

IBM Research – Business Analytics and Mathematical Sciences

Monitoring Entire-City Traffic using Low-Resolution Web Cameras

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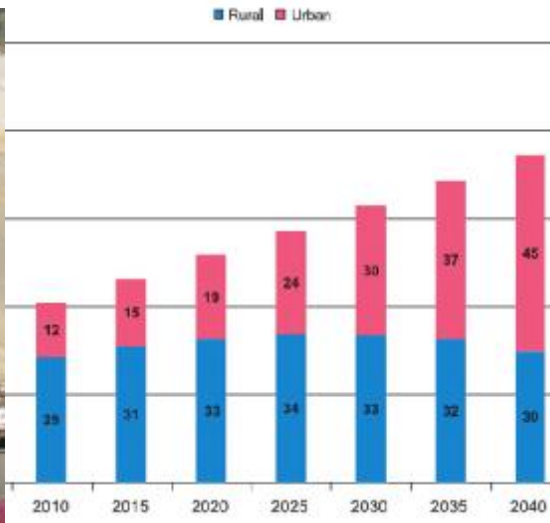
VP of Global Labs, IBM Research



Need lightweight Intelligent Transportation System (ITS) for developing countries



Day-to-day congestion



Rapidly growing urban traffic



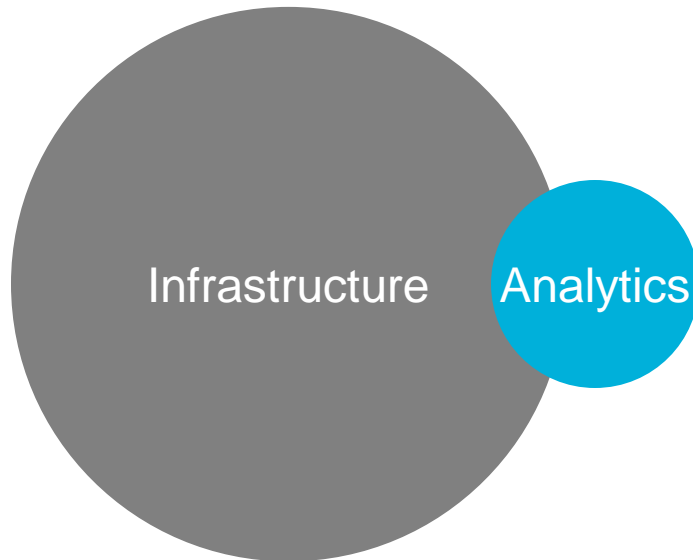
Natural disaster



Transportation infrastructure is premature

We propose a “Frugal innovation” approach that requires no expensive infrastructure but using cheap Web cameras

Standard approach



Data quality: High
Cost: Very High



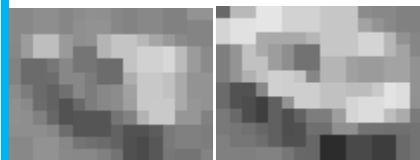
Frugal approach



Data quality: Very low
Cost: Very cheap !

Two technical hurdles: image quality and partial observations

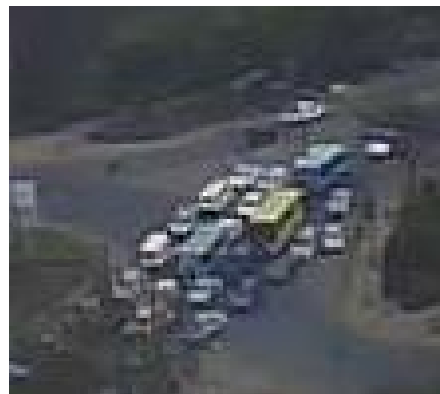
1. Images taken by Web-camera are Very Low-Quality



