Towards Certification in Deep Learning

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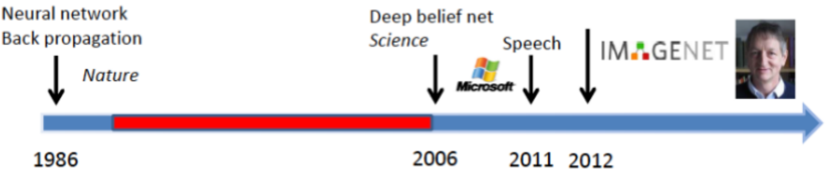
Deep Learning Success since 2010

- 90's / 2000's: difficult to train large deep models on existing databases

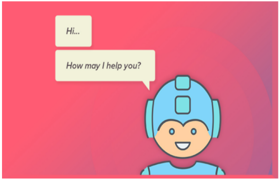


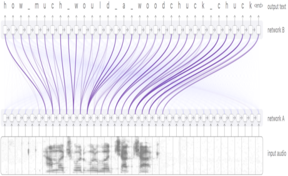
- **ILSVRC'12: the deep revolution**
  ⇒ outstanding success of ConvNets [Krizhevsky et al., 2012]

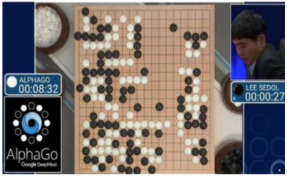
Rank	Name	Error rate	Description
1	**U. Toronto**	0.15315	Deep learning
2	U. Tokyo	0.26172	Hand-crafted features and learning models. Bottleneck.
3	U. Oxford	0.26979	
4	Xerox/INRIA	0.27058	

Deep Learning everywhere since 2012

- Image classification, speech recognition
- chatbots, translation,
- Games, robotics







Neural Networks (NN)

- **The formal Neuron**

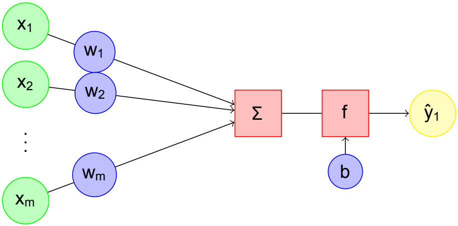
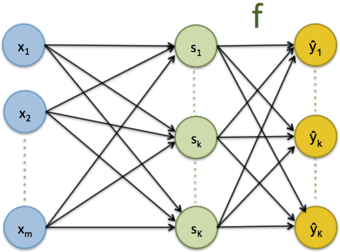


Figure: The formal neuron – **Credits: R. Herault**

x_i: inputs
w_i, b: weights
f: activation function
y: output of the neuron

$$y = f\left(w^\top x + b\right)$$

- **<u>Neural Networks:</u>** Stacking several formal neurons ⇒ **Perceptron**



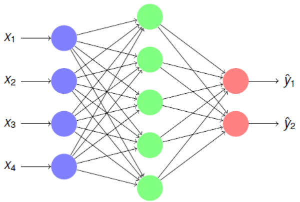
- **Soft-max Activation**:

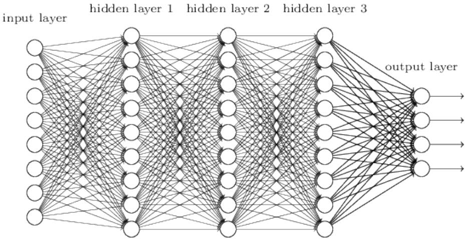
$$\hat{y_k} = f\left(s_k\right) = \frac{e^{s_k}}{\sum\limits_{k'=1}^{K} e^{s_{k'}}}$$

⇒ **Logistic Regression (LR) Model !**

Deep Neural Networks (DNN)

- **Multi-Layer Perceptron (MLP):** Stacking layers of neural networks
  - More complex and rich functions / Logistic Regression (LR)
  - **Neural network with one single hidden layer ⇒ universal approximator** [Cybenko, 1989]

