MULTI-LOSS WEIGHTING WITH COEFFICIENT OF VARIATIONS

ABSTRACT

Many interesting tasks in machine learning and computer vision are learned by optimising an objective function defined as a weighted linear combination of multiple losses. The final performance is sensitive to choosing the correct (relative) weights for these losses. Finding a good set of weights is often done by adopting them into the set of hyper-parameters, which are set using an extensive grid search. This is computationally expensive. In this paper, the weights are defined based on properties observed while training the model, including the specific batch loss, the average loss, and the variance for each of the losses. An additional advantage is that the defined weights evolve during training, instead of using static loss weights. In literature, loss weighting is mostly used in a multi-task learning setting, where the different tasks obtain different weights. However, there is a plethora of single-task multi-loss problems that can benefit from automatic loss weighting. In this paper, it is shown that these multi-task approaches do not work on single tasks. Instead, a method is proposed that automatically and dynamically tunes loss weights throughout training specifically for single-task multi-loss problems. The method incorporates a measure of uncertainty to balance the losses. The validity of the approach is shown empirically for different tasks on multiple datasets.

1 Introduction

In a variety of computer vision tasks, models are taught predictive capabilities through optimising some objective function. While it is valid to use a single loss function for training a model, for many single and multi-task problems a (weighted) combination of loss functions defines the learning objective. In general, these loss functions \( L \) are combined as a linear combination of terms:

\[
L_{\text{total}} = \sum_i \alpha_i L_i + R(\alpha),
\]

(1)

where \( R(\cdot) \) denotes some regularisation on the weights which are at times used.

Often the model performance is sensitive to choosing the correct weight ratios \( \alpha \). In literature, the weighing of different losses is usually based on static weights, either by weighing each loss equally in the composite objective function, or by some hand-tuned values, often found by a hyper-parameter grid-search. Even though an extensive grid search over possible values for \( \alpha \) is computationally expensive, manually tuning loss weights is still prevalent. It is for example performed in segmentation tasks [3, 4, 5], depth estimation tasks [6, 7], pose estimation tasks [8], style transfer tasks [9].
[9][10], adversarial learning [11]. Regardless, using static weights for the losses throughout training might not result in optimal performance. Ideally, the weights $\alpha$ are learned or inferred along with the model parameters $\theta$, and are adaptable over time.

In the context of multi-task learning, [12] propose to dynamically prioritise difficult tasks throughout training and make use of a task hierarchy architecture to train their method. As opposed to difficulty prioritisation, [13] argues that multi-task learning should focus on learning easy tasks first because of the analogy with human learning. The authors of [14][15] formulate a joint likelihood estimate to determine task weights based on homoscedastic aleatoric uncertainty. Variance estimates are learnt along the network parameters and used to perform loss weighing. [1] suggest a gradient normalisation approach that attempts to balance gradient norms for each task at each time step. The authors of [2] state that while multi-task learning can, in general, be beneficial for all tasks, some individual tasks could compete for model capacity. The authors explore Pareto optimal solutions using a Frank Wolve solver. A similar idea is proposed in the context of reinforcement learning in [16], in which task synergy is rewarded, while task interference is penalised. In [17] the multi-task problem is simplified to optimise a main task and several auxiliary tasks. The gradients of the auxiliary tasks are weighed based on their similarity to the gradient to the main task. Another work [18] uses a combination of task-attention modules and dynamic weight averaging to yield the task weights.

All of the methods above solve loss weighting in a multi-task setting. In this paper a method is proposed that explicitly makes use of the statistics inherent to the losses to estimate their relative weighing, specifically in a single-task setting. The proposed method, called CV-Weighting, is founded on the Coefficient of Variation, which relates the loss variance to its mean. By explicitly making use of a robust estimate of a loss ratio, the loss weightings using to Coefficient of Variation are in a common scale. Figure 1 shows how the loss weights of CV-Weighting develop throughout training.

