Supplementary material
Quantitative evaluation of confidence measures in a machine learning world

Matteo Poggi, Fabio Tosi, Stefano Mattoccia
University of Bologna
Department of Computer Science and Engineering (DISI)
Viale del Risorgimento 2, Bologna, Italy
{matteo.poggi8, fabio.tosi5, stefano.mattoccia}@unibo.it

This document provides additional details for paper *Quantitative evaluation of confidence measures in a machine learning world*. Single column format has been chosen to improve readability and to allow large tables to be fully displayed. Section 1 describes in detail all the confidence measures, their formulation and parameters. Section 2 reports execution time for, respectively, standalone and machine learning based measures.

1 Confidence Measures

We report a detailed description for each reviewed confidence measure. As shown in Figure 1, given a pixel $\mathbf{p} = (x, y)$, we will refer to its the minimum cost as $c_1(\mathbf{p})$, the second minimum as $c_2(\mathbf{p})$ and the second local minimum as $c_{2m}(\mathbf{p})$. We refer to a matching cost for any disparity hypothesis d as $c_d(\mathbf{p})$. The disparity hypothesis corresponding to $c_1(\mathbf{p})$ will be referred to as $d_1(\mathbf{p})$, the one to $c_2(\mathbf{p})$ as $d_2(\mathbf{p})$ and so on. If not specified, costs and disparities refer to left image pixels (L). When talking about right image (R), we introduce the ^{R} notations on both costs (e.g., $c_1^R(\mathbf{p})$) and disparities. We denote as $\mathbf{p}' = (x', y')$ the matching pixel for $\mathbf{p}$ according to d_1 (i.e., $x' = x - d_1(\mathbf{p})$, $y' = y$). Finally, we denote with ^{LL} matching costs and disparities related to self-matching stereo on the left image (i.e., using the left image as reference and target).

1.1 Minimum cost and local properties of the cost curve

These methods analyze local properties of the cost curve encoded by c_1, c_2 and c_{2m}.

- **MSM** (Matching Score Measure), reviewed in [1]

$$MSM(\mathbf{p}) = -c_1(\mathbf{p}) \tag{1}$$

- **MM** (Maximum Margin)

$$MM(\mathbf{p}) = c_{2m}(\mathbf{p}) - c_1(\mathbf{p}) \tag{2}$$

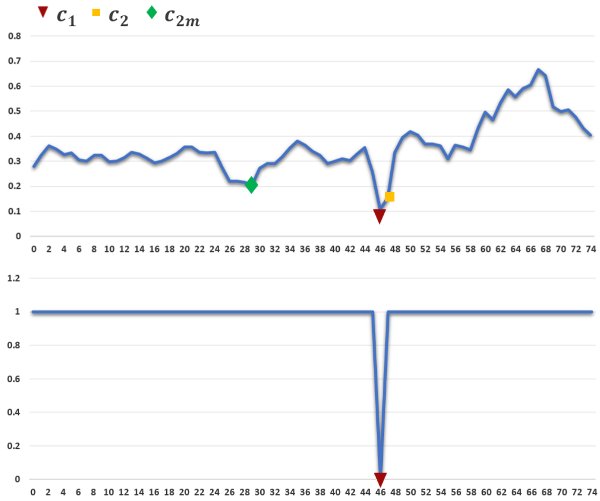

Fig. 1: Examples of ambiguous cost curve (top) and ideal one (bottom). We highlight on the ambiguous curve the minimum cost c_1, the second minimum c_2 and the second local minimum c_{2m}.

- **MMN** (Maximum Margin Naive), reviewed in [1]

$$MMN(\mathbf{p}) = c_2(\mathbf{p}) - c_1(\mathbf{p}) \tag{3}$$

- **NLM** (Non Linear Margin), [2]

$$NLM(\mathbf{p}) = e^{-\frac{c_{2m}(\mathbf{p}) - c_1(\mathbf{p})}{2\sigma^2_{NLM}}} \tag{4}$$

  We set σ_{NLM} to 2.