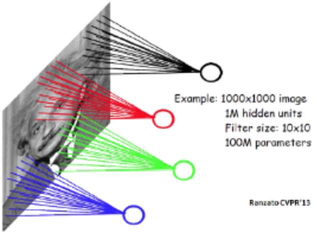


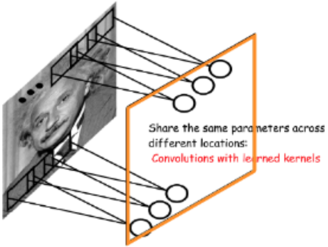


- **Basis of the "deep learning" field**
  - **Hidden layers: intermediate representations from data**
  - **Can be learned with Backpropagation algorithm [Lecun, 1985, Rumelhart et al., 1986]** (chain rule)

Convolutional Neural Networks (ConvNets)

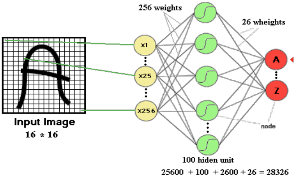
- **ConvNets:** sparse connectivity + shared weights

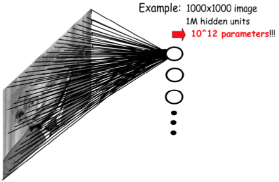




parameters: 100 !

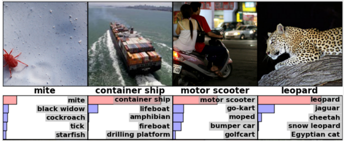
- **Local feature extraction (≠ FCN)**
- Overcome parameter explosion for FCN on images



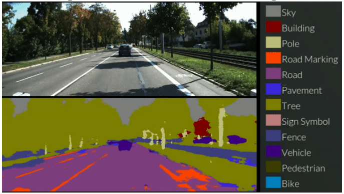


Deep Learning in Computer Vision

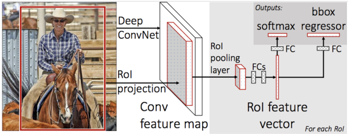
[*Krizhevsky*, 2012]



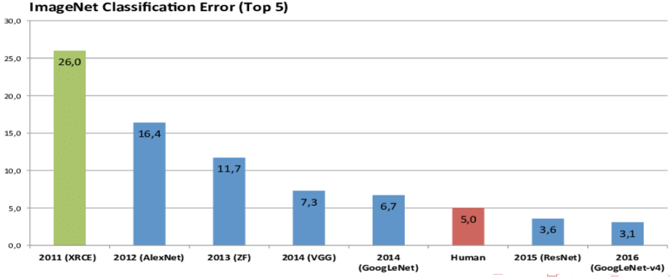
[*Kendall et al.* SegNet, 2015]



[*Girshick et al*. Fast R-CNN, 2015]

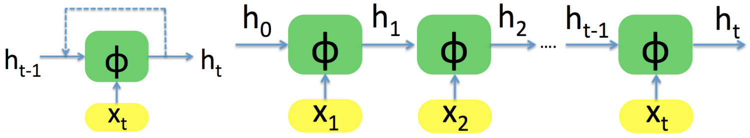


Brought significant improvements in multiple vision tasks



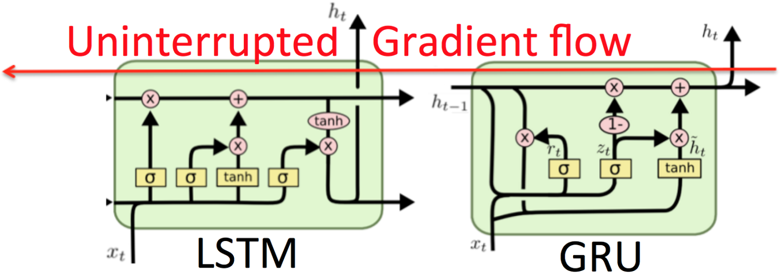
Recurrent Neural Networks (RNNs)

- **RNN Cell:** $h_t = \phi(x_t, h_{t-1}) = f(Ux_t + Wh_{t-1} + b_h)$ [Elman, 1990]
  - h_t: **network memory up to time t $\Rightarrow$ Sequence processing**