To validate the proposed method, extensive experimental evaluation across two tasks (depth prediction and semantic segmentation) and three datasets (KITTI, CityScapes, and PASCAL Context) is performed. The experiments show that CV-Weighting surpasses all multi-task loss weighting schemes and performs on par with hand-tuned weights in a single pass, with a learning rate optimised for the hand-tuned weighing. After a hyper-parameter search over the learning rate, CV-Weighting outperforms any of all current models.

## 2 Method

In this paper, the focus is on a single-task learning problem where the objective function is defined as a linear combination of loss terms. Each loss quantifies the cost with respect to a desired output or auxiliary objective, for example the pixel-wise L1 loss to measure the reconstruction error, or a softmax loss for (pixel-wise) classification. The goal is to find the (optimal) set of weights $\alpha$, see Eq. 1 for learning the task at hand. In order to find these weights, the following hypothesis is used:

**Hypothesis 1** A loss term has been satisfied when its variance has decreased towards zero.
In other words, this hypothesis says that a loss with a constant value should not be optimised any further. Variance alone, however, is not sufficient, given that it can be expected that a loss which has a larger (mean) magnitude, also has a higher absolute variance. Even if the loss is relatively less variant. Therefore, we propose to use a dimensionless measure of uncertainty, the Coefficient of Variation ($c_v$), which shows the variability of the data in relation to the (observed) mean:

$$c_v = \sigma / \mu,$$  \hspace{1cm} (2)

where $\mu$ denotes the mean and $\sigma$ the standard deviation. It allows to fairly compare the uncertainty in losses, even with different magnitudes, under the assumption that each loss measures in a ratio-scale, that is with a unique and non-arbitrary zero value.

### 2.1 Loss Weighing with Coefficient of Variation

Using the Coefficient of Variation as loss weighting is only sensible when all losses are defined in a common scale. This is not often the case when a broad range of different losses is used. To compute the Coefficient of Variation in a common loss scale at training iteration $t$, a loss ratio must be used. The loss ratio has previously been explored in [1], who define it as $l(t) = L(t)/L(0)$. This estimate is noisy and highly dependant on initialisation of parameters. Another example of the loss ratio was used in [18], who base the loss ratio on current loss at iteration $t$, $L(t)$, and previous loss at iteration $t - 1$, $L(t)$. Here a more robust loss ratio is proposed:

$$l_i(t) = \frac{L_i(t)}{\mu_{L_i}(t - 1)}$$  \hspace{1cm} (3)

where $\mu_{L_i}(t - 1)$ is the mean over all observed losses from iteration 1 to $(t - 1)$ for a specific loss $L_i$. The loss ratio $l(t)$ has the same meaningful zero point when $L_i(t)$ is zero and is a relative comparison of two measurements of the loss statistic. Now, the loss ratio is used as a point estimate of the mean to yield the following definition for loss weights:

$$\alpha_i = \frac{\sigma_i(t)}{l_i(t)}$$  \hspace{1cm} (4)

where $\sigma_i(t)$ is the standard deviation over all known loss ratios $L_i(t)$ until iteration $t - 1$. As a consequence of the above, there are two forces that simultaneously determine the loss weighting. These are:

- The loss ratio $l_i(t)$ which becomes more powerful as a specific loss $L_i(t)$ is below the mean loss $\mu_{L_i}$. This encourages losses that are learning quickly, and dampens the effect on high outliers on the magnitude of the loss.
- The standard deviation over the history of loss ratios $\sigma_i(t)$, which ensures that more learning occurs when a loss ratio is more variant. That is, when a particular objective has historically been more challenging, this term makes the cost function more powerful.

Finally, the weights are normalised to enforce $\sum \alpha_i = 1.0$. The full objective is thus:

$$\alpha_i = \frac{\sigma_i(t)}{\sum_j \left( \frac{\sigma_j(t)}{l_j(t)} \right)}$$  \hspace{1cm} (5)

The definition decouples the loss magnitude from loss weighting. That is, a loss with small magnitude may still be relatively impactful when it is complex and variant; a bigger loss that hardly values across training examples is assigned less weight.