Very low resolution



Overlapped



2. Web cameras only covered very limited areas



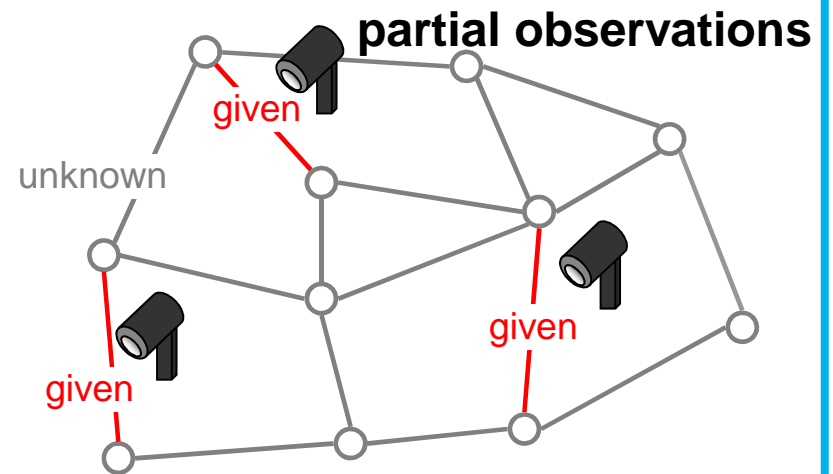
Two key analytics tasks for solving the problems: visual analytics and network analytics

1. Visual analytics for solving the first challenge



→ Estimate # of vehicles and average velocity

2. Network analytics for solving the second challenge



→ Estimate traffic flow on no-cam links

Visual analytics

We have developed two image processing technologies for estimating traffic information from Web-cams

Number of Vehicles

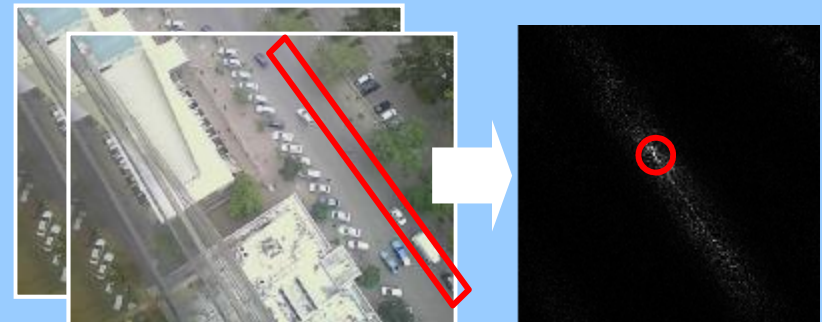
Area-based vehicle counting technology



Focus on vehicle-counting

Average Velocity

Cross-correlation-based velocity estimation technology



Standard vehicle-counting methods are not applicable for analyzing web-cam images due to low image quality