- **NLMN** (Non Linear Margin Naive),

$$NLMN(\mathbf{p}) = e^{-\frac{c_2(\mathbf{p}) - c_1(\mathbf{p})}{2\sigma^2_{NLM}}} \tag{5}$$

- **CUR** (Curvature), reviewed in [1]

$$CUR(\mathbf{p}) = -2c_1(\mathbf{p}) + c_{d_1-1}(\mathbf{p}) + c_{d_1+1}(\mathbf{p}) \tag{6}$$

- **LC** (Local Curve), proposed in [3]

$$LC(\mathbf{p}) = \frac{\max\left(c_{d_1-1}(\mathbf{p}), c_{d_1+1}(\mathbf{p})\right) - c_1(\mathbf{p})}{\gamma} \tag{7}$$

  As suggested in [3], we set γ to 480.

- **PKR** (Peak Ratio), reviewed in [1]

$$PKR(\mathbf{p}) = \frac{c_{2m}(\mathbf{p})}{c_1(\mathbf{p})} \tag{8}$$

- **PKRN** (Peak Ratio Naive), reviewed in [1]

$$PKRN(\mathbf{p}) = \frac{c_2(\mathbf{p})}{c_1(\mathbf{p})} \tag{9}$$

- **APKR** (Average Peak Ratio), proposed in [4]

$$APKR(\mathbf{p}) = \frac{1}{|N_{\mathbf{p}}|} \sum_{\mathbf{q} \in N_{\mathbf{p}}} \frac{c_{2m}(\mathbf{q}, d_{2m}(\mathbf{p}))}{c_1(\mathbf{q}, d_1(\mathbf{p}))} \tag{10}$$

being $N_{\mathbf{p}}$ a local patch centered on $\mathbf{p}$.

- **APKRN** (Average Peak Ratio Naive)

$$APKRN(\mathbf{p}) = \frac{1}{|N_{\mathbf{p}}|} \sum_{\mathbf{q} \in N_{\mathbf{p}}} \frac{c_2(\mathbf{q}, d_2(\mathbf{p}))}{c_1(\mathbf{q}, d_1(\mathbf{p}))} \tag{11}$$

- **WPKR** (Weighted Peak Ratio), proposed in [5]

$$WPKR(\mathbf{p}) = \frac{1}{|N_{\mathbf{p}}|} \sum_{\mathbf{q} \in N_{\mathbf{p}}} \alpha(\mathbf{p}, \mathbf{q}) \frac{c_{2m}(\mathbf{q}, d_{2m}(\mathbf{p}))}{c_1(\mathbf{q}, d_1(\mathbf{p}))} \tag{12}$$

with

$$\alpha(\mathbf{p}, \mathbf{q}) = \begin{cases} 1, |I(\mathbf{p}) - I(\mathbf{q})| < threshold \\ 0, \text{otherwise} \end{cases} \tag{13}$$

We set a threshold value of intensity of 60 to compute the binary weights.

- **WPKRN** (Average Peak Ratio Naive)

$$WPKRN(\mathbf{p}) = \frac{1}{|N_{\mathbf{p}}|} \sum_{\mathbf{q} \in N_{\mathbf{p}}} \alpha(\mathbf{p}, \mathbf{q}) \frac{c_2(\mathbf{q}, d_2(\mathbf{p}))}{c_1(\mathbf{q}, d_1(\mathbf{p}))} \tag{14}$$

with

$$\alpha(\mathbf{p}, \mathbf{q}) = \begin{cases} 1, |I(\mathbf{p}) - I(\mathbf{q})| < threshold \\ 0, \text{otherwise} \end{cases} \tag{15}$$

We set a threshold value of intensity of 60 to compute the binary weights.

- **DAM** (Disparity Ambiguity Measure), proposed in [6]

$$DAM(\mathbf{p}) = |d_1(\mathbf{p}) - d_2(\mathbf{p})| \tag{16}$$

– **SGE** (Semi-Global Energy), proposed in [6]

$$SGE(\mathbf{p}) = \sum_{r} \sum_{\mathbf{q} \in r(\mathbf{p})} c_1(\mathbf{q}) + P_1 T(|d_1(\mathbf{q}) - d_1(N(\mathbf{q}))| = 1) + P_2 T(|d_1(\mathbf{q}) - d_1(N(\mathbf{q}))| > 1) \quad (17)$$

We set P1 and P2 penalties to, respectively, 0.2 and 0.5 being matching costs normalized.

1.2 Analysis of the entire cost curve

Differently from previous confidence measures, those belonging to this category analyze for each point the overall distribution of matching costs.