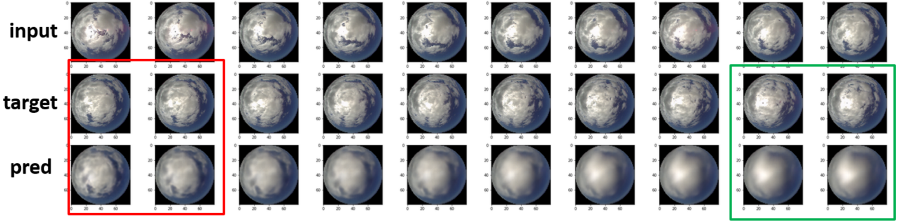
Folded RNN　　　　Unfolded RNN

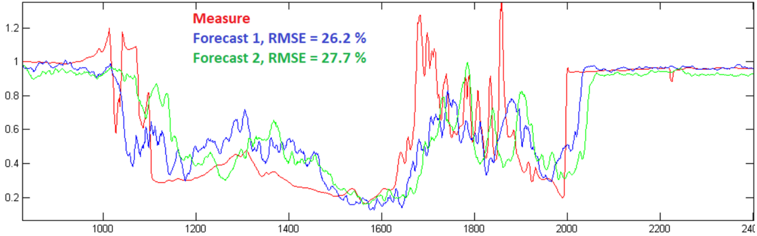
- **Specific architectures for vanishing gradients:**
  LSTM [Hochreiter and Schmidhuber, 1997], GRU [Cho et al., 2014]



Deep Learning for Sequence Processing

- RNNs SOTA for many sequential decision making tasks: speech, translation, text/music generation, times series, etc
- Ex: forecasting future frames for energy regulation (EDF)





Deep Learning Robustness

Deep Learning: huge gain in average performance, *e.g.* precision for classification, ℓ_2 loss for regression

- In several contexts, need to **optimize domain-specific metrics**
  $\Rightarrow$ **new DILATE loss for deep time series forecasting**
- Need for **performance certification in safety-critical applications: robustness**
  $\Rightarrow$ **new confidence / uncertainty measure for deep models**

[Evtimov et al., 2017]

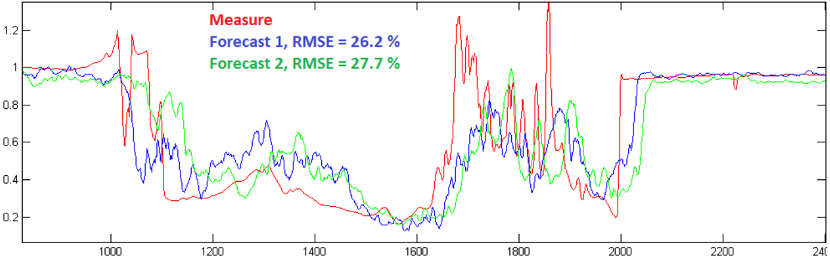
Outline

Context

Goal: Time series forecasting

- **multi-step** setting
- **non stationary** time series, that can present abrupt changes

Why ?: Important in many contexts, e.g. electricity (anticipate future drops of production), etc...



Traditional methods:

- Auto-Regressive models (ARMA, ARIMA,...) [Box et al., 2015]
- State Space Models (Exponential smoothing, ...) [Hyndman et al., 2008]

– Assumption: stationary time series

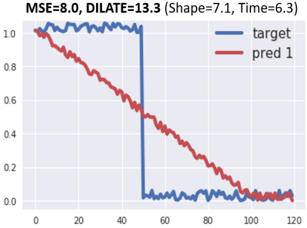
Deep learning models:

- Seq2Seq Recurrent Neural Networks [Yu et al., 2017b]
- Complex architectures for multivariate forecasting: attention mechanisms, tensor factorizations [Yu et al., 2016]
- Deep State Space Models for modeling uncertainty [Rangapuram et al., 2018]

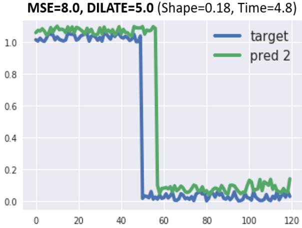
... but all models are trained with the Mean Squared Error (MSE) !