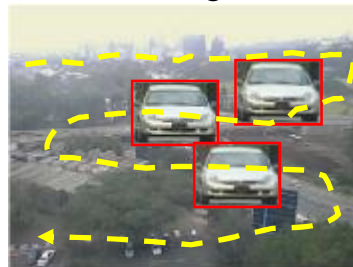
Two Standard Approaches

Template matching

- vehicles
- windshields
- headlights

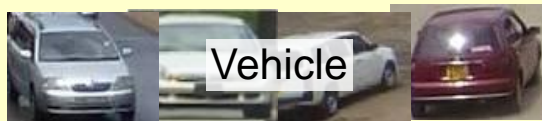


Identify independent vehicles by scanning over the image

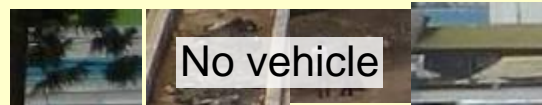


Feature-based classification

Training data



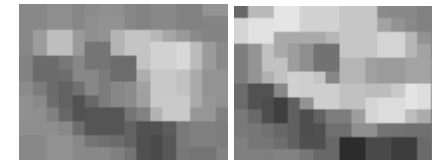
Vehicle



No vehicle

Build a binary classifier for image patches

Identification of independent vehicles is impossible for web-cam images, due to



Very low resolution



overlapped

We developed a new algorithm focused on area of vehicles

This is **not** based on techniques identifying independent vehicles

Input image



Manually choose a focused area



Optimized binarization

Compute the white area



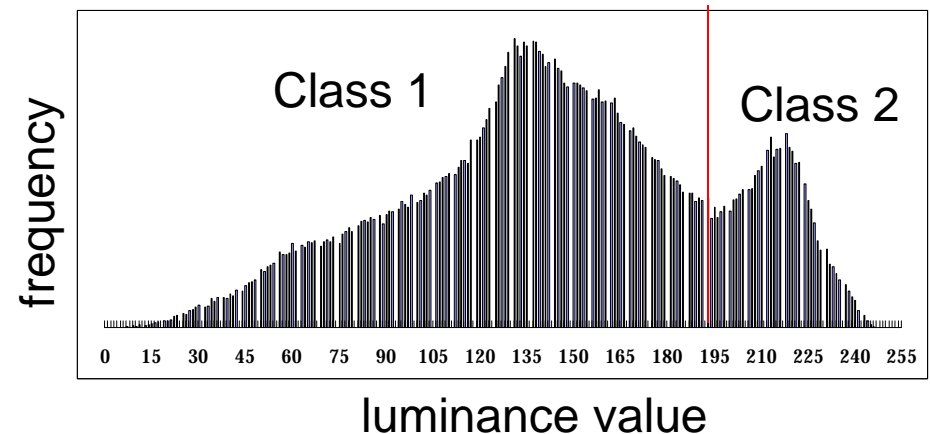
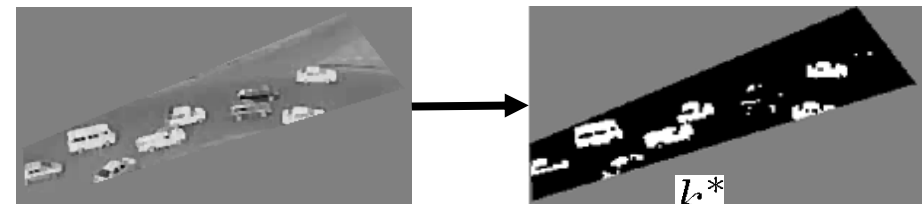
Regression function for the white area

of vehicles

Area-based vehicle counting technology

• Optimized binarization

- Determine the binarization threshold k^*
- Choose the threshold so that the inter-class variance is maximized
 - C.f. Otsu, IEEE Trans. Syst Man Cybern, 1979



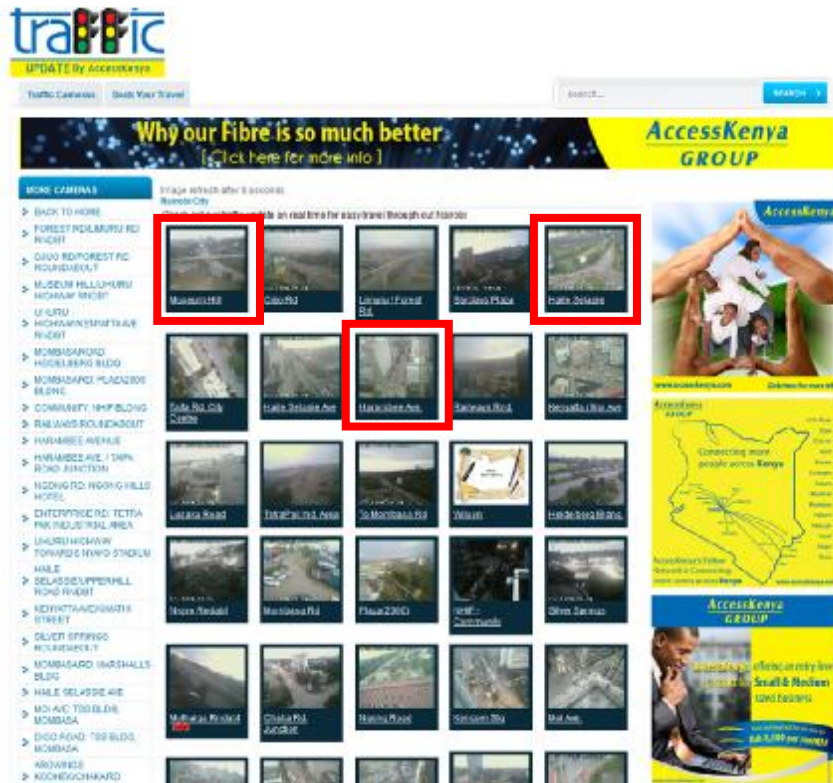
• Regression-based vehicle-counting

- Propose a simple regression model, which is a linear model between the white area x and the number of vehicles y as $y = ax + b$
- Determine the parameters a and b , based on the training data