– **PER** (Perturbation), proposed in [6]

$$PER(\mathbf{p}) = \sum_{d \neq d_1} e^{-\frac{(c_1(\mathbf{p}) - c_d(\mathbf{p}))^2}{s^2}} \quad (18)$$

We set s to 120.

– **MLM** (Maximum Likelihood Measure), proposed in [7] and reviewed in [1]

$$MLM(\mathbf{p}) = \frac{e^{-\frac{c_1(\mathbf{p})}{2\sigma^2_{MLM}}}}{\sum_d e^{-\frac{c_d(\mathbf{p})}{2\sigma^2_{MLM}}}} \quad (19)$$

We set σ_{MLM} to 2.

– **AML** (Attainable Likelihood Measure), proposed in [7] and reviewed in [1]

$$AML(\mathbf{p}) = \frac{1}{\sum_d e^{-\frac{c_d(\mathbf{p})}{2\sigma^2_{AML}}}} \quad (20)$$

We set σ_{AML} to 2.

– **NOI** (Number Of Inflections), reviewed in [1]

$$NOI(\mathbf{p}) = |M|$$
$$M = \{d_i : c_{d_i - 1}(\mathbf{p}) > c_{d_i}(\mathbf{p}) \wedge c_{d_i}(\mathbf{p}) < c_{d_i + 1}(\mathbf{p})\} \quad (21)$$

- **LMN** (Local Minima in Neighborhood), proposed in [4]

$$LMN(\mathbf{p}) = \sum_{\mathbf{q} \in N_{\mathbf{p}}} LM(\mathbf{q}) \tag{22}$$

with

$$LM(\mathbf{q}) = \begin{cases} 1, c_{d_1(\mathbf{p})}(\mathbf{q}) \text{ } \textit{is a local minima} \\ 0, \text{otherwise} \end{cases} \tag{23}$$

We set σ_{MLM} to 2.

- **WMN** (Winner Margin), reviewed in [1]

$$WMN(\mathbf{p}) = \frac{c_{2m}(\mathbf{p}) - c_1(\mathbf{p})}{\sum_d c_d(\mathbf{p})} \tag{24}$$

- **WMNN** (Winner Margin Naive), reviewed in [1]

$$WMNN(\mathbf{p}) = \frac{c_2(\mathbf{p}) - c_1(\mathbf{p})}{\sum_d c_d(\mathbf{p})} \tag{25}$$

- **NEM** (Negative Entropy Measure), reviewed in [1]

$$\begin{aligned} NEM(\mathbf{p}) &= -\sum_d p(d) \log p(d) \\ p(d) &= \frac{e^{-c_1(\mathbf{p})}}{\sum_d e^{-c_d(\mathbf{p})}} \end{aligned} \tag{26}$$

1.3 Left and right consistency

This category evaluates the consistency between corresponding points according to two different cues: one, symmetric, based on left and right maps and one, asymmetric, based only on the left map.

- **LRC** (Left-Right Consistency), reviewed in [1]

$$LRC(\mathbf{p}) = -|d_1(\mathbf{p}) - d^R(\mathbf{p'})| \tag{27}$$

- **LRD** (Left-Right Difference), reviewed in [1]

$$LRD(\mathbf{p}) = \frac{c_2(\mathbf{p}) - c_1(\mathbf{p})}{|c_1(\mathbf{p}) - \min_d c_d^R(\mathbf{p'}))|} \tag{28}$$

– **ZSAD** (Zero-Mean Sum of Absolute Differences), proposed in [6]

$$ZSAD(\mathbf{p}) = \sum_{\mathbf{q}\in N_\mathbf{p}} |I^L(\mathbf{q}) - \mu(I^L(\mathbf{p})) - I^R(\mathbf{q}') + \mu(I^R(\mathbf{p}'))| \quad (29)$$

– **ACC** (Asymmetric Consistency Check), proposed in [8]

$$ACC(\mathbf{p}) = \begin{cases} 0, \text{ if } d_1(\mathbf{p}) \in Q \text{ and } \theta \\ 1, \text{ otherwise} \end{cases} \quad (30)$$

being Q the set of pixels matching the same pixel on the right image and θ the following condition:
$d_1(\mathbf{p}) \neq \max_{\mathbf{p}\in Q} d_1(\mathbf{p})$ or $c_1(\mathbf{p}) \neq \min_{\mathbf{p}\in Q} c_1(\mathbf{p})$