Motivation: MSE Loss Limitation

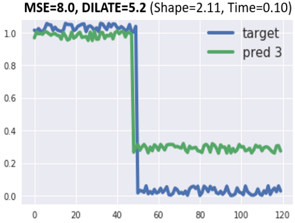
- MSE loss typically used for training forecasting problems not adapted to judge the quality of a forecast.



Non informative prediction

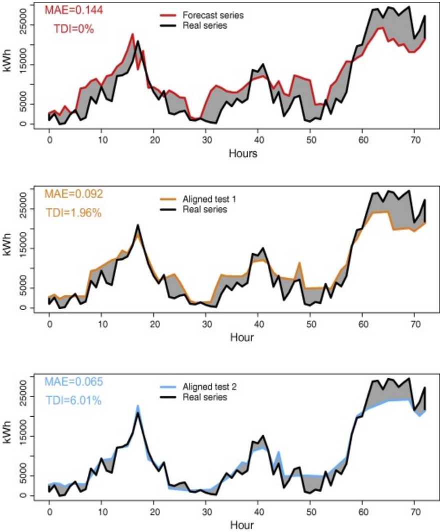


Correct shape, time delay



Correct time, inaccurate shape

Specific Metric for time series forecasting



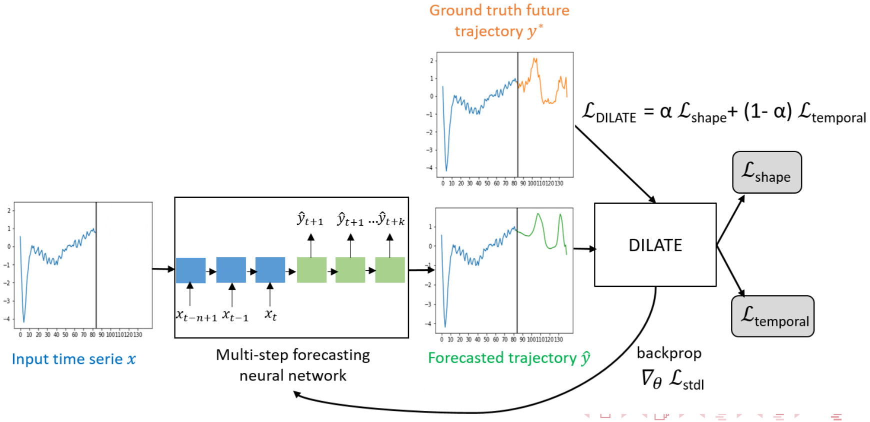
- Change Point Detection
  [Chang et al., 2019, Li et al., 2015]
- Hausdorff distance
  [Garreau et al., 2018, Truong et al., 2019]
- Ramp score
  [Florita et al., 2013, Vallance et al., 2017]
- Time Distrosion Index (TDI)
  [Frías-Paredes et al., 2017]

... but not differentiable! How to train deep models?

Proposal: DIstortion Loss with shApe and TimE (DILATE)

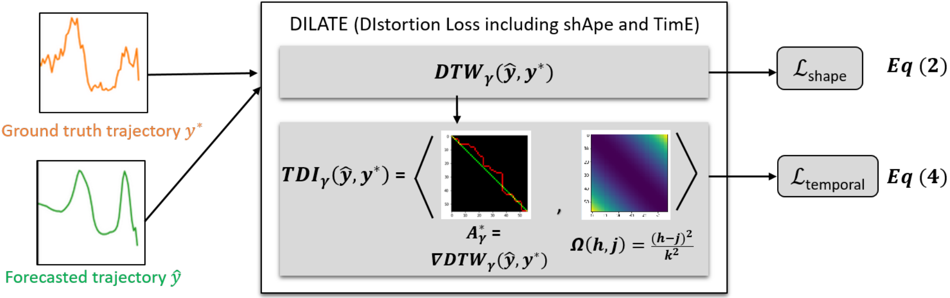
- Training dataset: N input time series $\mathcal{A} = \{\mathrm{x}_i\}_{i \in \{1:N\}}$
  - $\mathrm{x}_i = (\mathrm{x}_i^1, \ldots, \mathrm{x}_i^n) \in \mathbb{R}^{p \times n}$ input of length n
  - $\overset{*}{\mathrm{y}}_i = (\overset{*}{\mathrm{y}}_i{}^1, \ldots, \overset{*}{\mathrm{y}}_i{}^k)$ GT output of length k
  - $\hat{\mathrm{y}}_i = (\hat{\mathrm{y}}_i^1, \ldots, \hat{\mathrm{y}}_i^k) \in \mathbb{R}^{d \times k}$ predicted output of length k (deep forecasting model)

