Royal Netherlands
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*Ministry of Infrastructure
and Water Management*

DEEP NEURAL NETWORK APPROACH FOR AUTOMATIC FOG DETECTION USING TRAFFIC CAMERA IMAGES

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Outline

- Fog hazard
- Goal of the project
- The approach
- Machine learning
- Data
- Neural networks
- Image to features
- Model fitting
- Results
- Summary
- Future work

Fog as hazard

- Substantial impact on air, marine, and road traffic
- Appears and dissipates suddenly
- Large spatial differences (local phenomenon)
- Hard to accurately forecast

Goal

Short term

- Increase fog observations without placing new visibility sensors
- Use cameras to identify fog conditions and issue warnings

Long term

- Feed detected fog from camera observations to weather rooms and traffic control centers
- Assimilate detected fog into weather model to improve fog predictions

Limitations

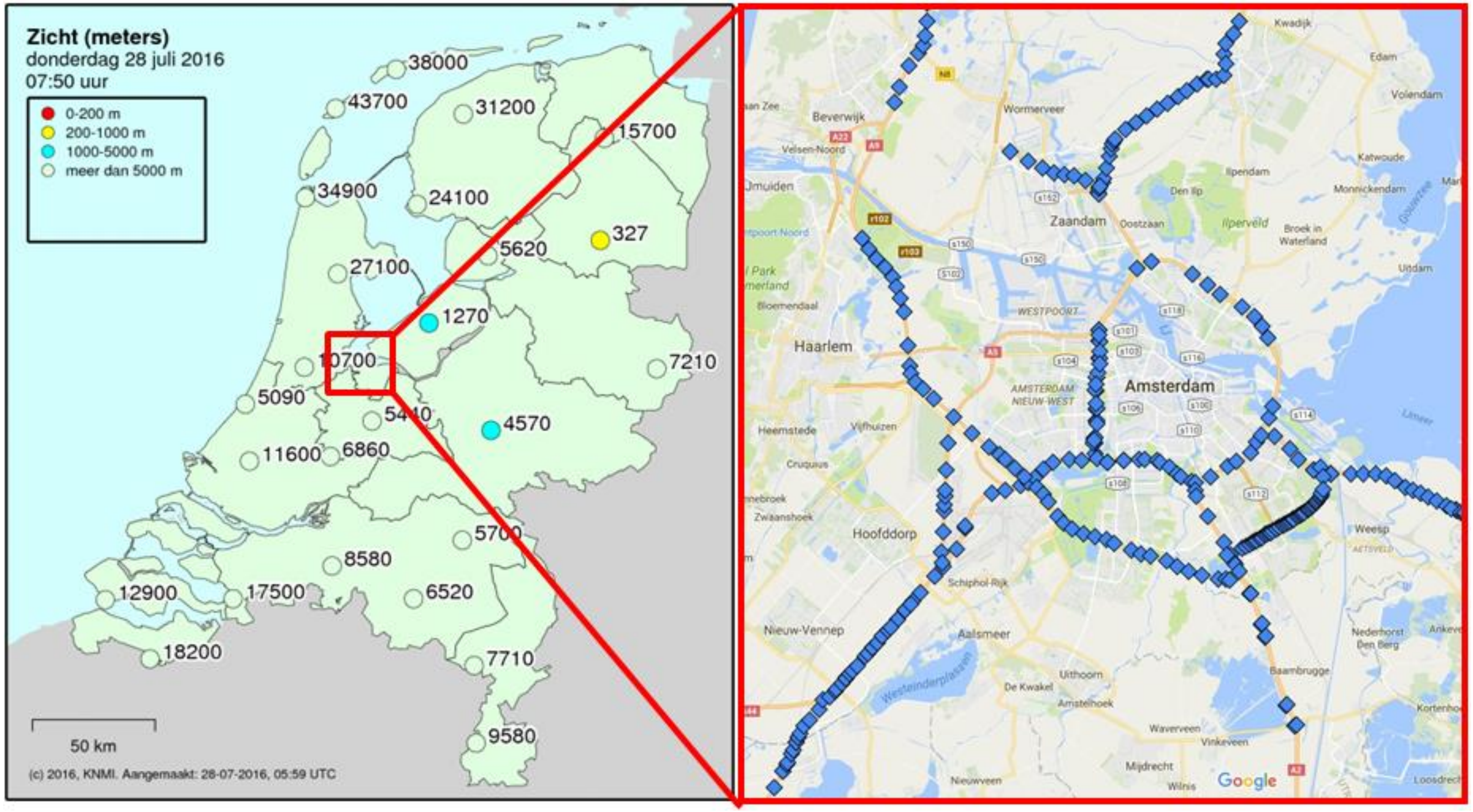
- Daylight fog identification from static and moving cameras using image analysis