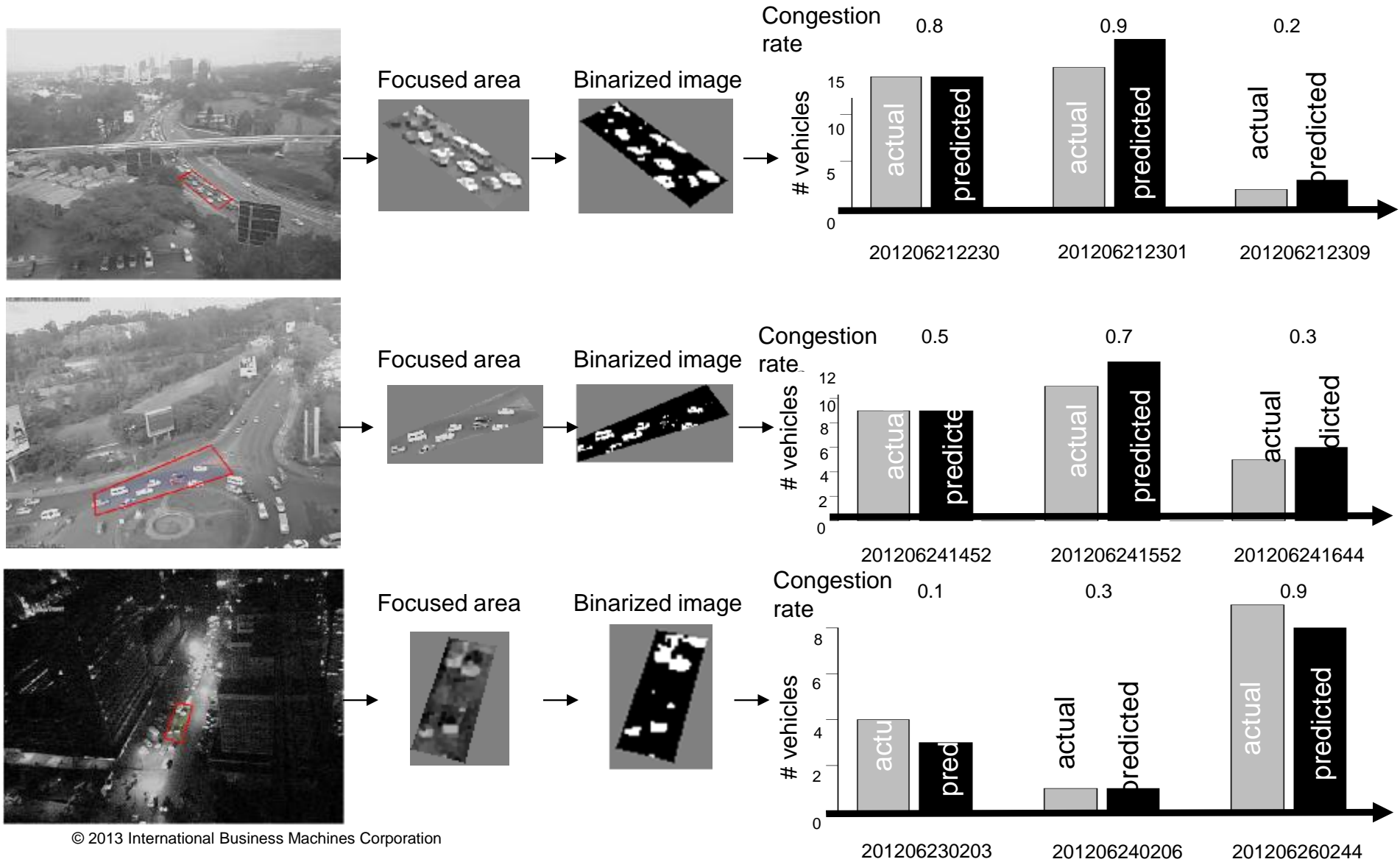


$$(a^*, b^*) = \arg \min_{a, b} \sum_{n=1}^N (y^{(n)} - ax^{(n)} - b)^2$$

[Vehicle counting] Evaluation using real web-cam images



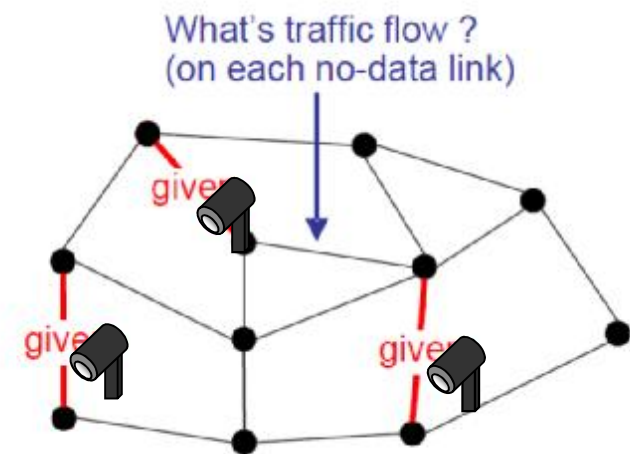
[Vehicle counting] Evaluation using real web-cam images