$$\mathcal{L}_{DILATE}(\hat{\mathrm{y}}_i, \overset{*}{\mathrm{y}}_i) = \alpha\ \mathcal{L}_{shape}(\hat{\mathrm{y}}_i, \overset{*}{\mathrm{y}}_i) + (1-\alpha)\ \mathcal{L}_{temporal}(\hat{\mathrm{y}}_i, \overset{*}{\mathrm{y}}_i) \qquad (1)$$



Training deep forecasting models with DILATE

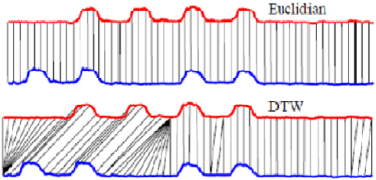
- $\mathcal{L}_{shape}$ and $\mathcal{L}_{temporal}$ based on Dynamic Time Warping [Sakoe and Chiba, 1990]



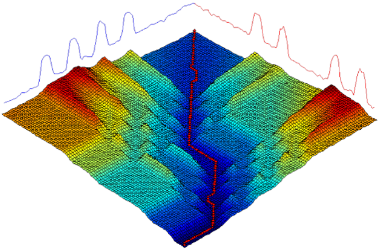
- $\mathcal{L}_{shape}$ and $\mathcal{L}_{temporal}$ differentiable wrt network parameters

Dynamic Time Warping (DTW) [Sakoe and Chiba, 1990]

- DTW: alignment between 2 time series: $DTW(\hat{y}_i, \overset{*}{y}_i) = \min_{A \in \mathcal{A}_{k,k}} \left\langle A, \Delta(\hat{y}_i, \overset{*}{y}_i) \right\rangle$
- $\mathcal{A}_{k,k} \subset \{0,1\}^{k \times k}$: alignment paths (binary matrices), authorized moves $\rightarrow, \downarrow, \searrow$
- $\Delta(\hat{y}_i, \overset{*}{y}_i) := [\delta(\hat{y}_i^h, \overset{*}{y}_i^j)]_{h,j}$ pairwise cost matrix, *e.g.* $\delta(\hat{y}_i^h, \overset{*}{y}_i^j) = (\hat{y}_i^h - \overset{*}{y}_i^j)^2$



MSE vs DTW loss



Pairwise cost matrix and optimal alignment

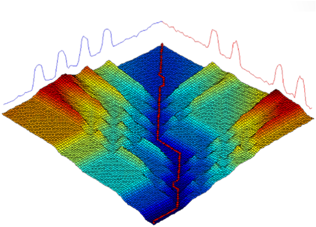
- $\oplus$ DTW good candidate for a shape loss
- $\ominus$ Not differentiable wrt Δ ...

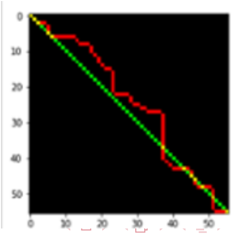
Shape term $\mathcal{L}_{shape}$ and Temporal term $\mathcal{L}_{temporal}$

- Soft min operator: $\min_\gamma(a_1, ..., a_n) = -\gamma \log(\sum_{i=1}^{n} \exp(-\frac{a_i}{\gamma})),\ \gamma > 0$
- Soft-DTW [Cuturi and Blondel, 2017] for shape term:

$$\mathcal{L}_{shape}(\hat{y}_i, \overset{*}{y}_i) = DTW_\gamma(\hat{y}_i, \overset{*}{y}_i) := -\gamma \log\left(\sum_{A \in \mathcal{A}_{k,k}} \exp\left(-\frac{\left\langle A, \Delta(\hat{y}_i, \overset{*}{y}_i)\right\rangle}{\gamma}\right)\right) \quad (2)$$