### 2.2 Relation to Other Methods

The proposed approach is compared in-depth to three multi-task methods: Gradient normalisation (GradNorm) [1], Multi-objective optimization [4], and Uncertainty weighing [15].

**GradNorm** In GradNorm [1] gradient normalisation is suggested to balance the gradient norms for each task at each training iteration step at a chosen layer $\mathcal{W}$. This layer is often the last shared layer between the different tasks. The authors argue that gradients are ideally balanced at this shared layer. To balance multiple loss terms, the weights $\alpha$ are learned along the model parameters, with a separate loss function. It can be derived, however, that the optimal weight values $\alpha$ (before normalisation) equal to:

$$\alpha_i \propto \frac{L_i(t)}{L_i(0)} g_i(t),$$  \hspace{1cm} (6)
where \( g_i(t) \) denotes the norm of the gradient of the parameters with respect to the loss \( \mathcal{L}_i \) at the shared layer, hence the name GradNorm. In other words, the loss ratio, between the loss at time \( t \) and the first loss at time \( 0 \), is divided by the current norm of the gradient. This is counter intuitive for single-task multi-loss learning, given that their loss ratio is an inverse measure: the smaller the value, the better the loss is training. So better performing losses are slowed down during training compared to difficult losses (where \( \mathcal{L}(t) \approx \mathcal{L}(0) \)), when they have an equal gradient norm.

Compared to the proposed loss ratio, in GradNorm the loss ratio is based on the initial loss value. When the network has just been initialised, this can be a poor estimate to measure the velocity with which a task-module learns. This is solved in CV-Weighting by using the loss ratio between the current loss and the mean of the observed losses. Finally, there is no hard constraint that prevents loss weights from becoming negative.

**Multi-Objective Optimization**  The authors of [2] state that while multi-task learning can, in general, be beneficial for all tasks, some individual tasks could compete for model capacity. That is, the shared encodings may not be equally informative for all tasks. Hence, the authors are interested in finding Pareto optimal solutions for tasks using a Frank-Wolfe solver. A potential issue in single-task learning for multi-objective optimisation is that single-task learning is inherently a single-objective optimisation. That is, the optimal solution cannot be assumed to be a Pareto optimum between the different loss functions. It is expected that dealing with auxiliary losses will be especially challenging for this method.

**Uncertainty Weighing**  The authors of [14, 15] formulate a joint likelihood estimate to determine task weights based on homoscedastic aleatoric uncertainty. In short, the observed loss \( \mathcal{L}_i \) is seen as an observation from a Gaussian distribution \( \mathcal{N}(\mathcal{L}_i; \sigma_i) \). The variance \( \sigma_i \) is estimated along the model parameters to perform weighting of the different losses. This is similar in spirit to CV-Weighting in which variance is also used for weighting. However, when optimising for the optimal variance of Uncertainty Weighting, the result is a parameterless log-loss: \( \sum_i \log(\mathcal{L}_i) \). This means the smallest loss has the most impact on the gradient.

As opposed to other methods, the uncertainty loss weighing in the original formulation cannot be formulated to satisfy \( \sum_i \alpha_i = 1 \). This makes it difficult to fairly compare against other methods, since the loss weights are coupled to the global learning rate.

### 2.3 Robust Estimation

Using the approach as outlined in this paper, it is no longer necessary to learn loss weighing as separate parameters of the model, like in [15, 1]. The loss weightings are inferred exclusively from from the history of the losses; these statistics are robustly estimated in an online fashion by the use of Welford’s algorithm [19]. A potential downside of this approach is that it can take large amounts of time for the means, standard deviations to converge. Also, variance statistics are not robustly estimated in an online fashion by the use of Welford’s algorithm [19]. A potential downside of this method.

