DERIVING TRAFFIC VOLUMES FROM PROBE VEHICLE DATA USING A FUNDAMENTAL DIAGRAM APPROACH

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ABSTRACT

With today's methods, area-wide direct measurements of traffic volumes on (urban) road networks are not achievable realistically. Since, however, such information is essential for traffic planning and control, traffic flows have to be extrapolated from point measurements or by other means via suitable models. This paper evaluates a simple approach which tries to derive traffic volumes from probe vehicle data by applying the speed-flow relationship of the fundamental diagram. In this context, the well-known Van Aerde model as a deterministic representation of this relationship is shortly reviewed. Results are presented for real-world data of about 600 local detectors and a taxi PVD fleet consisting of about 4,300 vehicles in Berlin, Germany.

Keywords: Traffic management, traffic monitoring, probe vehicle data, Van Aerde model

INTRODUCTION

Traffic volumes are one of the most important information in operational traffic management and traffic planning. Control algorithms for inner-city traffic signals, for instance, as well as road infrastructure planning rely on solid traffic demand values in terms of vehicles per hour. Using today's common sensor technologies (induction loops, radar, etc.), however, traffic volumes can be measured at selected points of the road network only. Consequently, they must be guessed for all other stretches of road using complex traffic assignment models (cf. Hensher and Button, 2007) or other approaches (cf. Vortisch, 2006). In this context, area-wide traffic volumes are either completely modelled from other data (e.g. mobility surveys) with traffic models being calibrated and validated based on a (small) number of local measurements or refer to suitable extrapolations of point-wise available traffic flow information. Needless to say, area-wide direct measurements would be a much preferred solution.

A quite successful and well established method for traffic monitoring with a wide spatial extension is the probe vehicle approach (cf. Schäfer et al., 2002; Jie et al., 2011). Unfortunately, it does not allow obtaining traffic volumes directly but only travel times and travel speeds. From traffic flow theory, however, it is well-known that there is a distinct relation between traffic flow and speed. That means it might be reasonable to use measured probe vehicle speeds in order to estimate the corresponding traffic volumes.

This paper evaluates such an approach based on the so-called Van Aerde model (cf. Van Aerde, 1995) which is a parameterized deterministic representation of the speed-flow relation of the fundamental diagram. The following section provides a short review of this model and deals with the task of calibrating its parameters. Then, the actual methodology is explained which includes some additional remarks concerning the difference between local and travel speeds as well as other relevant aspects. Finally, some results based on real-world data are presented which lead to a short conclusion chapter.

THE VAN AERDE MODEL

One of the interesting aspects of the well-known Van Aerde model (cf. Van Aerde, 1995) is that it combines the macroscopic and microscopic view on traffic flow. In this sense, it is based on a microscopic assumption about vehicle headways $h(v)$ in car-following, namely

$$h(v) = c_1 + \frac{c_2}{v_f - v} + c_3 v \tag{1}$$

where v_f is the free-flow speed and $v < v_f$ the current speed. The variables c_1, c_2 and c_3 are suitable real numbers.

From that, a macroscopic speed-density relation is derived by $d(v) = 1/h(v)$. Finally, the fundamental equation of traffic flow yields the corresponding speed-flow relation

$$q(v) = d(v) \cdot v = \frac{v}{c_1 + \frac{c_2}{v_f - v} + c_3 v} \tag{2}$$

for $0 \leq v < v_f$ which is the ground for the method of estimating traffic volumes from probe vehicle data (PVD) as it will be discussed further below.

Model parameters

As can be seen from Eq. (2), the Van Aerde model is defined by four parameters, i.e. free-flow speed v_f and the numbers c_1, c_2 and c_3 which do not have an obvious physical meaning. However, they can be written as functions of some other parameters which are much easier to interpret.