Traditional visibility sensors vs. traffic cameras

- 25 KNMI AWS with visibility sensor

vs

- 5000 cameras along highways

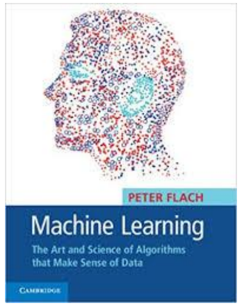


The dataset

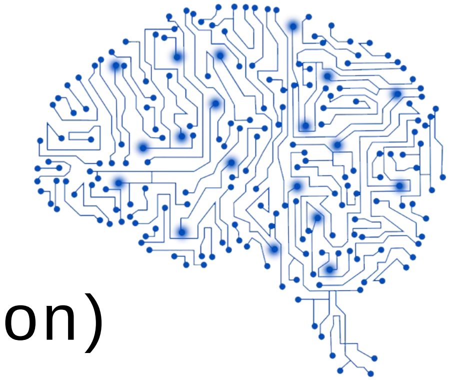
- Some facts:
- 7 cameras at KNMI AWS
- 160 cameras along Dutch highways (since June 2017) +160 new cameras (since October 2018)
- ~10 million images archived
- Image sampling every 10 minutes
- Upon collection day phase is associated (day, night, dawn, dusk)
- Limited camera metadata (only lat/long position)

Idea of machine learning

- *"Machine learning is the systematic study of algorithms and systems that improve their knowledge or performance with experience."* Prof. Flach author of Machine Learning: The Art and Science of Algorithms that Make Sense of Data



- Use an algorithm to train a model just on data
- Supervised learning:
  - The response variable is known and available (evidence, ground truth)



- Have a good understanding of the domain (feature selection)
- Key: have a sufficient amount and variability of (good) data

Labeling the data

- Visibility, Meteorological Optical Range (MOR) of visibility sensor
- From visibility to categorical indicator:
  - MOR<=250m → FOG
  - MOR>250m → NO FOG
- Only few cameras have co-located visibility sensors
- Trade-off:
  - automatic labeling vs. manual labeling
  - enough data and enough GOOD data

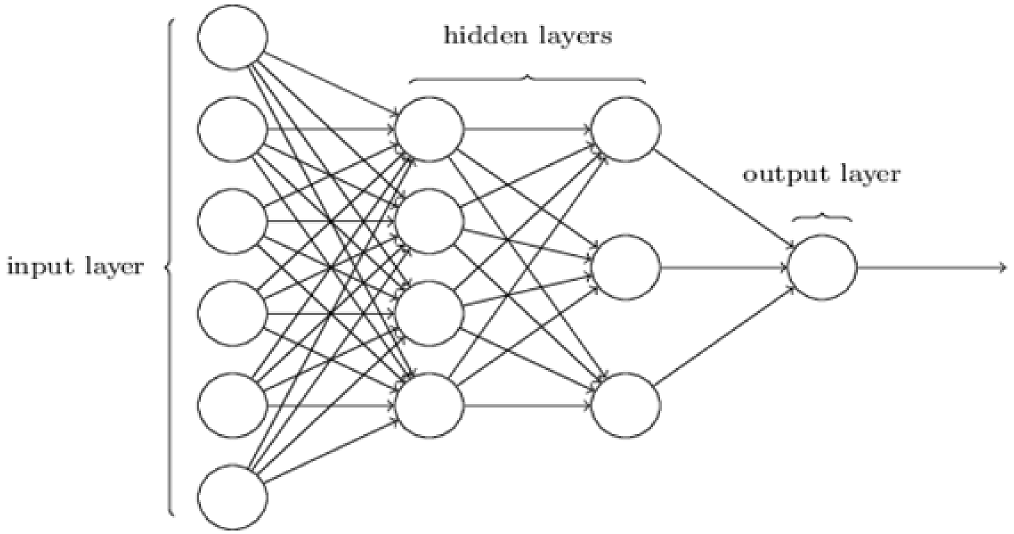
Labeling the data

- Two cases are considered:

- Case A: 16 cameras along the highways in range of 4 MOR sensors
- Case B: 82 cameras along the highways in range of 7 MOR sensors

Neural network

- Brain inspired
- Each node (neuron) operates on the inputs and if a threshold is passed it "fires"
- Goal: learn about the phenomenon under investigation without explicitly providing specific rules
- A node sums up the (weighted) inputs and applies a rectifier
- Choice for type of rectifier, # layers, # nodes

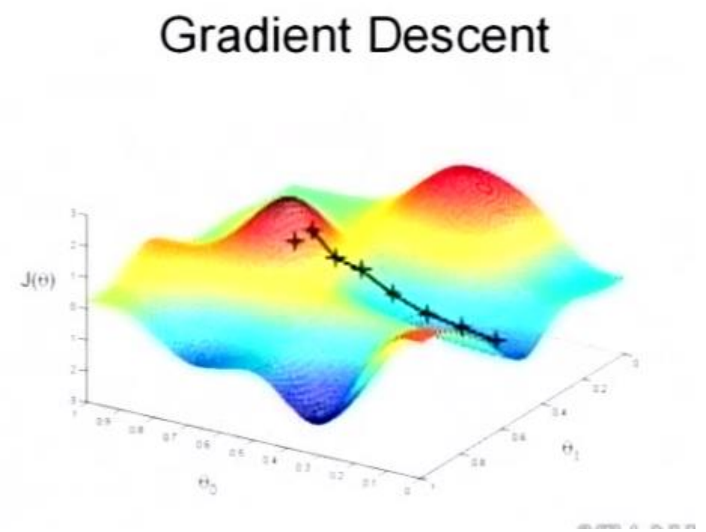


Neural network in action

- Learning phase: find the right weights that are best suited in approximating the desired output

- Weights start from an initial random guess and they are updated iteratively in order to minimize a loss function using some form of gradient descent

- By exposing to many (tens of thousands to millions) examples, the network will learn to approximate the output from the inputs provided



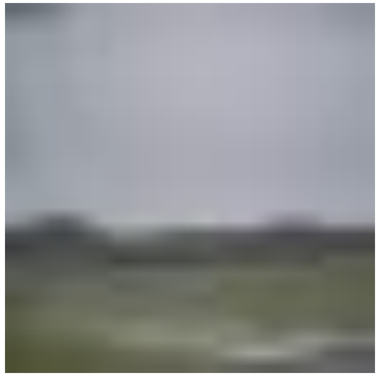
Why Neural Networks

- Used proficiently in image processing and image classification
- More general method of fog detection than decision trees and image features
- To handle sceneries are very different even from the same camera (e.g., zoom, pan, tilt)

Same camera, same day, few hours apart

Image pre-processing

Reshape to 28x28 px
Image blurring
to
Harmonize images
Reduce computation
Counter overfitting



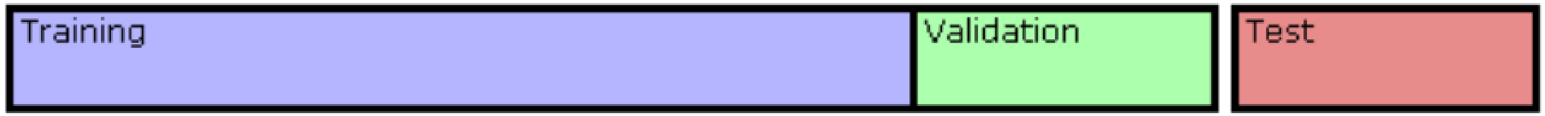
From image to features

- RGB channels extracted
- RGB pixel intensity
- Pixels intensity are the features (i.e., predictors)
- The input of the image to the neural network is constituted by a vector of 28x28x3=2352 variables