Network Analysis

A problem is the coverage of web-cams are very restricted in the whole road network

- About **5%** is covered in case of Nairobi, Kenya
 - Need to estimate rest 95% of roads from 5% observations
 - Related Technologies
 - **Network tomography**
 - Estimate the demands of the origin and the destination of a trip, instead of traffic flow
 - **Link cost prediction**
 - Need trajectories or dense observations for input
- **They are not applicable for this problem setting**

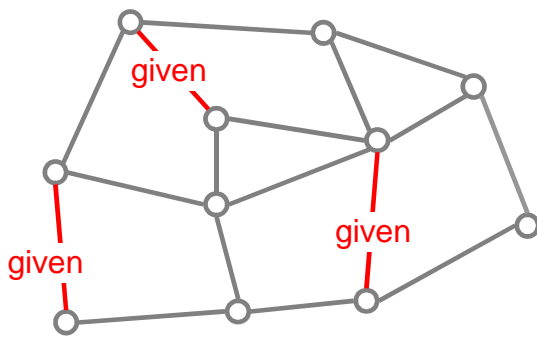


We formulate this problem as an inverse Markov chain problem

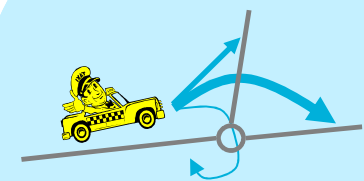
- **Overview: to approximate traffic system with Markov-chain model**
 - Traffic flow of every road is computed as a visiting probability of the road from the approximated Markov model
 - Define: inter-link transition probability matrix
 - Representing drivers' route selection probability at each intersection
 - Task: to determine the transition matrix
 - So that its stationary distribution is consistent to the observation
 - This is an **inverse problem of Markovian transition**

Input:

Traffic flow on a very limited link set



Analytical model



Estimate inter-link transition probabilities for all the intersections

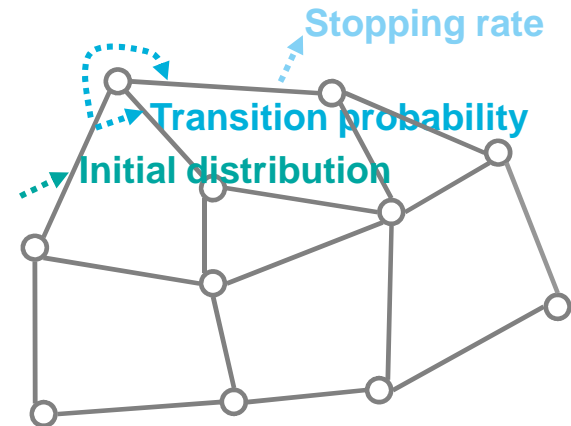
Output:

- Traffic flow on all of the links

Solving the inverse problem of Markov chain

- Formulation: Traffic Markov process

- Markovian driver model with three types of parameters
 - Initial road distribution for a trip
 - Inter-road transition probability
 - Stopping rate for a trip



- Learning the model to estimate traffic flows on **no-data links**

- Objective is to make its stationary distribution $d(i)$ be proportional to the observed traffic frequency $f(i)$

