Predicting a vehicles velocity using dashcam footage

A deep learning approach

Florian Wolf, Department of Mathematics and Statistics
Franz Herbst, Department of Physics

Machine Learning using Matlab
Universität Konstanz

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The "comma ai speed challenge"[1]

Motivation

- Autonomous driving is currently one of the most prominent problems in machine learning
- But quite hard to set up on a desktop pc
- Predicting a vehicles velocity from video footage is a related, but also a much more simplified task

Initial Dataset:

- Training video with 20400 frames (20 fps)
- Data file with velocity of the car at each frame
- Test video with 10798 frames (20 fps)

Evaluation:

- The mean squared error (MSE) is used to measure performance

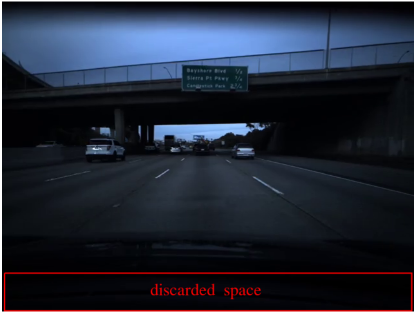
$$\mathcal{L} = \sum_i (p(x_i) - y_i)^2$$

[1] https://github.com/commaai/speedchallenge

Analysis of the dataset

Video data:

- Frame size of $(640, 480, 3)$ pixels
- Cut off last 60 pixels, to remove black frame inside the car
- Sample down the frame to half its size, to reduce computation time



Original frame

Cut off the last 60 pixels, downsampled

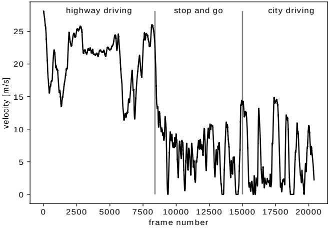
Analysis of the dataset

Splitting of the dataset

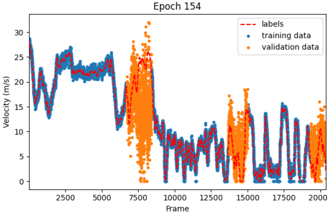
- Initial splitting: hard cut off after 80% of the frames
- Situational splitting: divide dataset into blocks of different driving scenarios, splitting with 80% test and 20% validation data on each

Evaluation:

- variance $\sqrt{\mathcal{L}} \gtrsim 16$: no fitting
- $10 \lesssim \sqrt{\mathcal{L}} \lesssim 16$: average velocity fitted
- $5 \lesssim \sqrt{\mathcal{L}} \lesssim 10$: qualitative detection
- $1 \lesssim \sqrt{\mathcal{L}} \lesssim 5$: quantitative detection
- $\sqrt{\mathcal{L}} \lesssim 1$: perfect detection



driving situations in v-t-plot



example performance on training set

training: $\sqrt{\mathcal{L}} = 0.4$, test: $\sqrt{\mathcal{L}} = 6.3$

Optical flow using “Farneback pyramid method” [2]

- Image sequence $(f_t)_t$ with $f_t : \Omega \to \mathbb{R}^3$, for all t
- Goal: find Global (dense) flow field $V : \Omega \to \mathbb{R}^2, \omega \mapsto (V_x(\omega), V_y(\omega))$, which solves the optical flow equation

$$\partial_x f \cdot V_x + \partial_y f \cdot V_y + \partial_t f = 0$$

- Uses a downsampling pyramid, to solve the equation for different resolutions of the image
- Parameters for the Farneback method

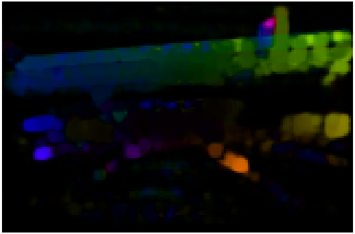
$$\begin{aligned} \text{pyramid levels} &:= 3 \\ \text{pyramid scaling} &:= 0.5 \\ \text{window size} &:= 6 \\ \text{SD of the gaussian filter} &:= 1.1 \end{aligned}$$