Full data transformation and feature extraction

Model fitting

- Dataset split



  - Training (60%) – Case A ~350k images – Case B ~1.2M images
  - Validation (20%)
  - Test (20%)
- Deep neural network fitting via R and H_2O library
- Hyper-parameters optimization via random grid search

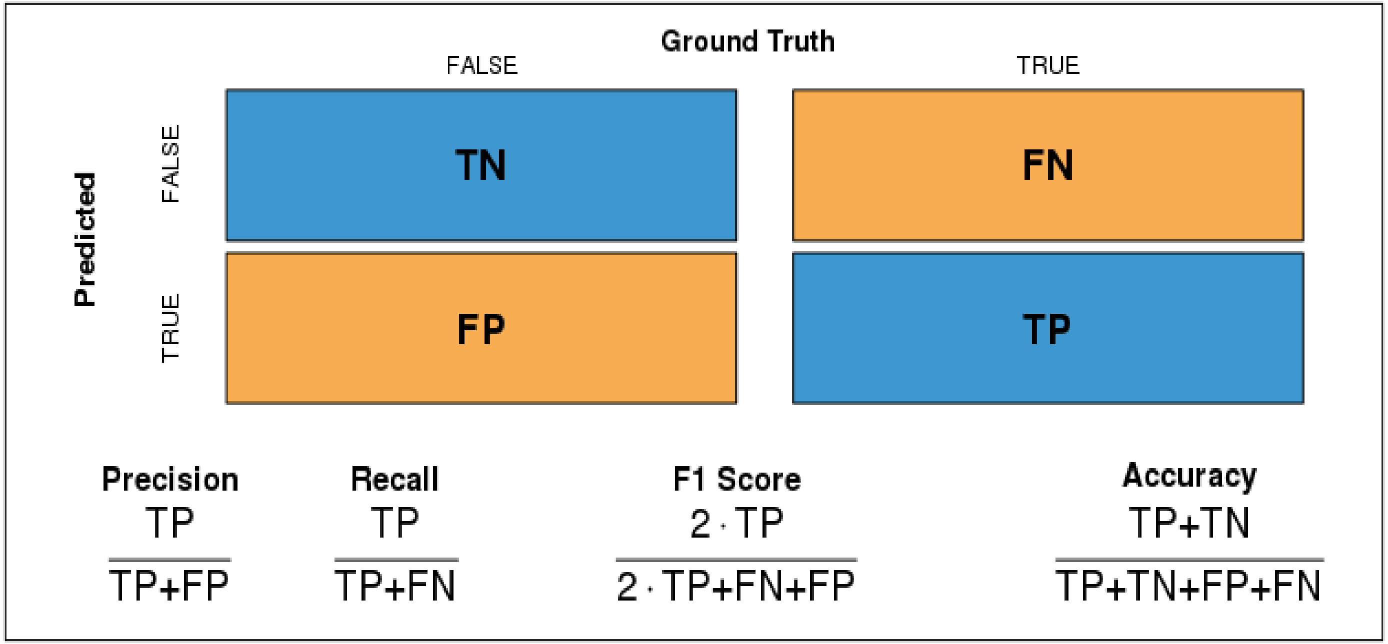
Model fitting

Case	Number of layers	Number of nodes in hidden layers	Activation function in hidden layers	F1 score training subset*
2.5km data set	7 (Input, 5 hidden layers, output)	75, 75, 50, 50, 10	Rectifier	0.986
7.5km data set	7 (Input, 5 hidden layers, output)	50, 50, 50, 25, 10	Rectifier	0.981

*F1 score computed on a balanced subset from the training set of 10000 images per class.