Formally, this approach is that it can take large amounts of time for the means, standard deviations to converge. Also, variance statistics are not robustly estimated in an online fashion by the use of Welford’s algorithm [19]. A potential downside of this method.

\[ l_t = \left( 1 - \frac{1}{t} \right) l_{t-1} + \frac{l_t}{t} \]  
\[ \sigma_t^2 = \sqrt{\frac{M_2}{t}} , \text{ with } M_2 = M_2^{t-1} + \left( l_t - \mu_t^{t-1} \right) \left( l_t - \mu_t^t \right) \]

where \( \mu_t^i \) is the mean loss ratio at time \( t \), \( M_2^t \) is the sum of squared distances from the mean loss, \( \sigma_t^2 \) the standard deviation over the known loss ratios. Assuming converging losses and ample training iterations, the approximate mean and standard deviation converge the true mean and standard deviation of the losses on the data.

### 3 Experiments

In this section, the proposed method is evaluated on two distinct scene understanding tasks: Depth estimation on KITTI [20, 21] and CityScapes [22], and semantic segmentation on the PASCAL Context dataset [23]. The purpose of these experiments is three-fold: First, to compare the proposed dynamic weights to a set of static weights (equal weighting or hand tuned). Second, to test the proposed method against three dynamic multi-task loss weighing approaches. Finally, an ablation study to assess the effects of the learning rate.

To fairly compare the different methods, our code include the proposed weighing scheme and implementations of the baseline methods [2]. The dynamic baselines that are used are Uncertainty weighing [15], GradNorm [1], and

\[ \text{Full implementation details can be found in the supplementary material.} \]
Table 1: Performance of depth estimation models trained on CityScapes. Performance measured in disparities (pixels). Evaluated on 1525 images in the test set. The first, second, and third best scoring methods are highlighted for each evaluation metric.

| Loss Type | ARD | SRD | RMSE | RMSE log | $\delta < 1.25$ | $\delta < 1.25^2$ | $\delta < 1.25^3$ |
|-----------|-----|-----|------|----------|-----------------|-----------------|-----------------|
| Single-Loss | DISP | 40.915 | 23841.930 | 560.953 | 3.349 | 0.000 | 0.000 | 0.000 |
| | LR | 1.000 | 36.133 | 45.492 | 12.761 | 0.000 | 0.000 | 0.000 |
| | L1 | 0.261 | 5.880 | 12.520 | 0.365 | 0.675 | 0.856 | 0.934 |
| | SSIM | 0.206 | 2.509 | 6.577 | 0.310 | 0.756 | 0.893 | 0.951 |
| Multi-Loss | Static Weights | Equal | 0.211 | 2.379 | 6.461 | 0.331 | 0.750 | 0.891 | 0.951 |
| | | Hand-tuned | 0.203 | 2.298 | 5.571 | 0.299 | 0.766 | 0.899 | 0.953 |
| | Dynamic Weights | Uncertainty | 1.000 | 36.133 | 45.493 | 17.031 | 0.000 | 0.000 | 0.000 |
| | | GradNorm | 0.254 | 3.056 | 9.493 | 0.329 | 0.670 | 0.853 | 0.938 |
| | | Multi-objective | 1.000 | 36.133 | 45.492 | 12.820 | 0.000 | 0.000 | 0.000 |
| | | CV-Weighting | 0.212 | 2.444 | 5.785 | 0.294 | 0.756 | 0.895 | 0.952 |

Table 2: Win rates for methods compared to either an equal weighting or hand-tuned weighting baseline. Evaluated on CityScapes.

| Weighting | Equal | Hand-tuned | Uncertainty | GradNorm | Multi-objective | CV-Weighting |
|-----------|-------|------------|-------------|-----------|-----------------|---------------|
| Equal | - | 0.747 | 0.0 | 0.104 | 0.0 | 0.641 |
| Hand-tuned | 0.253 | - | 0.0 | 0.069 | 0.0 | 0.387 |

Multi-objective optimization [2]. GradNorm requires an additional hyper-parameter as a form of temperature scaling on the loss weights (before normalisation). Preliminary experiments show that the performance is sensitive to this value; using grid-search it is set to 1.5 for all experiments.