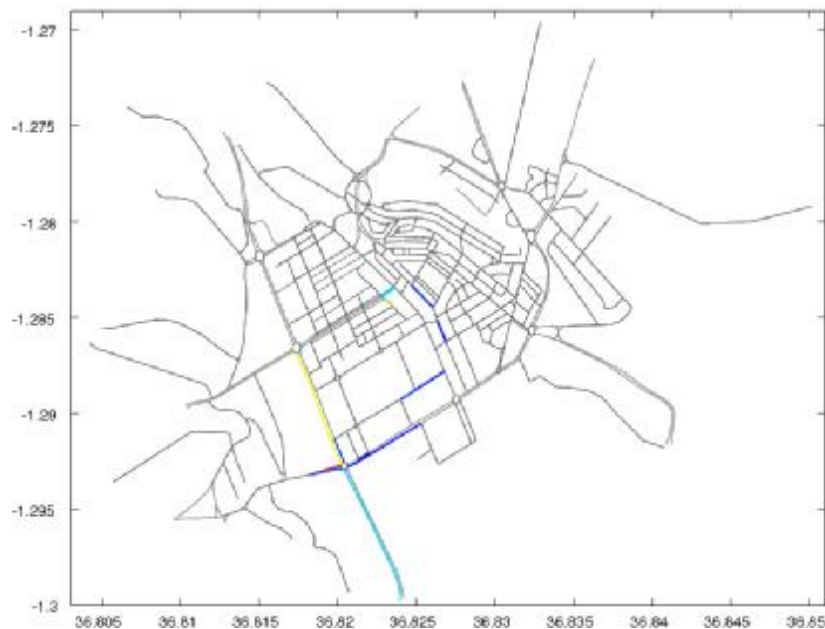
$$d(i) \propto f(i)$$

- Introduce **regularization terms** for some restrictions based on prior knowledge
 - Penalize right and left turns
 - Penalize inter-link transitions between different road types, e.g. from a highway to a side road
- Solve this learning problem using a gradient descent method

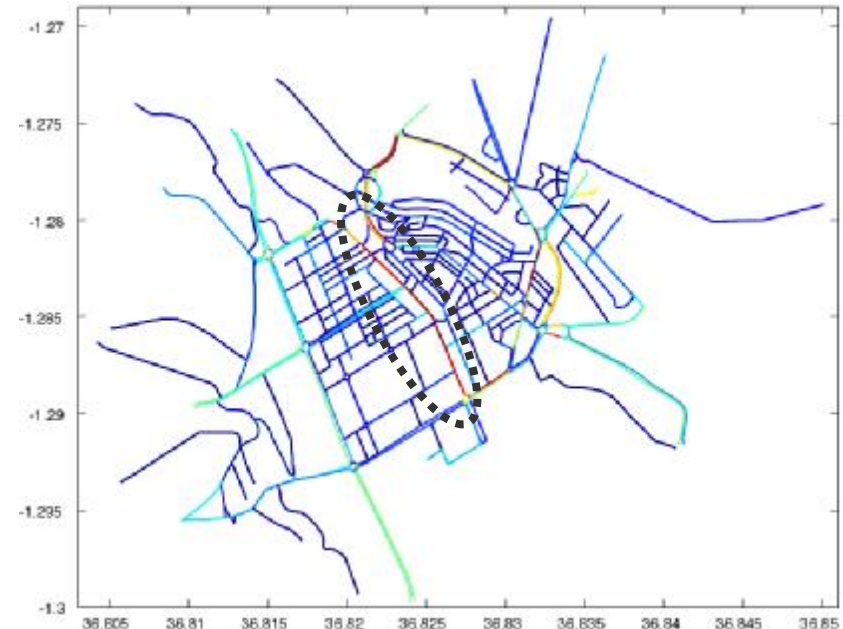
Evaluation of traffic flow using real data in Nairobi Central Business District (1/2)

- Good agreement at the Web-cam links
- Heavy congestion is indicated in the central area
 - Highlighted by the dotted circle
 - Notice that the heaviest congestion road has no Web cameras