Results

How to interpret



TRUE=foggy

Results on test set

Case A

Predicted \ Ground Truth	FALSE	TRUE
FALSE	115133	173
TRUE	255	398

Precision	Recall	F1 Score	Accuracy
0.609	0.697	0.65	0.996

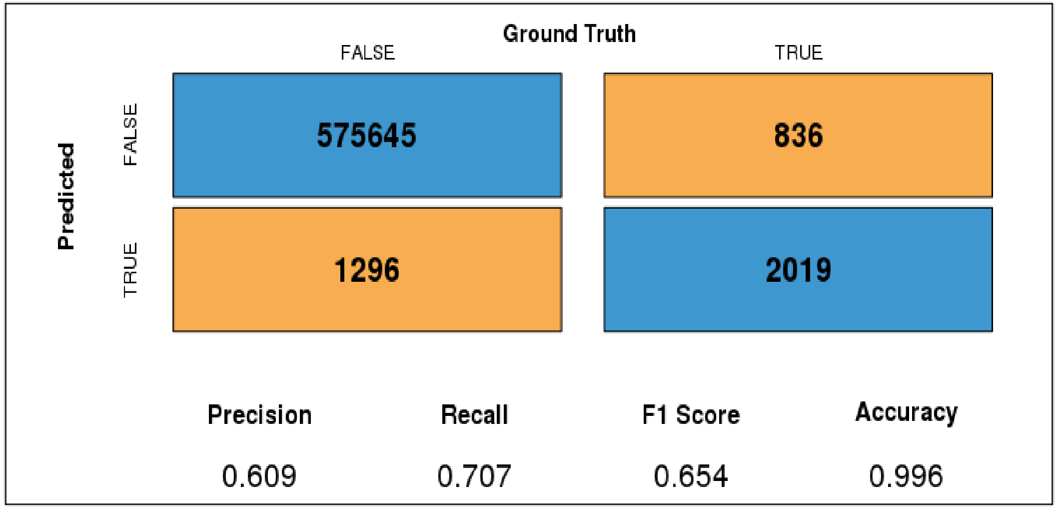
Case B

Predicted \ Ground Truth	FALSE	TRUE
FALSE	389094	998
TRUE	964	1033

Precision	Recall	F1 Score	Accuracy
0.517	0.509	0.513	0.995

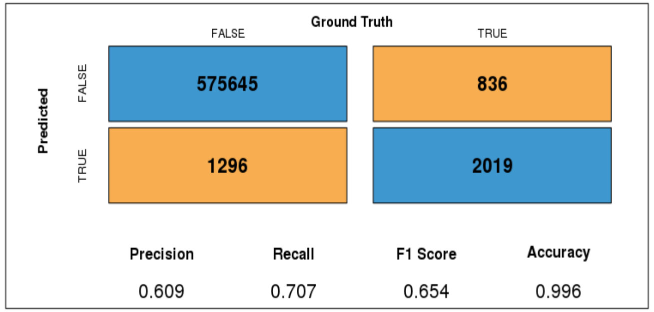
Results

- **All data of case A (training + validation + test)**



Analysis of results

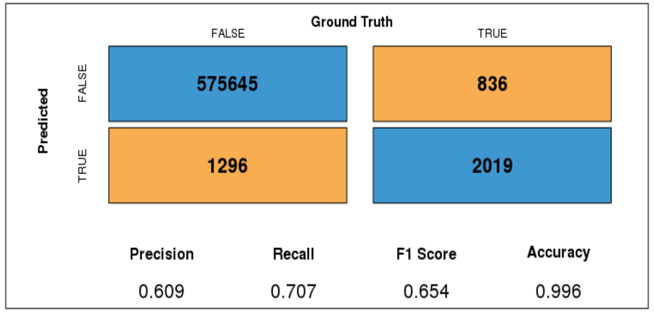
- 1296 FP cases (model predicts dense fog and the sensor reports no dense fog)
- 707 (55%) the sensor reports fog (MOR<1000m)
- 235 cases (18%) not even report haze (MOR<5000m)
- FP occur mainly isolated in time (603 cases) and space (914 cases)