For that purpose, let $q_{\max}$ be the capacity of the considered road section and $v_{\max}$ the speed of a traffic stream at capacity so that $q_{\max} = q(v_{\max})$. Then, $q_{\max}$ is the maximum of $q(v)$ in the interval $[0,v_f]$, i.e.

$$q_{\max} = \max_{0 \le v \le v_f} \frac{v}{c_1 + \frac{c_2}{v_f - v} + c_3 v} \tag{3}$$

and explicitly maximizing the right-hand side yields

$$v_{\max} = v_f + \frac{c_2}{c_1} - \sqrt{\frac{c_2}{c_1} v_f + \left(\frac{c_2}{c_1}\right)^2} \,. \tag{4}$$

Based on that – with $x := c_2/c_1$ – one obtains

$$x = \frac{(v_f - v_{\max})^2}{2v_{\max} - v_f} \tag{5}$$

so that, for instance,

$$c_2 = \frac{(v_f - v_{\max})^2}{2v_{\max} - v_f} \cdot c_1 \tag{6}$$

Now, let l_0 be the inverse of the jam density $d_{\max}$, i.e. $l_0 = h(0)$ which also is the gross headway between two consecutive standing vehicles in congestion. Consequently,

$$l_0 = c_1 + \frac{c_2}{v_f} \tag{7}$$

and inserting (6) yields

$$c_1 = l_0 \cdot \left(\frac{2v_f}{v_{\max}} - \frac{v_f^2}{v_{\max}^2} \right). \tag{8}$$

Furthermore, Eq. (5) shows that

$$c_2 = l_0 v_f \cdot \left(\frac{v_f}{v_{\max}} - 1 \right)^2 \tag{9}$$

then. Finally, we have $q_{\max} = q(v_{\max})$, i.e.

$$q_{\max} = \frac{v_{\max}}{l_0 \cdot \left(\frac{2v_f}{v_{\max}} - \frac{v_f^2}{v_{\max}^2} \right) + \frac{l_0 v_f \cdot \left(\frac{v_f}{v_{\max}} - 1 \right)^2}{v_f - v_{\max}} + c_3 v_{\max}} \tag{10}$$

using Eq. (4) together with Eqs. (8) and (9), and solving for c_3 results in

$$c_3 = \frac{1}{q_{\max}} - \frac{l_0 v_f}{v_{\max}^2} \,. \tag{11}$$

In summary, that means the Van Aerde model is completely defined via the four physical parameters v_f (free-flow speed), $q_{\max}$ (capacity), $v_{\max}$ (speed at capacity) and l_0 (gross vehicle headway for jammed traffic).

Model calibration

Calibration of the model then means to adjust these four parameters depending on different road classes (i.e. road function combined with classes of speed limit and number of lanes) so that the best possible fit of the model curves from Eq. (2) with real data is obtained for each of these road types. For this purpose, volume and speed data as measured by local sensors can be used (cf. Figure 1).

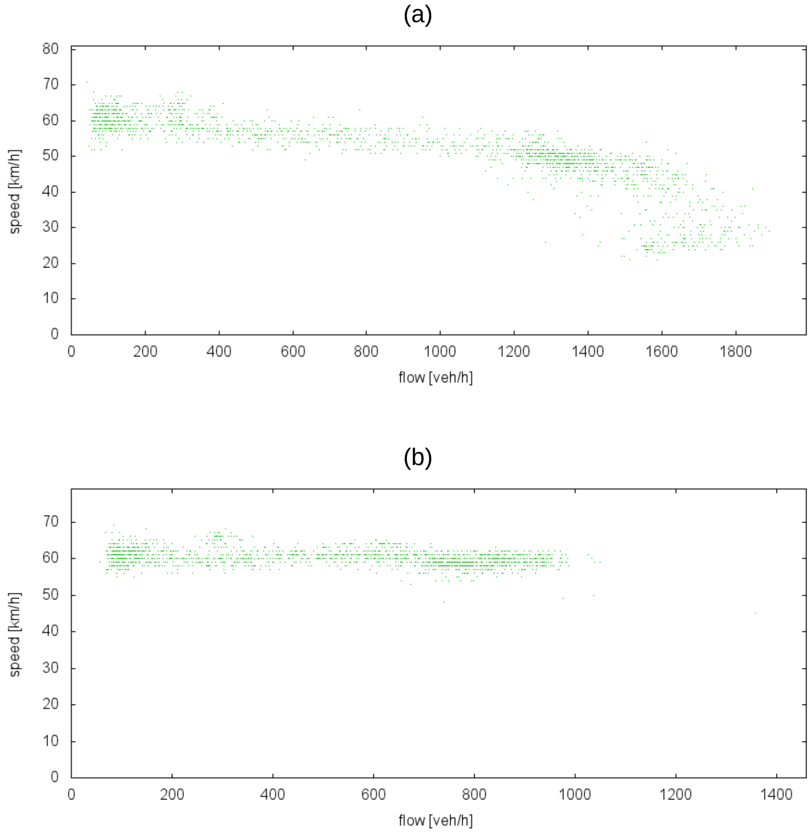

Figure 1: Measured speed-flow relations.