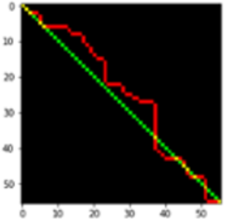
- Temporal term: based on DTW optimal path $A^* = \underset{A \in \mathcal{A}_{k,k}}{\text{argmin}} \left\langle A, \Delta(\hat{y}_i, \overset{*}{y}_i)\right\rangle$:
  - A^* along the main diagonal $\Rightarrow$ no temporal distortion
  - A^* departs from the diagonal $\Rightarrow$ presence of temporal distortion





Temporal term $\mathcal{L}_{temporal}$

- Generalized Time Distortion Index (TDI) [Frías-Paredes et al., 2017]



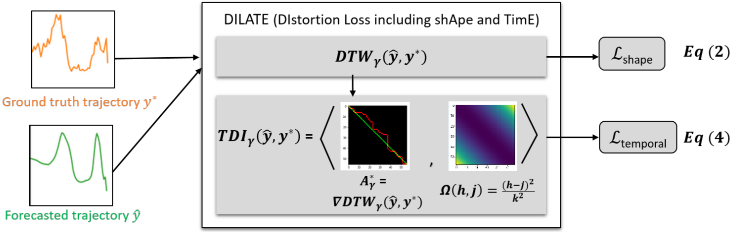
$$TDI(\hat{y}_i, \overset{*}{y}_i) = \langle A^*, \Omega \rangle = \left\langle \underset{A \in \mathcal{A}_{k,k}}{\arg\min} \left\langle A, \Delta(\hat{y}_i, \overset{*}{y}_i) \right\rangle, \Omega \right\rangle \quad (3)$$

- Ω: penalizing matrix of size $k \times k$, *e.g.* $\Omega(h,j) = \frac{1}{k^2}(h-j)^2$

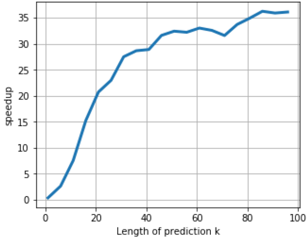
- $A^* = \nabla_\Delta \mathrm{DTW}(\hat{y}_i, \overset{*}{y}_i)$ not differentiable
- $A^* \approx A^*_\gamma = \nabla_\Delta DTW_\gamma(\hat{y}_i, \overset{*}{y}_i) = 1/Z \ \sum_{A \in \mathcal{A}_{k,k}} A \exp^{-\frac{\left\langle \mathbf{A}, \Delta(\hat{\mathbf{y}}_i, \overset{*}{\mathbf{y}}_i) \right\rangle}{\gamma}}$
- **Smooth temporal loss:** $\mathcal{L}_{temporal}$

$$\mathcal{L}_{temporal}(\hat{y}_i, \overset{*}{y}_i) := \left\langle A^*_\gamma, \Omega \right\rangle = \frac{1}{Z} \sum_{A \in \mathcal{A}_{k,k}} \langle A, \Omega \rangle \exp^{-\frac{\left\langle \mathbf{A}, \Delta(\hat{\mathbf{y}}_i, \overset{*}{\mathbf{y}}_i) \right\rangle}{\gamma}} \quad (4)$$

Training deep forecasting models with DILATE



- Direct computation of $\mathcal{L}_{shape}$ and $\mathcal{L}_{temporal}$ intractable ($|\mathcal{A}_{k,k}| = O(exp(k^2))$)
- Solution: dynamic programming $\Rightarrow$ custom forward/backward implementation



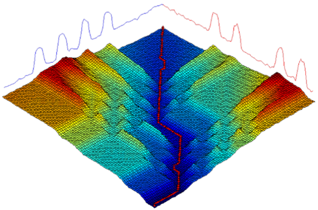
Variants of DILATE

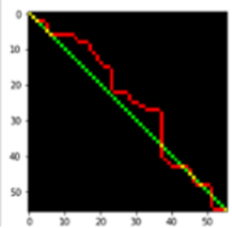
- DILATE-t: "tangled" variant of DILATE

DILATE	$\min_{A} {}_{\gamma}\langle A, \Delta\rangle + \langle A^*, \Omega\rangle$
DILATE-t	$\min_{A} {}_{\gamma}\langle A, \Delta + \Omega\rangle$