– **UC** (Uniqueness Constraint), proposed in [9]

$$UC(\mathbf{p}) = \begin{cases} 0, \text{ if } d_1(\mathbf{p}) \neq d_1^R(\mathbf{p} - d_1(\mathbf{p})) \text{ and } c_1 \neq \min_{\mathbf{q}\in Q} c_1(\mathbf{q}) \\ 1, \text{ otherwise} \end{cases} \quad (31)$$

– **UCC** (Uniqueness Constraint Cost),

$$UCC(\mathbf{p}) = \begin{cases} 0, \text{ if } d_1(\mathbf{p}) \neq d_1^R(\mathbf{p} - d_1(\mathbf{p})) \text{ and } c_1 \neq \min_{\mathbf{q}\in Q} c_1(\mathbf{q}) \\ -c_1(\mathbf{p}), \text{ otherwise} \end{cases} \quad (32)$$

– **UCO** (Uniqueness Constraint Occurrences),

$$UCO(\mathbf{p}) = -|Q| \quad (33)$$

1.4 Disparity map features

Confidence measures belonging to this group are obtained by extracting features from the reference disparity map.

– **DTD** (Distance to Discontinuities), proposed in [10]

$$DTD(\mathbf{p}) = \min_{\mathbf{q}\in D} \|\mathbf{p} - \mathbf{q}\| \quad (34)$$

– **DMV** (Disparity Map Variance), proposed in [6]

$$DMV(\mathbf{p}) = ||\nabla d_1(\mathbf{p})|| \quad (35)$$

– **VAR** (Variance of disparity), proposed in [6]

$$VAR(\mathbf{p}) = \frac{1}{N} \sum_{\mathbf{q}\in N_\mathbf{p}} (d_1(\mathbf{q}) - \mu_r(d_1(\mathbf{p})))^2 \quad (36)$$

with

$$\mu_r(\mathbf{p}) = \frac{1}{N} \sum_{\mathbf{q}\in N_\mathbf{p}} d_1(\mathbf{q}) \quad (37)$$

- **DA** (Disparity Agreement), proposed in [11]

$$DA(\mathbf{p}) = H_{N_{\mathbf{p}}}(d_1(\mathbf{p})) \tag{38}$$

with $H_{N_{\mathbf{p}}}$ histogram of interval $[d_{min}, d_{max}]$ computed on image patch $N_{\mathbf{p}}$. $H_{N_{\mathbf{p}}}(D_1(\mathbf{p}))$ encodes the number of pixels in $N_{\mathbf{p}}$ sharing the same disparity value with $\mathbf{p}$.

- **MDD** (Median Deviation of Disparity), proposed in [10]

$$MDD(\mathbf{p}) = -|D_1(\mathbf{p}) - MED_{N_{\mathbf{p}}}(D_1(\mathbf{p}))| \tag{39}$$

where $MED_{N_{\mathbf{p}}}$ indicates the median value of a patch $N_{\mathbf{p}}$ centered on $\mathbf{p}$.

- **DS** (Disparity Scattering), proposed in [11]

$$DS(\mathbf{p}) = -log \frac{\sum_d 1 - \delta(H_{N_{\mathbf{p}}}(d, 0))}{|N_{\mathbf{p}}|} \tag{40}$$

being $|N_{\mathbf{p}}|$ number of pixels in $N_{\mathbf{p}}$ and δ a Kronecker delta:

$$\delta(H_{N_{\mathbf{p}}}(d, 0)) = \begin{cases} 1, \text{ if } H_{N_{\mathbf{p}}}(d) = 0 \\ 0, \text{ otherwise} \end{cases} \tag{41}$$

1.5 Reference image features

Confidence measures belonging to this category use as input domain only the reference image.

- **DB** (Distance to Border), proposed in [10]

$$DB(\mathbf{p}) = \min(x, y, W - x, H - y) \tag{42}$$

- **DLB** (Distance to Left Border), proposed in [12]

$$DLB(\mathbf{p}) = \min(x, d_{max}) \tag{43}$$

- **HGM** (Horizontal Gradient Magnitude), proposed in [6]

$$HGM(\mathbf{p}) = ||\nabla_x I^L(\mathbf{p})|| \tag{44}$$

- **DTE** (Distance to Edge)

$$DTE(\mathbf{p}) = \min_{\mathbf{q} \in E} \|\mathbf{p} - \mathbf{q}\| \tag{45}$$

being E the set of edge pixels.