- Result: **Flow field with** $(160, 105, 2)$ **pixels**

Visualization of the flow field

- Flow field is a two-dimensional vector field
- RGB representation via
  - Transform flow field into polar coordinates $(V_x, V_y) \overset{\cong}{\mapsto} (r, \varphi)$
  - Normalize magnitudes r for the third channel
  - Values of the second channel are all set to 255
  - Multiply angle φ by factor $\frac{180}{2\pi}$ for the first channel
- Sample down the resolution again to speed up the training

Input frame



Corresponding flow field

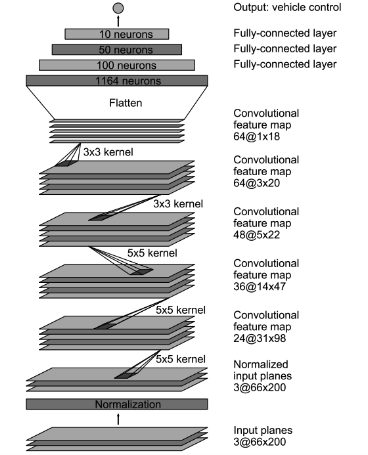
Choosing an initial architecture

Method selection

- Speed prediction is a non-linear regression task ⇒ neural network
- Task involves feature extraction ⇒ convolutional neural network (CNN)

Initial architecture

- Using paper of *NVIDIA* work group [1] of a CNN for self-driving cars adapted on our initial data
- Enough complexity and layers to handle the task and lots of possibilities to fine-tune it
- Initial results with the raw model: $\mathcal{L} < 3$ on the training set and about $\mathcal{L} \approx 19$ (initial splitting) on the test set



Original architecture of the *NVIDIA* paper [1]

Our approaches to optimize the results

1. **Change components of the initial architecture**
   - Adding different pooling layers
   - Use other activation functions
2. **Change the architecture**
   - Expand structure to Siamese network
   - Use different setups
3. **Change the input data**
   - Acquire more data
   - Use brightness augmentation

Batch Normalization, Dropout layers, activation function and pooling

- Batch normalization to speed up the training [3]
- Initial activation function: $\mathrm{ReLu} : \mathbb{R} \to \mathbb{R}_0^+, x \mapsto \max\{0, x\}$, still MSE of over 15 on the testing set, less then 2 on the training set
  $\Rightarrow$ Overfitting problems
- Dropout layers [4] to make the model more robust and reduce overfitting
- Solve problems of dead neurons using

$$\mathrm{leakyReLU} : \mathbb{R} \to \mathbb{R}, x \mapsto \begin{cases} x, x \geq 0 \\ c \cdot x, x < 0 \end{cases}$$

with $c = 0.01$, MSE of around 11 on the testing set and less than 3 on the training set

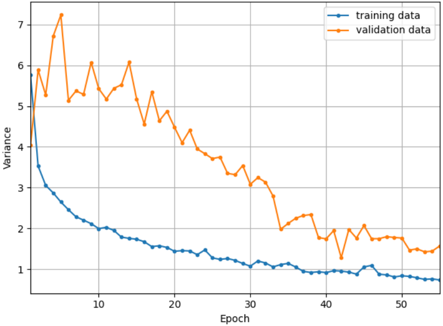
Pooling layers (initial splitting)

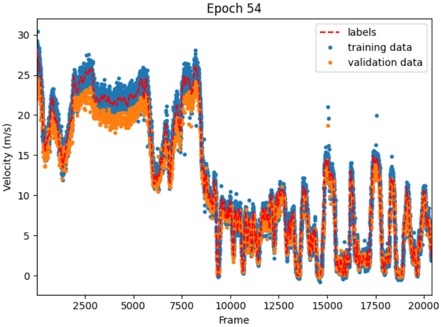
Initial splitting, 8 epochs	ReLU		leakyReLU	
	Train	Test	Train	Test
No pooling	2.85	12.08	2.45	10.75
Max pooling	5.62	11.82	5.52	10.29
Max pooling (15 epochs)	-	-	**3.22**	**9.63**
Average pooling	7.70	11.40	6.08	13.09

Table: MSE results of the network using different pooling strategies, one dropout layer, two different activation functions and the initial splitting. We trained each of the models for eight epochs.