- DILATE-t: penalization matrix Ω inside the minimization of DTW
  - Shape and temporal term mixed during minimization
- DILATE-t subsumes well-known temporally-constrained DTW methods:

Sakoe-Chiba hard band constraint	$\Omega(h, j) = +\infty$ if $\lvert h - j\rvert > T$, 0 otherwise
Weighted DTW	$\Omega(h, j) = f(\lvert i - j\rvert)$, f increasing function





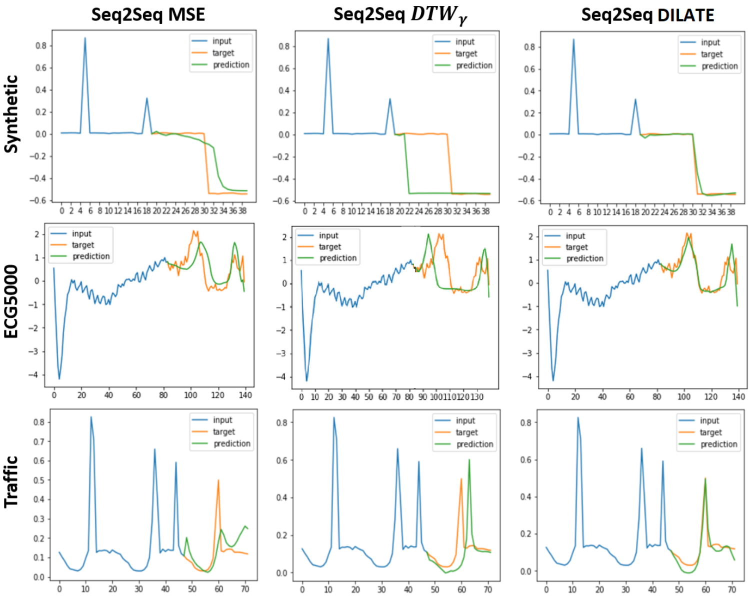
Experiments

Experimental setup: evaluate the k-step future trajectories

3 non stationary datasets from various domains:

- Synthetic
- ECG5000
- Traffic

Qualitative forecasting results



Quantitative results

Training with DILATE vs MSE leads to:

- Equivalent results evaluated on MSE
- Better results evaluated on shape (DTW)
- Better results evaluated on timing (TDI)

		Fully connected network (MLP)			Recurrent neural network (Seq2Seq)		
Dataset	Eval	MSE	DTW_γ	DILATE (ours)	MSE	DTW_γ	DILATE (ours)
Synth	MSE	**1.65** ± **0.14**	4.82 ± 0.40	**1.67**± **0.184**	**1.10** ± **0.17**	2.31 ± 0.45	**1.21** ± **0.13**
	DTW	38.6 ± 1.28	**27.3** ± **1.37**	32.1 ± 5.33	**24.6** ± **1.20**	**22.7** ± **3.55**	**23.1** ± **2.44**
	TDI	15.3 ± 1.39	26.9 ± 4.16	**13.8** ± **0.712**	17.2 ± 1.22	20.0 ± 3.72	**14.8** ± **1.29**
ECG	MSE	**31.5** ± **1.39**	70.9 ± 37.2	37.2 ± 3.59	**21.2** ± **2.24**	75.1 ± 6.30	30.3 ± 4.10
	DTW	19.5 ± 0.159	18.4 ± 0.749	**17.7** ± **0.427**	17.8 ± 1.62	17.1 ± 0.650	**16.1** ± **0.156**
	TDI	**7.58** ± **0.192**	38.9 ± 8.76	**7.21** ± **0.886**	8.27 ± 1.03)	27.2 ± 11.1	**6.59** ± **0.786**
Traffic	MSE	**0.620** ± **0.010**	2.52 ± 0.230	1.93 ± 0.080	**0.890** ± **0.11**	2.22 ± 0.26	**1.00** ± **0.260**
	DTW	24.6 ± 0.180	**23.4** ± **5.40**	**23.1** ± **0.41**	24.6 ± 1.85	**22.6** ± **1.34**	**23.0** ± **1.62**
	TDI	**16.8** ± **0.799**	27.4 ± 5.01	**16.7** ± **0.508**	**15.4** ± **2.25**	22.3 ± 3.66	**14.4**± **1.58**

Table: Forecasting results evaluated with MSE, Shape and Time metrics, averaged over 10 runs (mean ± standard deviation). For each experiment, best method(s) (Student t-test) in bold.

