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DCTD: Deep Conditional Target Densities for Accurate Regression

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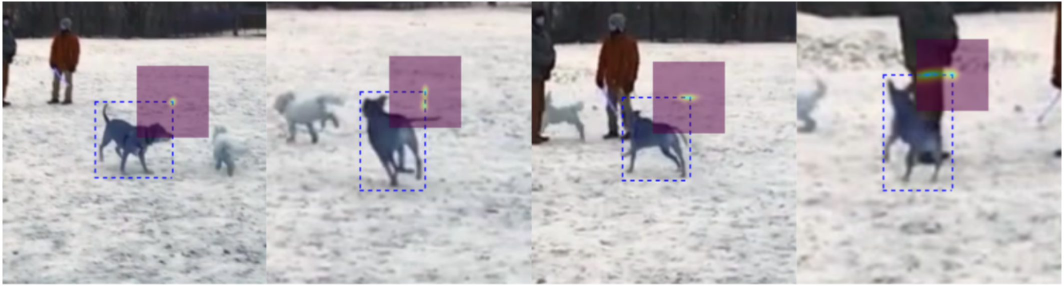
DCTD: Deep Conditional Target Densities for Accurate Regression

Fredrik K. Gustafsson*, Martin Danelljan* (ETH Zurich), Goutam Bhat (ETH Zurich), Thomas B. Schön

We propose Deep Conditional Target Densities (DCTD), a novel and general regression method with a clear probabilistic interpretation. DCTD models the conditional target density $p(y|x)$ *by using a neural network to directly predict the un-normalized density from the input-target pair* (x, y). *This model of* $p(y|x)$ *is trained by minimizing the associated negative log-likelihood, approximated using Monte Carlo sampling. Notably, our method achieves a* 1.9% *AP improvement over Faster-RCNN for object detection on COCO, and sets a new state-of-the-art on visual tracking when applied for bounding box regression.*



Outline

1. Background: regression using deep neural networks
   1.1 Direct regression
   1.2 Probabilistic regression
   1.3 Confidence-based regression
2. Deep Conditional Target Densities (DCTD) for accurate regression
   2.1 Training
   2.2 Prediction
3. Experiments
   3.1 Age estimation, head-pose estimation, object detection
   3.2 Generic visual object tracking

Supervised regression: learn to predict a continuous target value $y^\star \in \mathcal{Y} = \mathbb{R}^K$ from a corresponding input $x^\star \in \mathcal{X}$, given a training set $\mathcal{D}$ of i.i.d. input-target examples, $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^N$, $(x_i, y_i) \sim p(x, y)$.

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Deep neural network (DNN): a function $f_\theta : \mathcal{U} \to \mathcal{O}$, parameterized by $\theta \in \mathbb{R}^P$, that maps an input $u \in \mathcal{U}$ to an output $f_\theta(u) \in \mathcal{O}$.

1.1 Direct regression

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The DNN model parameters θ are learned by minimizing a loss function $\ell(f_\theta(x_i), y_i)$, penalizing discrepancy between the prediction $f_\theta(x_i)$ and the ground truth y_i:

$$J(\theta) = \frac{1}{N} \sum_{i=1}^{N} \ell(f_\theta(x_i), y_i), \quad \theta = \underset{\theta'}{\operatorname{argmin}}\, J(\theta').$$

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For example, the L^2 loss corresponds to a fixed-variance Gaussian model (1D case):

$$p(y|x;\theta) = \mathcal{N}(y; f_\theta(x), \sigma^2).$$

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Probabilistic regression: train a DNN $f_\theta : \mathcal{X} \to \mathcal{O}$ to predict the parameters ϕ of a certain family of probability distributions $p(y;\phi)$, then model $p(y|x)$ with:

$$p(y|x;\theta) = p(y;\phi(x)), \quad \phi(x) = f_\theta(x).$$

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For example, a general 1D Gaussian model can be realized as:

$$p(y|x;\theta) = \mathcal{N}\big(y;\mu_\theta(x),\, \sigma_\theta^2(x)\big), \quad f_\theta(x) = [\, \mu_\theta(x) \quad \log\sigma_\theta^2(x)\,]^\mathsf{T} \in \mathbb{R}^2.$$

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The negative log-likelihood $\sum_{i=1}^{N} -\log p(y_i|x_i;\theta)$ then corresponds to the loss:

$$J(\theta) = \frac{1}{N}\sum_{i=1}^{N} \frac{(y_i - \mu_\theta(x_i))^2}{\sigma_\theta^2(x_i)} + \log \sigma_\theta^2(x_i).$$

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Confidence-based regression: train a DNN $f_\theta : \mathcal{X} \times \mathcal{Y} \to \mathbb{R}$ to predict a scalar confidence value $f_\theta(x, y)$, and maximize this quantity over y to predict the target:

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The DNN model parameters θ are learned by generating *pseudo* ground truth confidence values $c(x_i, y_i, y)$, and minimizing a loss function $\ell\big(f_\theta(x_i, y), c(x_i, y_i, y)\big)$.