Web-cam observation



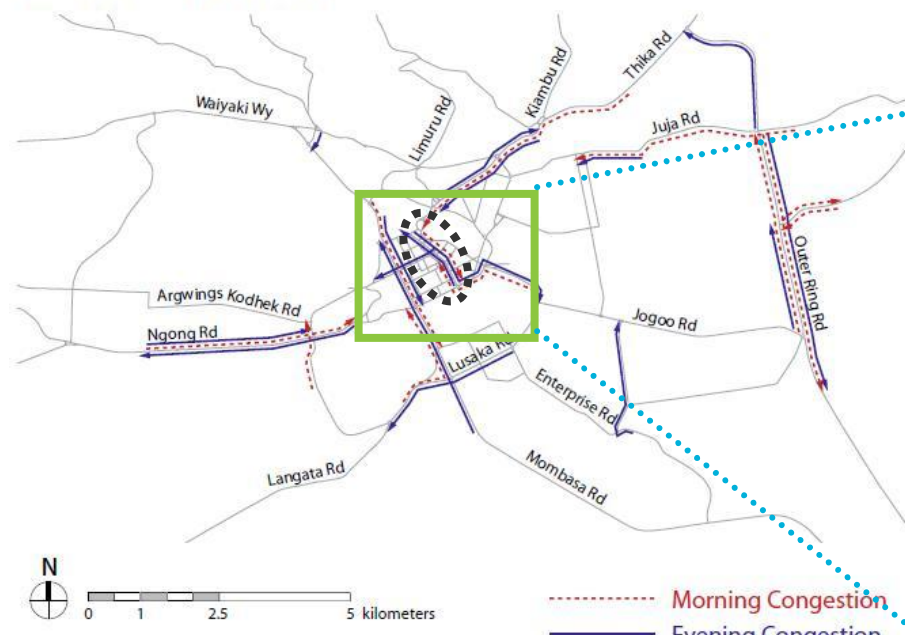
Estimated traffic flow



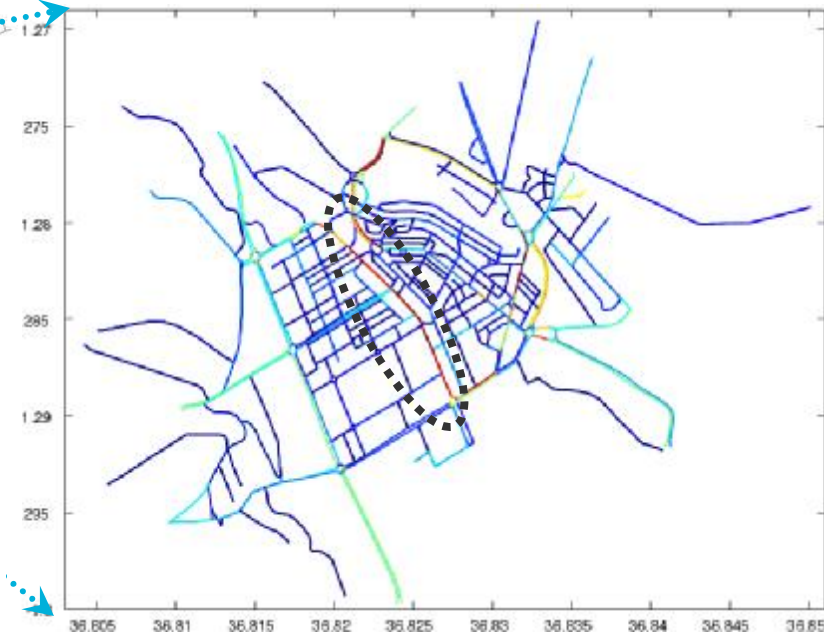
Evaluation of traffic flow using real data in Nairobi Central Business District (2/2)

- The predicted congestion is actually confirmed by a traffic survey report
 - i.e. Our algorithm successfully predicted unseen traffic !

Traffic Congestion in Nairobi
Streets with Speeds Under 20 km/hr



Estimated traffic flow



Multimodal Transport modeling for Nairobi, Kenya: Insights and Recommendations with an Evidence-Based Model (2009)

CONCLUSION

- We have proposed a new approach to ITS.
 - Web-camera-based traffic monitoring
 - Network flow estimation from partial observation
- Using real Web cameras deployed in Nairobi, Kenya, we assessed the accuracy of our approach
- To the best of authors' knowledge, this is the first practical framework for monitoring an entire city's traffic without special and expensive infrastructure and time-consuming data calibrations.

Details of individual technology

- [Visual analytics]
 - Takayuki Katsuki, Tetsuro Morimura, Tsuyoshi Idé, "Bayesian Unsupervised Vehicle Counting," Technical Report RT0951, IBM Research - Tokyo, 2013.
- [Network analytics]
 - Tetsuro Morimura, Takayuki Osogami, Tsuyoshi Idé, "Solving inverse problem of Markov chain with partial observations," to appear in Neural Information Processing Systems (NIPS 2013).
 - Published also as Technical Report RT0952, IBM Research - Tokyo, 2013.