Obviously, there are data sets which are more suitable than others. For instance, the second data set (see Figure 1b) is not very helpful regarding the estimation of capacity since measured traffic never gets congested in this example. Consequently, the calibration process has to start with a careful selection of suitable sensor locations where the full fundamental diagram, i.e. mostly the complete relation between volumes and speed can be observed over time. Then, adjusting the parameters v_f, $q_{\max}$, $v_{\max}$ and l_0 (cf. Figure 2) is done either manually or preferably via numerical optimization.

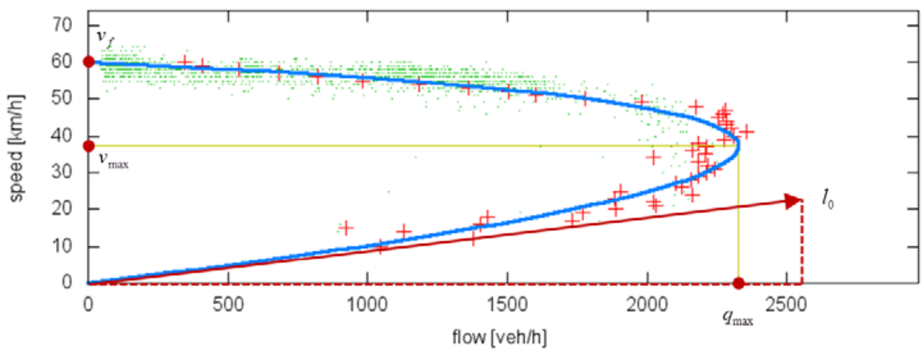

Figure 2: Model calibration.

In context of the automatic approach, measured volumes are averaged per discretized speed level first (resolution: 1 km/h; see the red crosses in Figure 2) in order to harmonize the influence of different traffic conditions (free-flow and congestion) on the subsequent optimization routine. Without such averaging, the typically much larger number of data points belonging to free-flow traffic would completely dominate the optimization so that reasonable estimates of capacity, for instance, were not possible. The target function f, which has to be minimized, then simply is the quadratic deviation between the Van Aerde curve as defined by Eq. (2) and the measured average volumes q_v, i.e.

$$f(v_f, q_{\max}, v_{\max}, l_0) := \sum_{v=0}^{\infty} \left(q(v) - q_v\right)^2 \tag{12}$$

where $q(v) := 0$ for all $v \geq v_f$. Of course, the summation in (12) is restricted to that speed levels v where corresponding q_v-values are available. From a technical perspective, the minimization of f is done by a combination of gradient search and enumeration while keeping the natural constraints

$$\begin{aligned} &0 \leq v_{\max} \leq v_f \\ &q_{\max}, l_0 \geq 0 \end{aligned} \tag{13}$$

as well as a just technical constraint

$$v_f \leq v_{f,bound} \tag{14}$$

where $v_{f,bound}$ is a fixed sufficiently large number, e.g. $v_{f,bound} = 200$ km/h.
Figure 2 depicts a sample result for the case of automatic model calibration based on real-world data from a local sensor on an urban road section. As can be seen, the estimated model (blue curve) fits the original data very well.
In this context, note that the optimization routine in Figure 2 minimizes the deviation between model and data in horizontal direction. That means speed is interpreted as the independent and volume as the dependent variable. Needless to say, this is quite natural regarding the idea of this paper, namely estimating traffic volumes from measured PVD speeds where we also want to minimize the error regarding volumes rather than speeds. Moreover, horizontal optimization in Figure 2 avoids the obvious mathematical problem of ambiguity of speed when it was described as function of traffic volume.

ESTIMATING TRAFFIC VOLUMES

With regard to the real-world example below, it was possible to calibrate Van Aerde curves for a total number of 25 road classes (from freeways to minor roads with different speed limits and numbers of lanes) based on real data from 60 carefully selected local detectors in the city of Berlin (Germany) by applying the above methods. Road classes without suitable data sets available were mapped onto one of the others which is expected to have more or less the same characteristics regarding road topology and traffic conditions.

