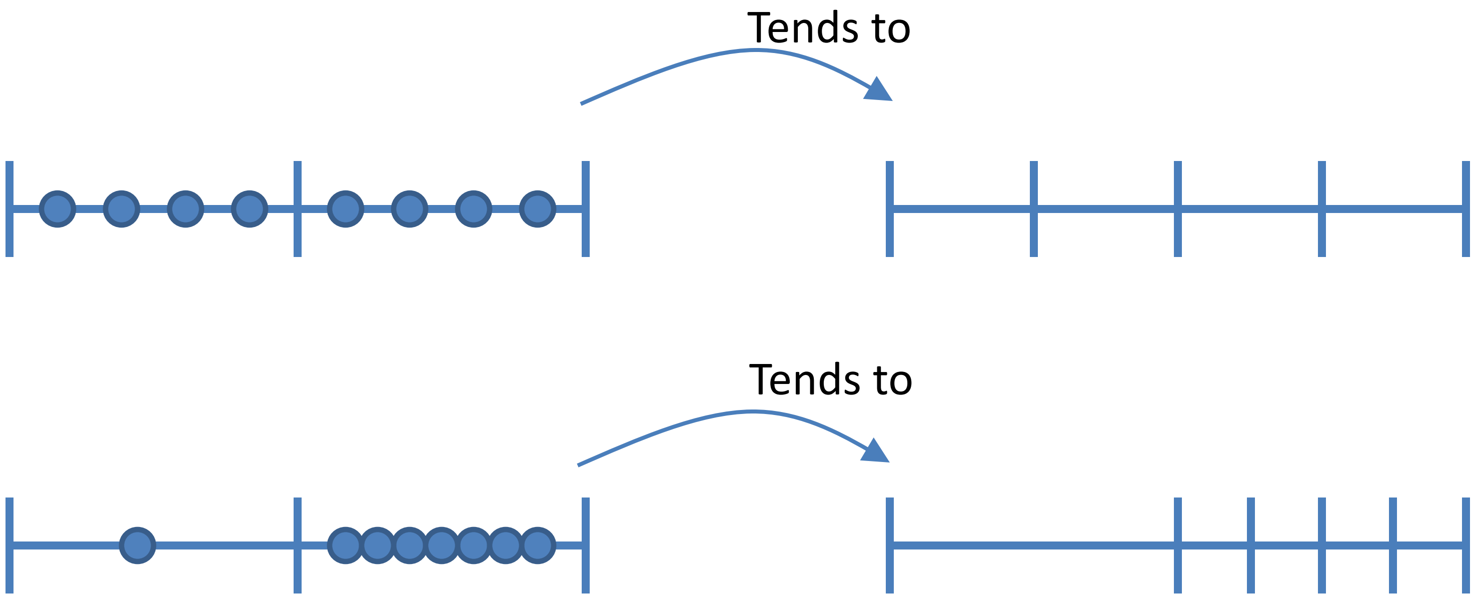
$$|\mu(a, x_{R(a)}) - \mu(a, x'_{R(a)})| \le L \cdot |x_{R(a)} - x'_{R(a)}|$$

Error estimate $\le L \cdot$ Length of active partition = Noise

Subtle Point

! Context arrival process matters:

for partitioning, estimates, decisions, performance



Learning performance

- **Regret** Reg(T): Cumulative (expected) loss up to time T from suboptimal action choices.
- Reg(T)/T: Rate of learning (to the optimal average reward).

- Regret is connected to *speed* of convergence.

Bounded	**Logarithmic**	**Sublinear**	**Linear**
$\mathrm{Reg}(T) < C$	$\mathrm{Reg}(T) < C \log T$	$\mathrm{Reg}(T) < CT^{\gamma}$ $\gamma < 1$	$\mathrm{Reg}(T) \sim CT$
Extremely fast convergence	Very fast convergence	Convergence	Non-convergence

Theoretical Results

Theorem: worst-case regret bound

$$\mathrm{Reg}(T) = \tilde{O}(T^{(2D_{rel}+3)/(2D_{rel}+4)})$$

– Optimal performance can be asymptotically achieved

$$\lim_{T \to \infty} \mathrm{Reg}(T)/T = 0$$

Better bounds can be derived depending on the arrival process

Experiments

- Online traffic data
  - Traffic sensor data from 9300 traffic loop-detectors
  - 5400 miles
  - Traffic parameters (occupancy, volume, speed) – one reading per sensor per minute
  - Traffic incident data (severity, location, type etc.)

- Evaluation Method
  - Different spatial settings
    - 100 locations, around 300 requests for each location.
  - Predict traffic congestion upon each prediction request
    - Congestion: traffic speed drops below a threshold

Performance

- Overall accuracy (with different congestion threshold)

	CA-Traffic	MU	AU	GDU
$\lambda = 50$ mph	0.94	0.83	0.83	0.82
$\lambda = 30$ mph	0.91	0.82	0.80	0.78

- Break-out accuracy

$(\lambda = 50\text{mph})$	**CA-Traffic**	MU	AU	GDU
10am	0.93	0.81	0.85	0.83
2pm	0.93	0.86	0.81	0.80
5pm	0.99	0.86	0.87	0.88
$(\lambda = 30\text{mph})$	**CA-Traffic**	MU	AU	GDU
10am	0.93	0.83	0.83	0.81
2pm	0.91	0.80	0.83	0.82
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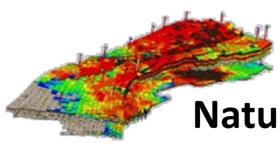
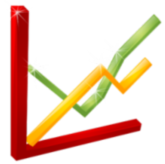
Benchmarks: Weighted Majority Methods

Additive Update (AU), Multiplicative Update (MU), Gradient Descent Update (GDU)

Methods - useful in **Many Applications**



Natural Systems
- Seismic monitoring
- Wildfire management
- Water management



Stock Markets
- Impact of weather on securities prices
- Analysis of market data at ultra-low latencies

Virology

Personalized e-Learning

Smart Cities

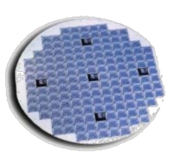
Energy

Transportation
- Intelligent traffic management
- Collision forecasting

Cyber-security

- Real time attack detection
- Real time attack prevention

Social media
- Popularity forecasting



Manufacturing
- Process control for microchip fabrication

Healthcare Informatics
- Remote healthcare monitoring
- Long-term care
- Assist-diagnosis tools
- Many patients: screening, clinical trials

Telecom
- Infrastructure adaptation
- Real-time services, billing, advertising