A comparative analysis of implicit models for real-time short-term traffic predictions

Authors:
Gaetano Fusco
Chiara Colombaroni
Natalia Isaenko
Introduction

- Traffic maps are becoming familiar to most travelers.
- Tracking connected personal devices allows major web providers (Google, Apple) and specialized companies (TomTom, Inrix) supplying real-time traffic information.
Introduction

• On-board and web traffic information services display both real-time and usual traffic conditions.
• They also supply users with route suggestions based on the desired departure time.
• However, methods for predicting future travel times are not known.
Introduction

- Precision of prediction methods is not yet fully satisfactory.
Introduction

• Since ‘70s, academics developed many prediction methods to allow Intelligent Transportation Systems proactive features.
• Explicit models simulate demand-supply interactions: they can estimate unobserved conditions and prevent overreaction.
• Implicit models extrapolate short-term predictions from observed trend (data-driven): they are often applied to short-term predictions on freeways, because of their simple physical structure.
Introduction

• However, these models are not used in commercial applications.
• TomTom doesn’t supply dynamic traffic predictions.
Object of the study

• We want to assess implicit models in short-term traffic predictions on urban networks.

• Advantages of implicit models:
  – Standard automatable calibration methods
  – Fast computation for real-time applications
  – Easy parallelization for dealing with large graphs
  – Independence from specific conditions for easy generalization

• Drawbacks of implicit models:
  – Lack of correspondence with the physics of vehicle traffic

• Specific goal:
  – Relate model structure to network topology
State of the art of implicit models

- Time-series models (AR, ARMA, ARIMA, SARIMA)
- Artificial Neural Networks (ANN): Feed-Forward, Kohonen Maps, Fuzzy NN, NAR, NARX
- Bayesian networks
- Non-parametric estimates (clustering, nearest neighbor, fuzzy classifiers)
- Combination of different methods (Bayesian committee, Bayesian combination, ARIMA-NN)
Definitions

- Short-term implicit prediction model

\[ \hat{v}_{t+1}^a = f \left( v_t^a, v_{t+s}^a, v_{t+2s}^a, \ldots, v_{t+hs}^a \right) \quad a: \text{prediction link}; \quad t: \text{current time} \]

- Multi-input model (data from different links)

\[ \hat{v}_{t+1}^a = f \left( V_t, V_{t+s}, V_{t+2s}, \ldots, V_{t+hs} \right); \quad V_t = \{ v_t^a, v_t^b, \ldots, v_t^m \}; \quad a, b, \ldots, m \in L \]

- Multi-input with exogenous variables

\[ \hat{v}_{t+1}^a = f \left( v_t, v_{t+s}, v_{t+2s}, \ldots, v_{t+hs}; X_t, X_{t+s}, \ldots, X_{t+hs} \right) \]

\[ X_t = \{ x_t^a, x_t^b, \ldots, x_t^m; y_t^a, y_t^b, \ldots, y_t^m; \ldots; z_t^a, z_t^b, \ldots, z_t^m \} \]

- Multi-step prediction

\[ \{ \hat{v}_{t+1}^a, \hat{v}_{t+2}^a, \ldots, \hat{v}_{t+p}^a \} = f \left( v_t, v_{t+s}, v_{t+2s}, \ldots, v_{t+hs}; X_t, X_{t+s}, \ldots, X_{t+hs} \right) \]
Feed-Forward Neural Network

- Well known A.I. paradigm inspired by natural brain biology

\[
\hat{v}_a(t+1) = f(Cz + c) \\
z = f(Bv(t, t-1, \ldots, t-h) + D)
\]

- \( f \): nonlinear function
- \( g_C, g_D \): thresholds
- \( B, C \): weight matrices
A comparative analysis of implicit models for real-time short-term traffic predictions

Time dependent Neural Network

\[ \hat{v}_a(t+1) = f(\hat{v}_a(t), \hat{v}_a(t-1), \ldots, \hat{v}_a(t-h); v(t), v(t-1), \ldots, v(t-h)) \]

Non AutoRegressive eXogenous model (NARX)
Bayesian Networks (BN)

- Bayesian Networks are graphical models whose nodes represent random variables and arcs represent conditional assumptions.
- Unlinked nodes are stochastically independent variables.
- Link direction indicates cause-effect relationship.
- Network structure provides a compact representation of joint probability:

\[ P(C, S, R, W) = P(C) \cdot P(S|C) \cdot P(R|C) \cdot P(W|S,R) \]
Application of BN to traffic prediction

- Nodes of the Bayesian Network are traffic variables
- Bayesian Network architecture should reproduce traffic interaction on the road network
- Cause-effect mechanisms are hidden and stochastic independence prevails

“z” affects “x” because it is parent of its children

If observations of traffic on u lack
Experimental application

• TomTom HD data (speed):
  – 6 sub-areas in the town of Rome
  – 3 months of observations (March 2014 – May 2014)
  – 5-min. intervals speed aggregation
  – qData reliability expressed by “confidence factor”
• Forecasts for 5-15-30-45-60 minutes:
  – ANN NARX
  – ANN Feed Forward
  – Bayesian Network
  – Naïve method
  – Historical Average
• Research project with DUEL SpA (funded by FILAS)
Real case studies: TomTom Dataset
Bayesian Network Architecture

- Different architectures were tested to reflect physical relationships between close links.
- Serial links are useful when some data of a parent node are missing.
Model test

- Different model network architecture related to road network topology
- Different number of parameters and training algorithms

\[ V_X(t+p) \]

\[ V_B^m(t) \]

Forward star  \quad Backward star
Multistep BN prediction horizon

A comparative analysis of implicit models for real-time short-term traffic predictions

$\mathbf{p} = 5, 15, 30, 45, 60 \text{ min.}$
Application of Neural Networks

• Neural Network architecture:
  – One hidden layer;
  – 2-40 hidden neurons;
  – 4 different architectures considered;
  – Training algorithms: classical Levenberg-Marquardt and Levenberg-Marquardt with Bayesian regularization;
  – Input-output correlation, convergence and autocorrelation examined.

• The final structure: 12 hidden neurons; input data collected in 6 previous time intervals on forward and backward star links
From a priori to a posteriori

A comparative analysis of implicit models for real-time short-term traffic predictions
Results: recurrent noisy congestion

- for 5 min. interval both models provide good estimates
- for 30 min. noisy data lead to overestimate by Neural Network.
Results: non-recurrent congestion

Lungotevere Tor di Nona

- for 5 minutes interval both models provide good estimates;
- for 30 minutes only Neural Network follows the actual speed trend.
Neural Network is better for short term forecasts.

Bayesian Network is better for long term forecasts because of a priori estimate.

A comparative analysis of implicit models for real-time short-term traffic predictions.
Conclusions

• Application of Neural and Bayesian Networks shows that an appropriate graph structure of models can improve forecast performances with respect to historical average or naïve predictions
• Accuracy worsens as prediction horizon increases:
  • FFW Neural networks can be applied up to 15-minute predictions
  • Bayesian Network with statistical a priori forecast is better in standard conditions for longer predictions
  • Time-dependent Neural Network outperforms BN in anomalous conditions
• A supervisor can be introduced to choose the best model depending on observed data pattern