1.6 Image distinctiveness

The idea behind these confidence measures is to exploit the notion of distinctiveness of the examined point within its neighborhoods along the horizontal scanline of the same image.

- **DTS** (Distinctiveness), proposed in [13] and reviewed in [1]

$$DTS^L(\mathbf{p}) = \min_{d \in d_s, d \neq 0} c_d^{LL}(\mathbf{p}) \tag{46}$$

  with

$$d_{min} - d_{max} \leq d_s \leq d_{max} - d_{min} \tag{47}$$

- **DSM** (Distinctive Similarity Measure), proposed in [14] and reviewed in [1]

$$DSM(\mathbf{p}) = \frac{DTS^L(\mathbf{p}) \times DTS^R(\mathbf{p}')}{c_1(\mathbf{p})^2} \tag{48}$$

- **SAMM** (Self-Aware Matching Measure), proposed in [15] and reviewed in [1]

$$SAMM(\mathbf{p}) = \frac{\sum_d (c_{d-d_1}(\mathbf{p}) - \mu)(c_d^{LL}(\mathbf{p}) - \mu^{LL})}{\sigma^{LL}\sigma} \tag{49}$$

  being μ and σ, respectively, average and standard deviation of costs.

1.7 Learning-based approaches

Random forest approaches

- **ENS** (Ensemble), proposed in [6]

$$\begin{aligned} f_{23} = (&PKR^1, PKR^2, PKR^3, NEM^1, NEM^2, NEM^3, PER^1, PER^2, \\ &PER^3, LRC^1, HGM^1, HGM^2, HGM^3, DMV^1, DMV^2, DMV^3, \\ &DAM^1, DAM^2, DAM^3, ZSAD^1, ZSAD^2, ZSAD^3, SGE^1) \end{aligned} \tag{50}$$

  being features marked with superscript ^{1} computed at full resolution, with superscript ^{2} at half resolution and with superscript ^{3} at quarter resolution.

- **GCP** (Ground Control Points), proposed in [10]

$$f_8 = (MSM, DB, MMN, AML, LRC, LRD, DD, MDD) \tag{51}$$

- **LEV** (Leveraging-Stereo), proposed in [12]

$$\begin{aligned} f_{22} = (&PKR, PKRN, MSM, MM, WMN, MLM, PER, NEM, \\ &LRD, LC, VAR^1, VAR^2, VAR^3, VAR^4, DD, MDD^1, MDD^2, \\ &MDD^3, MDD^4, LRC, HGM, DLB) \end{aligned} \tag{52}$$

  being features marked with superscripts ^{1},^{2},^{3},^{4} computed, respectively, on image patches of size 5×5, 7×7, 9×9 and 11×11.

– **O1** (O1), proposed in [11]

$$f_{20} = (DA^1, DA^2, DA^3, DA^4, DS^1, DS^2, DS^3, DS^4, MED^1, MED^2, MED^3, MED^4, VAR^1, VAR^2, VAR^3, VAR^4, MDD^1, MDD^2, MDD^3, MDD^4) \quad (53)$$

being features marked with superscripts $^1, ^2, ^3, ^4$ computed, respectively, on image patches of size 5×5, 7×7, 9×9 and 11×11.

CNN approaches

– **PBCP** (Patch Based Confidence Prediction), proposed in [16]

$$\begin{aligned} PBCP &= CNN(p_1, p_2) \\ p_1 &= [d_1(\mathbf{q}) - d_1(\mathbf{p})]_{\mathbf{q} \in W} \\ p_2 &= [d_1^{RL}(\mathbf{q}) - d_1(\mathbf{p})]_{\mathbf{q} \in W} \end{aligned} \quad (54)$$

being W a local patch centered on $\mathbf{p}$ and d^{RL} the right disparity map reprojected into the left domain.