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Commonly employed for image-coordinate regression, e.g. human pose estimation [11], where the DNN predicts a 2D confidence heatmap over image-coordinates y. Recently, the approach was also employed by IoU-Net [4] for bounding box regression in object detection, which in turn was utilized by the ATOM [3] visual tracker.

Outline

2. Deep Conditional Target Densities (DCTD) for accurate regression

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While **confidence-based regression** methods have demonstrated impressive results, they require important task-dependent design choices (e.g. how to generate the pseudo ground truth labels) and usually lack a clear probabilistic interpretation.

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$$\begin{aligned}
-\log p(y_i|x_i;\theta) &= \log\left(\int e^{f_\theta(x_i,y)} dy\right) - f_\theta(x_i,y_i) \\
&= \log\left(\int \frac{e^{f_\theta(x_i,y)}}{q(y)} q(y) dy\right) - f_\theta(x_i,y_i) \\
&\approx \log\left(\frac{1}{M}\sum_{k=1}^{M} \frac{e^{f_\theta(x_i,y^{(k)})}}{q(y^{(k)})}\right) - f_\theta(x_i,y_i), \quad y^{(k)} \sim q(y).
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We use a proposal distribution $q(y) = q(y|y_i) = \frac{1}{L}\sum_{l=1}^{L}\mathcal{N}(y; y_i, \sigma_l^2)$ that depends on the ground truth target y_i.

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We use a proposal distribution $q(y) = q(y|y_i) = \frac{1}{L}\sum_{l=1}^{L}\mathcal{N}(y;y_i,\sigma_l^2)$ that depends on the ground truth target y_i. The final minimization objective $J(\theta)$ is thus given by:

$$J(\theta) = \frac{1}{N}\sum_{i=1}^{N}\log\left(\frac{1}{M}\sum_{m=1}^{M}\frac{e^{f_\theta(x_i,y^{(i,m)})}}{q(y^{(i,m)}|y_i)}\right) - f_\theta(x_i,y_i), \quad \{y^{(i,m)}\}_{m=1}^{M} \sim q(y|y_i).$$

The DCTD model $p(y|x;\theta) = e^{f_\theta(x,y)}/Z(x,\theta)$ is highly flexible and can learn complex target densities directly from data, including multi-modal and asymmetric densities.

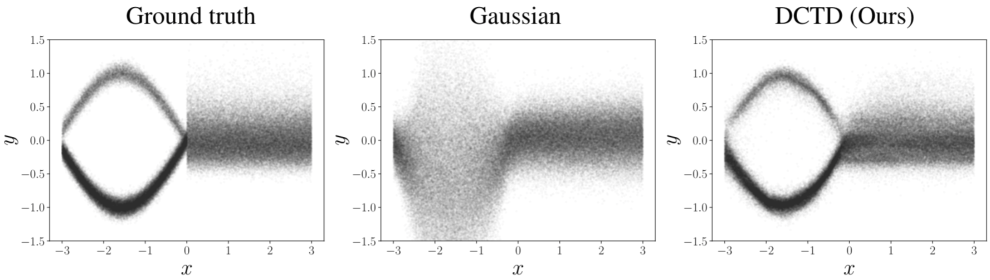

Figure 2: An illustrative 1D regression problem. The training data $\{(x_i, y_i)\}_{i=1}^{2000}$ is generated by the ground truth conditional target density $p(y|x)$.

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Given an input $x^\star$ at test time, we predict the target $y^\star$ by maximizing $p(y|x^\star;\theta)$:

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By designing the DNN f_θ to be differentiable w.r.t. targets y, the gradient $\nabla_y f_\theta(x^\star, y)$ can be efficiently evaluated using auto-differentiation. We can thus perform *gradient ascent* to find a local maximum of $f_\theta(x^\star, y)$, starting from an initial estimate $\hat{y}$.

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Algorithm 1 Prediction via optimization-based refinement

Input: $x^\star$, $\hat{y}$, T, λ, Ω_1, Ω_2.

1: $y \leftarrow \hat{y}$.
2: **for** $t = 1, \ldots, T$ **do**
3: $\quad$ $\texttt{PrevValue} \leftarrow f_\theta(x^\star, y)$.
4: $\quad$ $y \leftarrow y + \lambda \nabla_y f_\theta(x^\star, y)$.
5: $\quad$ $\texttt{NewValue} \leftarrow f_\theta(x^\star, y)$.
6: $\quad$ **if** $|\texttt{PrevValue} - \texttt{NewValue}| < \Omega_1$ **or** $(\texttt{NewValue} - \texttt{PrevValue}) < \Omega_2$ **then**
7: $\quad\quad$ **Return** y.
8: **Return** y.