Methodology

Based on probe vehicle data (PVD) from about 4,300 taxis, traffic volumes for all major (and to some extent also minor) roads of Berlin could be estimated, then. For this purpose, travel speeds v_{PVD} as the inverse of travel time were computed from the measured GPS data (cf. Schäfer et al., 2002) which then are the inputs for the calibrated speed-flow relation from Eq. (2).

To be more precise, the actual inputs are defined by

$$v'_{PVD} = v_{PVD} \cdot \frac{v_f}{v_{f,PVD}} \tag{15}$$

where $v_{f,PVD}$ is the free-flow travel speed as estimated through the mean travel speed measured between 10pm and 4am in the night. The reason for this kind of normalization is that local speeds as observed by local detectors and travel speeds from PVD typically differ to some extent. That is, travel speeds are usually somewhat lower because they also include delays (e.g. intersection delays) which occur apart from the specific locations of the local detectors. By adjusting the speeds to the free-flow speed parameter of the calibrated Van Aerde curve, large systematic errors in traffic volume estimation can be avoided.

Let, for instance, $v_{f,PVD}$ be just 5 km/h lower than v_f in Figure 2, then a measured travel speed of 55 km/h ($= v_{f,PVD}$) would correctly yield a traffic volume near to 0 veh/h when Eq. (15) is applied, but would give a wrong estimated traffic volume of about $1{,}000$ veh/h otherwise. Thus, needless to say, Eq. (15) is essential for obtaining reasonable results.

Results

Figure 3 shows an exemplary daily curve of estimated and true traffic volumes as observed by a local detector which, of course, has not been used for model calibration (Aggregation level: 1 hour). In this context, road class "2663" (cf. Figure 3) represents an inner-city major road with speed limit up to 50 km/h and 3 or more lanes.

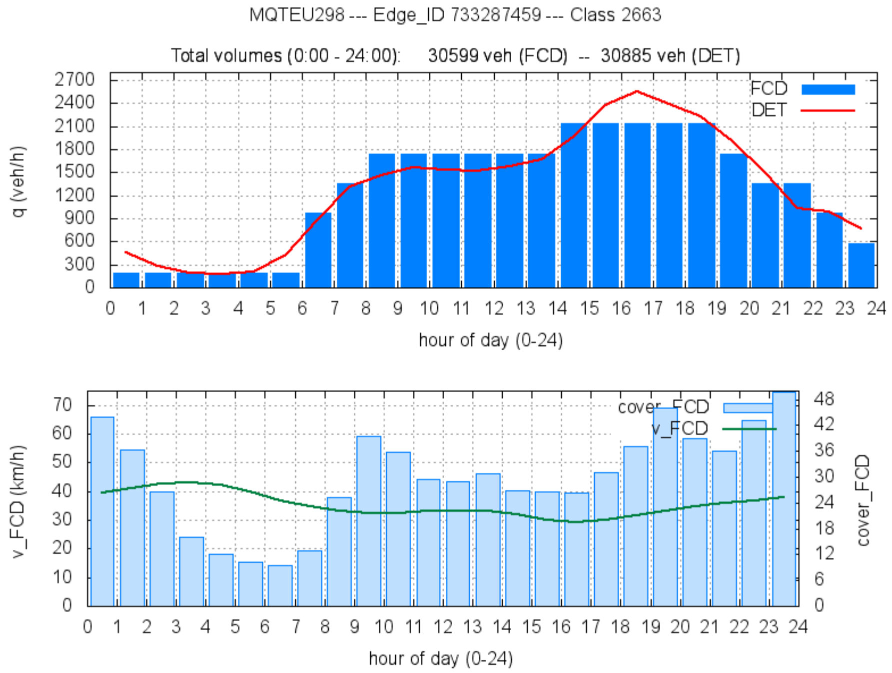

Figure 3: Exemplary daily curve of estimated (FCD) and true (DET) traffic volumes (inner-city main road).