3.1 Depth Estimation

Depth estimation is performed by means of photo-metric reconstruction of a left/right image pair, using an estimated disparity map; depth can be inferred by warping the disparity map using the camera intrinsics. In the current experiment, the network architecture and objective function of [6] are used. The objective function combines the L1 loss, Structural Similarity loss (SSIM), left-right consistency loss (LR), and disparity gradient loss (DISP) to train a single network. Following [6], the hand-tuned weights are set to $\{\alpha_{L1} = 0.15, \alpha_{SSIM} = 0.85, \alpha_{LR} = 1.0, \alpha_{DISP} = 0.1\}$, which are normalised such that $\sum \alpha_i = 1.0$.

Dataset & Implementation Details

Depth estimation is evaluated on the KITTI dataset [20, 21] using the Eigen split [24] and on the main split of the CityScapes dataset [22]. For all methods, images are down-sampled to a resolution of 256x512 and fed to an encoder-decoder network using batch normalisation [25]. The encoder is based on a ResNet50 [26] network; the decoder alternates bilinear interpolation up-sampling and convolutional layers [6]. The models are trained for 100 epochs on CityScapes and for 30 epochs on KITTI, using an Adam optimiser with a learning rate of $1e-4$ (selected based on related works). For quantitative evaluation, a set of common metrics is used [24, 6]: Absolute Relative Distance (ARD), Squared Relative Distance (SRD), Root Mean Squared Error (RMSE), log Root Mean Squared Error (log RMSE), and multiple accuracies $\delta$ within a threshold $t$ ($\delta_t$, with $t \in \{1.25, 1.25^2, 1.25^3\}$). For CityScapes disparities are evaluated, as is common in much contemporary work [2, 15, 18]. On KITTI, depth is used, like in [6].

Results

In this set of experiments, CV-Weighting is compared against static weights and a set of baselines for depth estimation. Depth estimation results are shown in Table 1 (CityScapes) and Table 3 (KITTI). The performances of the single-loss models show that using only the SSIM loss is close to the hand-tuned multi-loss counterpart. Whereas LR and DISP losses are auxiliary losses that by themselves do not correctly estimate depth. The LR loss is tasked with rewarding symmetry in left and right disparity predictions; training with only the LR loss results in predicting purely zero-valued disparity maps, a perfect symmetry, albeit not valuable for depth estimation.
| Loss | Single-Loss | Multi-Loss |
|------|-------------|------------|
|      | DISP        | LR         | L1         | SSIM     | Equal      | Hand-tuned | Uncertainty | GradNorm | Multi-objective | CV-Weighting |
| ARD  | 0.904       | 1.000      | 0.148      | 0.118     | 0.119      | 0.121      | 0.093       | 0.021    | 0.092          | 0.119       |
| SRD  | 13.835      | 15.798     | 1.475      | 0.912     | 0.933      | 0.949      | 0.964       | 0.496    | 0.933          | 0.923       |
| RMSE | 18.719      | 19.544     | 5.654      | 5.106     | 5.106      | 5.228      | 5.228       | 5.020    | 5.106          | 5.106       |
| RMSE log | 2.587     | 9.475      | 0.240      | 0.214     | 0.215      | 0.222      | 0.222       | 0.214    | 0.213          | 0.213       |
| $\delta < 1.25$ | 0.000      | 0.000      | 0.807      | 0.842     | 0.840      | 0.828      | 0.828       | 0.839    | 0.839          | 0.839       |
| $\delta < 1.25^2$ | 0.000      | 0.000      | 0.931      | 0.943     | 0.941      | 0.937      | 0.937       | 0.941    | 0.941          | 0.941       |
| $\delta < 1.25^3$ | 0.000      | 0.000      | 0.970      | 0.975     | 0.970      | 0.970      | 0.970       | 0.970    | 0.970          | 0.970       |

Table 3: Performance of depth estimation models on KITTI in depth (meters). Evaluated on the Eigen test set \[24\]. The **first**, second, and third best scoring methods are highlighted.