Outline

We evaluate DCTD on four diverse computer vision regression tasks: **age estimation**, **head-pose estimation**, **object detection** and **generic visual object tracking**.

3. Experiments

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DCTD outperforms the confidence-based IoU-Net [4] method for bounding box regression in direct comparisons, both when applied in object detection on the COCO dataset [6], and in the state-of-the-art ATOM [3] visual tracker.

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DCTD outperforms the confidence-based IoU-Net [4] method for bounding box regression in direct comparisons, both when applied in object detection on the COCO dataset [6], and in the state-of-the-art ATOM [3] visual tracker.

(IoU-Net trains a DNN $f_\theta : \mathcal{X} \times \mathcal{Y} \rightarrow \mathbb{R}$ to predict the IoU overlap between a bounding box y and the corresponding ground truth y_i. For training, boxes are sampled around y_i and the difference between predicted and true IoU is minimized. For prediction, an initial estimate $\hat{y}$ is refined using gradient-based maximization of the predicted IoU.)

Age estimation: refinement using DCTD consistently improves MAE (lower is better) for the age predictions outputted by a number of baselines.

+DCTD	Cao et al. [2]	Direct	Gaussian	Laplace	Softmax (CE, L^2)	Softmax (CE, L^2, Var)
	5.47 ± 0.01	4.81 ± 0.02	4.79 ± 0.06	4.85 ± 0.04	4.78 ± 0.05	4.81 ± 0.03
✓	-	**4.65** $\pm$ 0.02	4.66 ± 0.04	4.81 ± 0.04	**4.65** $\pm$ 0.04	4.69 ± 0.03

Head-pose estimation: refinement using DCTD consistently improves the average MAE for Yaw, Pitch and Roll for the predicted pose outputted by our baselines.

+DCTD	Yang et al. [12]	Direct	Gaussian	Laplace	Softmax (CE, L^2)	Softmax (CE, L^2, Var)
	3.60	3.09 ± 0.07	3.12 ± 0.08	3.21 ± 0.06	3.04 ± 0.08	3.15 ± 0.07
✓	-	3.07 ± 0.07	3.11 ± 0.07	3.19 ± 0.06	$\mathbf{3.01} \pm 0.07$	3.11 ± 0.06

Object detection: when applied to refine the Faster-RCNN detections on COCO [6], DCTD both improves the original detections and outperforms the IoU-Net refinement.

Formulation Approach	Direct Faster-RCNN [10]	Gaussian	Laplace	Confidence IoU-Net [4]	Confidence IoU-Net†	**DCTD**
AP (%)	37.2	36.7	37.1	38.3	38.2	**39.1**
AP_{50}(%)	**59.2**	58.7	59.1	58.3	58.4	58.5
AP_{75}(%)	40.3	39.6	40.2	41.4	41.4	**41.8**

Generic visual object tracking: given *any* target object defined by a bounding box in the first frame of a video, estimate its bounding box in all subsequent video frames.

3.2 Generic visual object tracking

Generic visual object tracking: given *any* target object defined by a bounding box in the first frame of a video, estimate its bounding box in all subsequent video frames.

ATOM [3] trains a classifier *online* to first roughly localize the target object in a new frame. Its bounding box is then estimated by using an IoU-Net, trained *offline*, to refine this initial estimate.

Video: https://youtu.be/UP_eLvwskzU

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Results: when applied to refine the initial estimate provided by the classifier in ATOM, DCTD outperforms the original method (which uses IoU-Net for refinement). DCTD also outperforms other state-of-the-art trackers.

Dataset	Metric	SiamFC [1]	MDNet [9]	DaSiamRPN [13]	SiamRPN++ [5]	ATOM [3]	ATOM†	**DCTD**
TrackingNet [7]	Precision (%)	53.3	56.5	59.1	**69.4**	64.8	66.7	68.9
	Norm. Prec. (%)	66.6	70.5	73.3	**80.0**	77.1	78.3	79.5
	Success (%)	57.1	60.6	63.8	73.3	70.3	72.1	**73.7**
UAV123 [8]	$OP_{0.50}$ (%)	-	-	73.6	75*	78.9	79.6	**80.1**
	$OP_{0.75}$ (%)	-	-	41.1	56*	55.7	56.0	**59.8**
	AUC (%)	-	52.8	58.4	61.3	65.0	65.0	**66.5**

Qualitative results for DCTD:

https://youtu.be/AAnr0g38UeA

https://youtu.be/JyhgUYpwQ5c

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