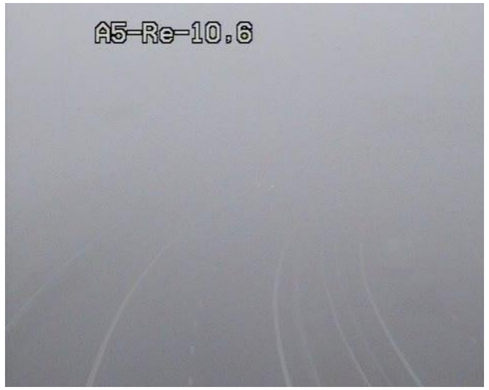
Examples FP cases

Analysis of results

- 836 FN cases (model predicts no dense fog and the sensor reports dense fog)
- FN isolated in time (270 cases)
- FN occurs less often spatially isolated (305 cases)



Examples FN cases



Possibilities of post processing

- Based on consistency in space and time

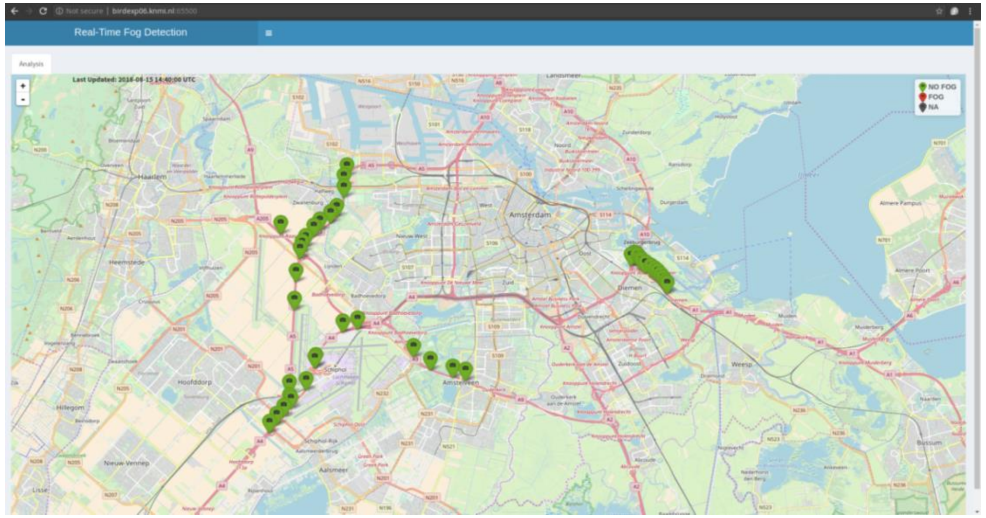
Post processing	Precision	Recall	F1 score	Accuracy	% omitted	Precision*	% fog
none	60.9%	70.7%	65.4%	0.9963	0.00%		
change	70.2%	74.7%	72.4%	0.9975	0.26%	22.5%	11.7%
change F --> T	70.2%	69.3%	69.7%	0.9972	0.11%	21.5%	4.8%
change T --> F	60.9%	76.0%	67.6%	0.9967	0.15%	23.3%	6.9%
difference with nearest	74.8%	77.6%	76.2%	0.9982	0.37%	31.2%	23.7%
change OR nearest	79.7%	80.6%	80.2%	0.9986	0.54%	28.4%	31.0%
change AND nearest	67.4%	72.7%	69.9%	0.9971	0.09%	23.4%	4.3%

Summary

- A deep learning approach to fog (binary) classification
- Reuse of images from traffic cameras surveillance
- Good performance given:
  - Ground truth, spatial differences
  - High dynamic scenery
- Issues in generalization
- Possibilities of post processing

Future work

- Test the solution benefit in weather room and traffic control centers
- Implement spatial consistency in the NN model
- Train new models for night, dawn/dusk
- Test convolutional neural network




Thank
You
Vinaka
köszönöm
Kiitos
Maake
Asante
Shukria
Dhanyavadagalu
감사합니다
Dankscheen
спасибо
Kam Sah Hammida
اركش
Manana
Dankon
Dank Je
Mauruuru
Biyan
Diolch i Chi
Terima Kasih
Matondo
Taiku
Blagodaram
Ngiyabonga
Dziekuje
Chokrane
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Grazie
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Gracias
Khap
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