– **CCNN** (Confidence Convolutional Neural Network), proposed in [17]

$$\begin{aligned} CCNN &= CNN(d_1) \\ d_1 &= [d_1(\mathbf{q})]_{\mathbf{q} \in W} \end{aligned} \quad (55)$$

1.8 SGM-specific

– **PS** (Local-global relation), proposed in [18]

$$PS(\mathbf{p}) = \frac{c_2(\mathbf{p})^l - c_1(\mathbf{p})^l}{c_1(\mathbf{p})^l} \Big(1 - \frac{min\{|d_2^l - d_1^l|, \gamma\}}{\gamma}\Big)\Big(1 - \frac{min\{|d_1^l - d_1^g|, \gamma\}}{\gamma}\Big) \quad (56)$$

with superscript ^{l} referring to local costs/disparities (i.e., before SGM optimization) and with superscript ^{g} to global disparities (i.e., after SGM). We set γ, according to [18], to 10.

– **SCS** (Sum of Consistent Scanlines), proposed in [19]

$$SCS(\mathbf{p}) = |C(\mathbf{p})| \quad (57)$$

$$C = \{s_i \in S : s_i(\mathbf{p}) = d_1(\mathbf{p})\} \quad (58)$$

being S the set of scanlines deployed by SGM.

Confidence Measure	**Time (s)**	**Confidence Measure**	**Time (s)**
MSM	0.000893	ACC	0.004975
MM	0.001578	UC	0.005961
MMN	0.001571	UCC	0.005968
NLM	0.013377	UCO	0.005969
NLMN	0.012779	DTD	0.009434
CUR	0.002705	DVM	0.012755
LC	0.017225	VAR (5×5)	0.002220
PKR	0.002705	VAR (7×7)	0.004345
PKRN	0.002701	VAR (9×9)	0.006379
APKR (5×5)	0.172175	VAR (11×11)	0.008415
APKR (7×7)	0.315316	DA (5×5)	0.322387
APKR (9×9)	0.506297	DA (7×7)	0.513795
APKR (11×11)	0.742124	DA (9×9)	0.685317
APKRN (5×5)	0.165924	DA (11×11)	0.868976
APKRN (7×7)	0.314898	MDD (5×5)	0.003329
APKRN (9×9)	0.504986	MDD (7×7)	0.015852
APKRN (11×11)	0.740950	MDD (9×9)	0.029476
WPKR (5×5)	0.232535	MDD (11×11)	0.045260
WPKR (7×7)	0.442289	DS (5×5)	0.392312
WPKR (9×9)	0.728776	DS (7×7)	0.513374
WPKR (11×11)	1.054834	DS (9×9)	0.685316
WPKRN (5×5)	0.225042	DS (11×11)	0.868976
WPKRN (7×7)	0.414786	DB	0.003109
WPKRN (9×9)	0.689999	DLB	0.004056
WPKRN (11×11)	1.001287	HGM	0.003466
DAM	0.001424	DTE	0.006493
SGE	0.126254	DTS	0.984348
PER	3.914982	DSM	1.987799
MLM	3.699845	SAMM	4.042467
AML	4.391692	Ens_c	32.563072
NOI	0.000001	Ens_r	32.563072
LMN	0.085781	GCP	5.468391
WMN	0.002841	LEV	15.707940
WMNN	0.002743	O1	3.534228
NEM	9.529354	PBCP*	0.5
LRC	0.003529	CCNN*	0.1
LRD	0.004162	PS	0.084721
ZSAD	0.016995	SCS	3.453257

Table 1: Execution time processing a stereo pair of the KITTI 2012 dataset with an Intel(R) Core(TM) i7-6700K CPU 4.00 GHz processor. For PBCP and CCNN execution time on a GPU (Nvidia Titan X).

2 Execution time

In this section we report execution time of our implementation in C++ of each confidence measure described in Section 1. Execution times, with an Intel(R) Core(TM) i7-6700K CPU 4.00 GHz processor, reported in Table 1 refer to the processing of a stereo pair of the KITTI 2012 dataset with all confidence measures excluding PBCP and CCNN. A preliminary extraction of input cues such as c_1, c_2, c_{2m}, local minima and disparity maps is executed with the aim to facilitate the computation. Such operation runs approximately in 2.2 seconds. Concerning [11] the execution time refers to an unoptimized implementations not based on O1 methodologies and thus not invariant to window size. Concerning PBCP and CCNN we report[1] the execution time provided in [16] and [17] with a Titan X GPU.

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[1] Superscript * refers to the execution time reported in the original papers obtained with a Titan X GPU

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