Training of the optimized model

Performance (Max Pooling):

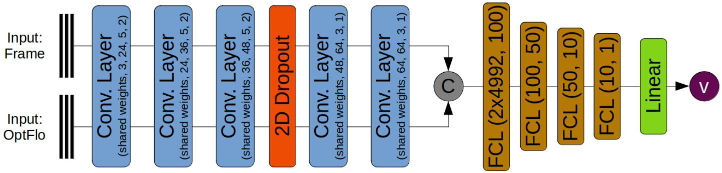




- model converges on training data $\sqrt{\mathcal{L}} < 1$
- test data only with qualitative fitting $\sqrt{\mathcal{L}} = 6.3$

Siamese Architecture: Setup

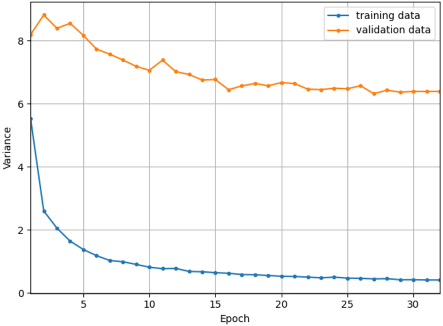
- Based on the initial architecture
- Using the same convolutional layers on raw frame and optical flow
- Weighted sum of the results into fully connected layers

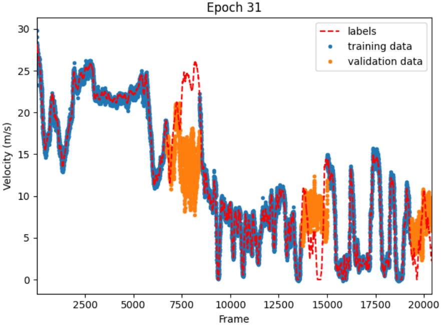

Input: Frame
Input: OptFlo
Conv. Layer (shared weights, 3, 24, 5, 2)
Conv. Layer (shared weights, 24, 36, 5, 2)
Conv. Layer (shared weights, 36, 48, 5, 2)
2D Dropout
Conv. Layer (shared weights, 48, 64, 3, 1)
Conv. Layer (shared weights, 64, 64, 3, 1)
C
FCL (2x4992, 100)
FCL (100, 50)
FCL (50, 10)
FCL (10, 1)
Linear
v

- Use model also for two consecutive frames f_t and f_{t+1}
  $\Rightarrow$ advantage: no previous calculation of optical flow needed

Siamese Architecture: Performance

Performance (Siamese network frame with optical flow):

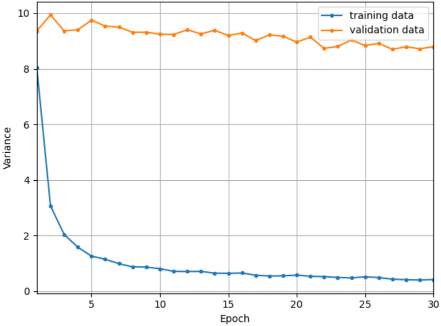


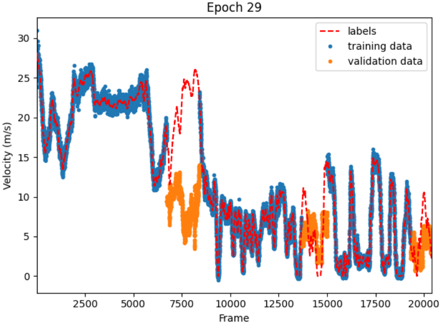


- model converges on training data $\sqrt{\mathcal{L}} < 1$
- test data only with qualitative fitting $\sqrt{\mathcal{L}} = 6.3$

Siamese Architecture: Performance

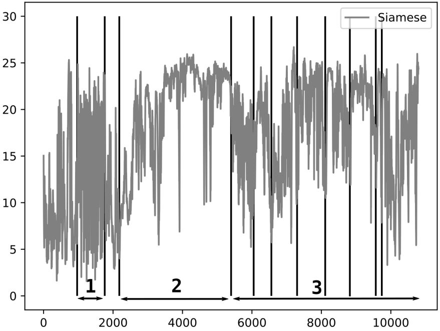
Performance (Siamese network with two frames):





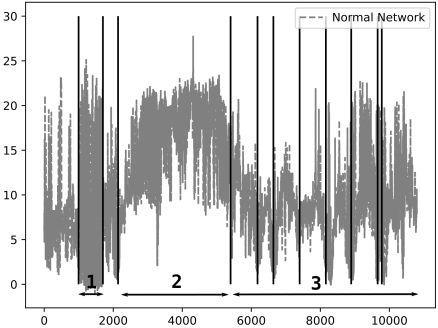
Evaluation on the test video

Siamese network:



- 1: longer halt at crossroads
- 2: highway driving: quite stable detection
- 3: city driving: velocity to high but several stops detected

Original (optimized) network:

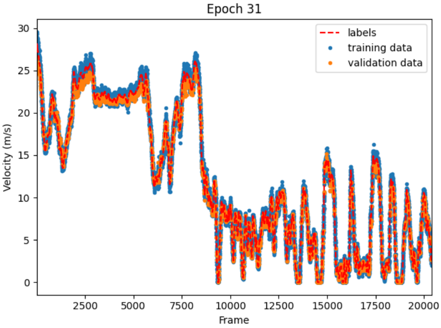


- 1: longer halt at crossroads
- 2: highway driving: quite stable detection but velocity to slow
- 3: city driving: velocity good and several stops detected

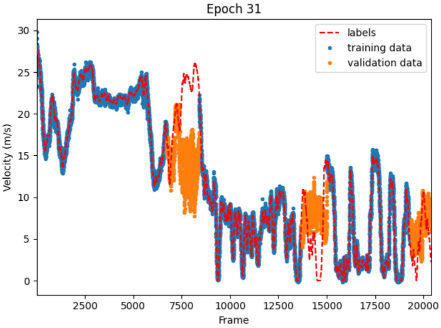
Problems

We identified two problems

1. Overfitting, when validation data is not randomly distributed in the data but a of continuous blocks
2. Predictions are very susceptible for brightnesses/illumination changes in the frames, because of unstable calculations of the optical flow



random shuffled validation data



block validation data

Problems and possible solutions

Problems

- Predictions are limited to data very similar to the training data
- Predictions do not generalize well

Most likely explanations:

- Very limited dataset for a complex model
- Network is not prepared for unseen situations
- Changes in brightness and illumination

Solution:

- Acquire more data for various driving situations and/or use a less complex model
- Add noise to the data, more robustness in the optical flow calculation

Acquire more data and evaluation of the test video

Method

- Video producing and velocity detection with common apps
  - *open street maps*: GPS tracking (`.gpx`-files)
  - *open camera*: dashcam footage

Advantages and Issues

- Easy method to create a lot of data (if a car is available)
- Velocity has some uncertainties (needs to be extrapolated to cover all frames; uncertainties of GPS vs. car sensors)
- Frame rate differs a little from original data (24 fps vs 20 fps)

Contrast and brightness augmentation

- Additional noise to frames **before** calculating the flow field.
- Change the brightness and contrast of an image via

$$\text{frame}_{\mathrm{augmented}}(i,j) = \alpha(i,j) \cdot \text{frame}(i,j) + \beta(i,j)$$

with functions α (contrast: >1 increase, <1 decrease) and β (brightness). To get some noise into the frames, we used

$$\alpha \sim \mathcal{U}(0,1) + 0.35$$
$$\beta \sim \mathcal{U}(-5,35),$$

where $\mathcal{U}(a,b)$ is the uniform distribution in an interval $[a,b]$ for $a<b$.

Summary and outlook

- So far good results and quite promising models
  ⇒ Short demo video
- Still a lot work to do, to get a truly convincing model
- Currently working on own data gathering and brightness/contrast augmentation to improve and generalize models
  ⇒ Idea: pick the so far best (two) model(s) and train them on the bigger and augmented dataset

References

[1] Mariusz Bojarski et al. "End to End Learning for Self-Driving Cars". In: (Apr. 2016). URL: https://arxiv.org/pdf/1604.07316v1.pdf.

[2] Gunnar Farnebäck. "Two-Frame Motion Estimation Based on Polynomial Expansion". In: Scandinavian Conference on Image Analysis (2003), pp. 363–370.

[3] Sergey Ioffe and Christian Szegedy. "Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift". In: (Feb. 2015). URL: https://arxiv.org/pdf/1502.03167.pdf.

[4] Nitish Srivastava et al. "Dropout: A Simple Way to Prevent Neural Networks from Overfitting". In: Journal of Machine Learning Research 15.56 (2014), pp. 1929–1958. URL: http://jmlr.org/papers/v15/srivastava14a.html.

Thank you for your attention.