The fact that estimated traffic volumes are constant over time is simply because of a technical discretization of the results into a small number of equidistant volume clusters. Obviously, this is also the reason for the constant increments when estimated traffic volumes change in the daily curve of Figure 3. Apart from that, the correlation between both displayed curves in the upper plot is very good. In addition, the lower plot of Figure 3 shows the corresponding travel speeds as well as the coverage which is the average number of observed GPS measurements per hour for the considered road section.
However, the quality of estimation is not always as good as above. In particular, on freeways or roads sections with similar characteristics, the results can be much worse or even inacceptable (cf. Figure 4).

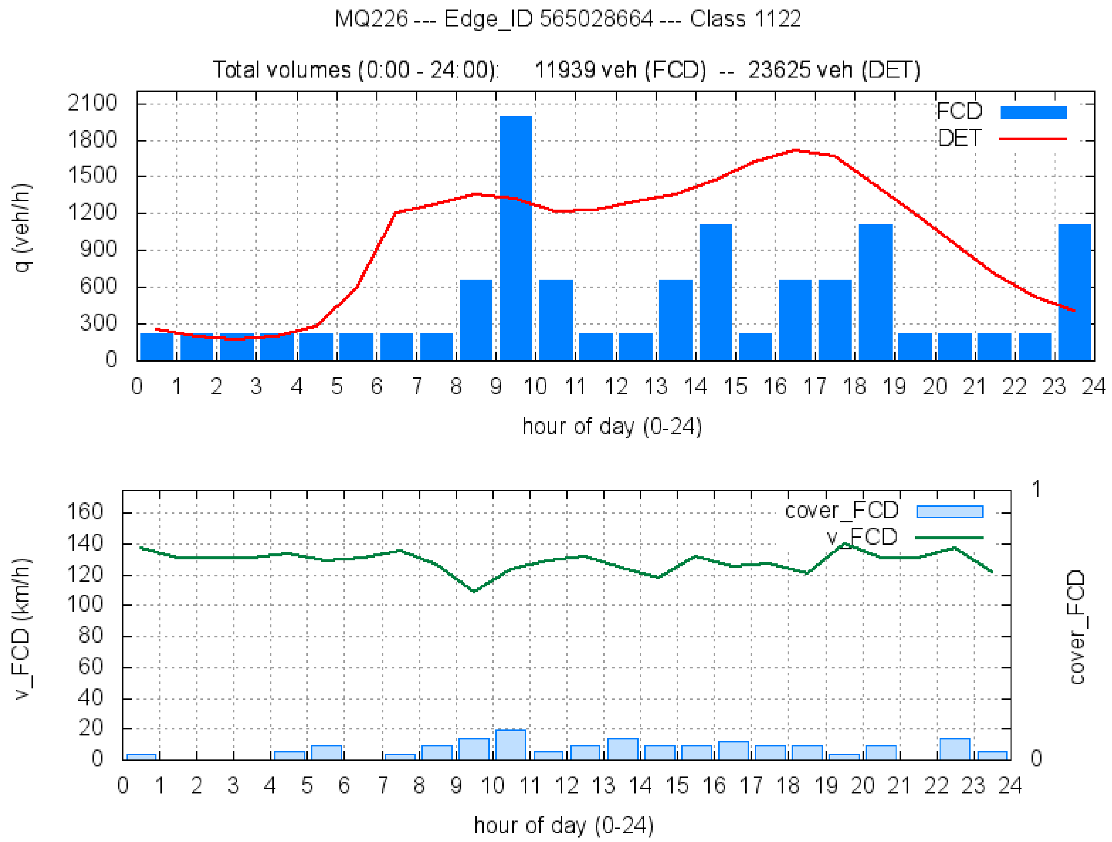

Figure 4: Daily curve of estimated (FCD) and true (DET) traffic volumes (freeway).

This is mainly because of two reasons. The first one refers to the extremely low coverage values in the example of Figure 4 which is quite typical for taxi probe systems in case of road sections far away from the city center as in the presented plot. The second and even more crucial reason, however, is that the speed-flow relation, which is essential for the whole described approach, often is a nearly constant function for the undersaturated branch (cf. Figure 5). Consequently, even large changes in traffic volume may not be visible in the corresponding speed curves in this case.