| Baselines | Equal | Hand-tuned | Uncertainty | GradNorm | Multi-objective | CV-Weighting |
|-----------|-------|------------|-------------|----------|-----------------|------------|
| Equal     | -     | 0.597      | 0.0         | 0.357    | 0.0             | 0.534      |
| Hand-tuned| 0.403 | -          | 0.0         | 0.326    | 0.0             | 0.422      |

Table 4: Win rates for methods compared to either an equal weighting or a hand-tuned baseline. Evaluated on KITTI.

The multi-loss static weights models slightly outperform the best single-loss model. And hand-tuning the weights is beneficial over using equal weighting. Two of the dynamic weight baselines (Uncertainty weighting and Multi-Objective optimisation) have difficulties training for this task; while GradNorm obtains performances below the SSIM-only baseline. CV-Weighting yields performance close to the performance of models with hand-tuned parameters, without manually having to tune loss weights.

In Figure 1, the weights throughout training is shown for hand-tuned weights, GradNorm, Multi-objective optimisation, and CV-Weighting. It is clear that Multi-objective optimisation underestimates the importance of SSIM and/or L1. GradNorm uses a very high DISP weight, but at least also maintains a high value for L1. A possible explanation for the high weight of the DISP loss in GradNorm, is that its defined in such a way that its loss gradients are highest at image colour gradients. It is thus possible that there is a relatively low loss gradient with respect to homogeneous image patches. When these image patches compose large parts of the image, the total gradient norm is relatively small. GradNorm then makes the DISP loss weight disproportionally large, due to the division by the gradient norm. CV-Weighting attach relatively low importance to SSIM and high importance to the L1 loss compared to the static weights. Also it gradually assigns more weight to SSIM and L1, and less to LR.

Besides the common set of metrics, Table 2 (CityScapes) and Table 4 (KITTI) show the win rates \[27\] of the methods compared to the static multi-loss baselines. The win rate is the percentage of images in the test set for which a method outperforms a baseline. It is implemented as a majority voting scheme over the 7 metrics. CV-Weighting outperforms equal weighting, and is able to match the performance of hand-tuned models without manually having to tune the loss weights.

Two-sided Wilcoxon signed-rank tests are performed to verify that CV-Weighting is significantly different from equal weighting. To be robust for initialisation, both CV-Weighting and equal weighting methods are restarted 5 times; the best model is selected for each image for each of the metrics. We then compare the performance using the Wilcoxon test. CV-Weighting outperforms equal weighting significantly (rejecting null hypothesis at H=0.01) on 6 out of 7 metrics on CityScapes and 4 out of 7 metrics on KITTI. Based on these results, it is concluded that CV-Weighting is thus significantly better than equal weighting.

### 3.2 Semantic Segmentation

The method is further evaluated on a semantic segmentation task to verify how well it generalises to other tasks. To this end, all loss weighting methods are implemented in conjunction with a Context Encoding Network (EncNet) \[5\].
The authors of [5] propose a Context Encoding module, that jointly learns to predict the presence of semantic classes in an image as well as the actual pixel-level class predictions. This module leverages global contextual information to aid pixel-level prediction. Additionally, it is possible to add another head to the penultimate layer of the encoder network to further aid prediction. In total the objective function consists of a standard Cross-Entropy loss (CE), a Semantic Encoding loss (SE), and an auxiliary Cross-Entropy loss (AUX) from a separate Fully Convolutional (FCN) head. The hand-tuned parameters $\alpha$ as given in [5] are \{\alpha_{CE} = 1.0, \alpha_{SE} = 0.2, \alpha_{AUX} = 0.2\} Again, these weights are normalised to ensure $\sum \alpha_i = 1.0$.

**Implementation Details** The EncNet is adapted and augmented with all loss weighing methods. The methods are tested on the PASCAL Context dataset [23, 28] which uses 4998 training images and 5105 validation images. For each image, there are annotations for up to 59 semantic classes. The encoder network is a ResNet50 [26] network using batch normalisation [25]; For the decoders, there is one Encoding Context Module that is attached to the final layer of the encoder, and one FCN head attached to the penultimate layer of the decoder. For optimisation, an SGD optimiser is used with a learning rate of 1e-4, unless otherwise stated. The network is pre-trained on ImageNet [29] and then trained for 40 epochs on PASCAL Context. For quantitative evaluation, Pixel Accuracy (pACC) and Mean Intersection over Union (mIoU) are used, as in [5]. Background pixels are ignored during evaluation.

**Results** The results on PASCAL Context are depicted in Table 5. Interestingly, only using the CE loss yields performance on par with or slightly better than the hand-tuned weights. This could be due to the more shallow encoder network used (compared to [5]) or because the FCN head could be replaced with another Context Encoding module to improve performance as suggested in [5]. For this task, uncertainty weighing yields superior performance compared to all other methods. However, it seems that the comparison is not completely fair, given that uncertainty weighing does not have normalised weights, i.e. $\sum \alpha_i$ can have any value. This in turn yields a higher global learning rate. CV-Weighting performs on par with hand-tuned parameters.

In the final experiment, the effect of the global learning rate on our model is studied. Therefore, the model is trained with different learning rates. The performances of depth estimation and semantic segmentation are given in Table 6. Unsurprisingly, the results show that CV-Weighting benefits significantly from finding the best learning rate and that learning rates from literature do not necessarily pass on to novel methods. With optimal learning rates, CV-Weighting outperforms all other methods on both tasks.

### Table 5: Performance of semantic segmentation models trained on PASCAL Context. Evaluated on 5104 images in the validation set. The first, second, and third best scoring methods are highlighted for each evaluation metric.

| Loss Weighing Method | pACC | mIoU |
|----------------------|------|------|
| Single-Loss CE       | 0.769| 0.440|
| AUX                  | 0.012| 0.004|
| SE                   | 0.010| 0.001|
| Dynamic Weights      |      |      |
| Uncertainty [15]     | 0.781| 0.448|
| GradNorm [1]         | 0.750| 0.404|
| Multi-objective [2]  | 0.012| 0.003|
| Static Weights & Proposed |   |      |
| Equal                | 0.759| 0.419|
| Hand-tuned           | 0.768| 0.437|
| CV-Weighting         | 0.768| 0.436|

### Table 6: Performance of the current method at different learning rates for different datasets. Default learning rate for all tasks was 1e-4. Best performance is highlighted.

| Learning Rates | CityScapes | KITTI | PASCAL Context |
|----------------|------------|-------|----------------|
|                | ARD | RMSE log | $\delta < 1.25$ | ARD | RMSE log | $\delta < 1.25$ | pACC | mIoU |
| 1e-2           | 1.000 | 17.031 | 0.0 | 4.957 | 5.080 | 0.007 | **0.779** | **0.455** |
| 1e-3           | **0.194** | **0.277** | **0.769** | 0.134 | 0.221 | **0.848** | 0.770 | 0.441 |
| 1e-4           | 0.212 | 0.294 | 0.756 | **0.119** | **0.213** | 0.839 | 0.768 | 0.436 |
| 1e-5           | 0.248 | 0.482 | 0.702 | - | - | - | 0.666 | 0.256 |

**Conclusion**

In this paper, CV-Weighting has been introduced to automate tuning of loss weights specifically on single-task problems. Related methods from multi-task learning [2][15][1], are shown to not always be suited in a single-task setting, given that
auxiliary losses cannot be weighed too heavily because they by themselves do not solve the task. These losses are often comparatively small and less complex. Consequently, the losses show less variance throughout training. CV-Weighting explicitly makes use of these statistics, inspired by the Coefficient of Variation and assigns higher weights to losses that show higher relative variance. Experimentally CV-Weighting performs on par with hand-tuned defined weights and outperform these when the optimal learning rate is used.

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