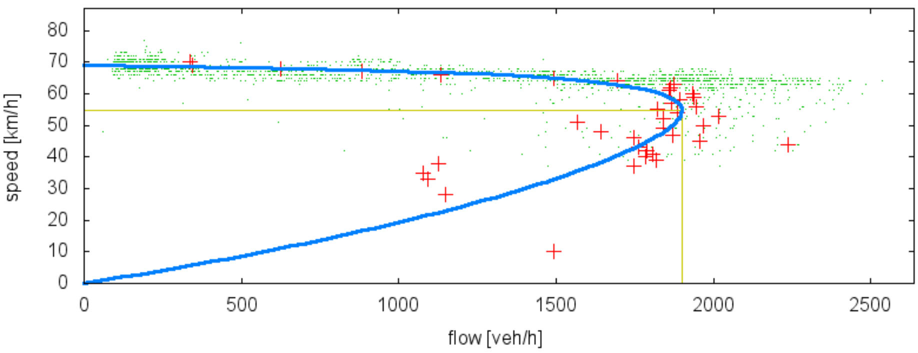

Figure 5: Nearly constant speed-flow relation in case of undersaturation.

Finally, in order to get a more founded picture about the quality of the analysed approach, estimated traffic volumes were compared with the true volumes at about 600 detector locations in Berlin covering all relevant major road types. Figure 6 shows the complete observed error distribution.

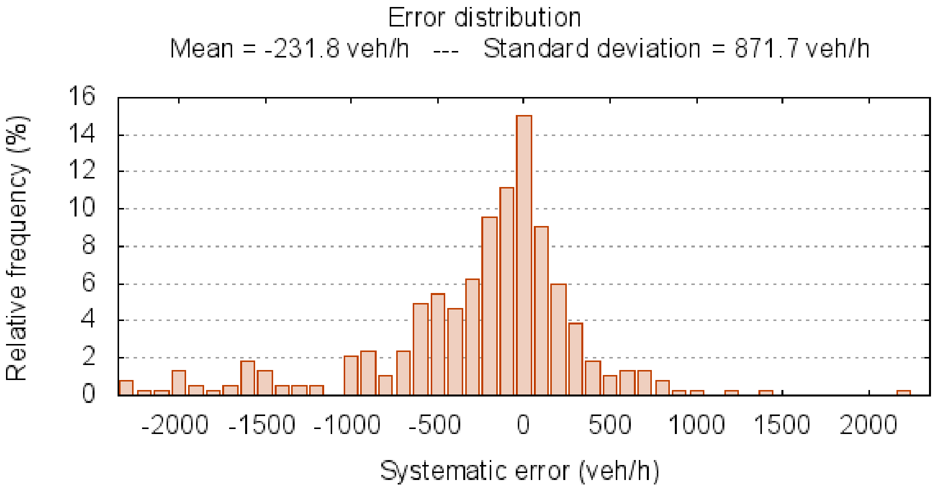

Figure 6: Error distribution (about 600 detector locations).

As can be seen, the maximum of this distribution is close to zero as required. Nonetheless, there still is a significant systematic bias of –231.8 veh/h and a quite large standard deviation of about 871.7 veh/h. Of course, outliers such as in Figure 4 may be an explanation for this non-satisfying result. Even more, however, the deterministic representation of the speed-flow relation by Van Aerde curves as well as the structure of the fundamental diagram itself seem to be a stumbling block for highly reliable estimates of traffic volume via the discussed approach. Maybe, a stochastic variant of the Van Aerde representation which explicitly incorporates the stochastic noise contained in real speed-flow relationships could help to reduce the observed errors.

CONCLUSION

Probe vehicle data (PVD) are an important tool for conducting area-wide traffic measurements, in particular for urban areas. However, it is not possible to directly obtain traffic volumes with this approach so that additional efforts have to be made in order to derive flow information from PVD.

This contribution showed that calibrated speed-flow curves can principally be used to translate observed travel speeds (computed from GPS measurements) into traffic volumes. The quality of estimation, however, was in total not very convincing in the considered scenario although there are many examples for reasonable results, too (cf. Figure 3). The reasons for these non-satisfying findings have already been discussed in the previous section, namely that the specific structure of the fundamental diagram together with its simplifying representation via deterministic Van Aerde curves makes deriving traffic volumes from travel speeds (or speeds in general) very difficult.

Future attempts could apply a more realistic stochastic representation of the fundamental diagram in addition to the use of information about the transitions between speeds or volumes of subsequent time slices in order to tackle the above-mentioned problems.

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