Evaluation with external metrics

- Shape: **ramp score** [Vallance et al., 2017]
- Time: **Hausdorff distance** between 2 sets of change points

		MSE	DTW_γ	DILATE (ours)
Synthetic	Hausdorff	2.87 ± 0.127	3.45 ± 0.318	**2.70 ± 0.166**
	Ramp score (x10)	5.80 ± 0.104	**4.27 ± 0.800**	4.99 ± 0.460
ECG5000	Hausdorff	**4.32 ± 0.505**	6.16 ± 0.854	**4.23 ± 0.414**
	Ramp score	**4.84 ± 0.240**	**4.79 ± 0.365**	**4.80 ± 0.249**
Traffic	Hausdorff	**2.16 ± 0.378**	**2.29 ± 0.329**	**2.13 ± 0.514**
	Ramp score (x10)	6.29 ± 0.319	**5.78 ± 0.404**	**5.93 ± 0.235**

Table: Forecasting results of Seq2Seq evaluated with Hausdorff and Ramp Score, averaged over 10 runs (mean ± standard deviation). For each experiment, best method(s) (Student t-test) in bold.

Comparison to tangled variants of DILATE

Eval loss		DILATE (ours)	DILATE^t-Weighted	DILATE^t-Band Constraint
Euclidian	MSE (x100)	**1.21** ± **0.130**	1.36 ± 0.107	1.83 ± 0.163
Shape	DTW (x100)	**23.1** ± **2.44**	**20.5** ± **2.49**	**21.6** ± **1.74**
	Ramp	**4.99** ± **0.460**	**5.56** ± **0.87**	**5.23** ±**0.439**
Time	TDI (x10)	**14.8** ± **1.29**	17.8 ± 1.72	19.6 ± 1.72
	Hausdorff	**2.70** ± **0.166**	**2.85** ± **0.210**	3.30 ± 0.273

Table: Comparison to the tangled variants of DILATE for the Seq2Seq model on the Synthetic dataset, averaged over 10 runs (mean ± standard deviation).

State of the art comparison

Baselines:

- LSTNet [Lai et al., 2018]: mono-step model, applied recursively for multi-step
- Deep AR [Laptev et al., 2017]: trained with MSE
- TT-RNN [Yu et al., 2017a]: SOTA Seq2Seq model

Eval loss		LSTNet-rec (MSE)	TT-RNN (MSE)	Deep AR (MSE)	Seq2Seq (DILATE)	TT-RNN (DILATE)
Euclidian	MSE	1.74 ± 0.11	**0.840 ± 0.106**	0.966 ± 0.068	1.00 ± 0.260	**0.930 ± 0.09**
Shape	DTW	42.0 ± 2.2	25.9 ± 1.99	27.8 ± 1.55	23.0 ± 1.62	**21.4 ± 0.79**
	Ramp	9.00 ± 0.577	6.71 ± 0.546	7.56 ± 0.42	5.93 ± 0.235	**5.27 ± 0.27**
Time	TDI	25.7 ± 4.75	17.8 ± 1.73	**14.6 ± 0.94**	**14.4 ± 1.58**	**15.7 ± 1.02**
	Hausdorff	2.34 ± 1.41	2.19 ± 0.12	2.04 ± 0.11	2.13 ± 0.514	**1.88 ± 0.153**

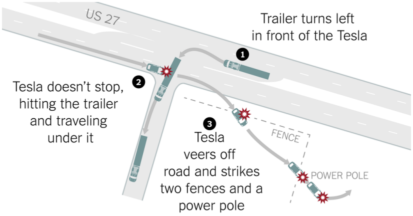
$\Rightarrow$ DILATE can improve the performance of SOTA multi-step architecture on shape and time metrics, and equivalent on MSE

Outline

1. DILATE loss for training deep forecasting models
2. ConfidNet for confidence estimation

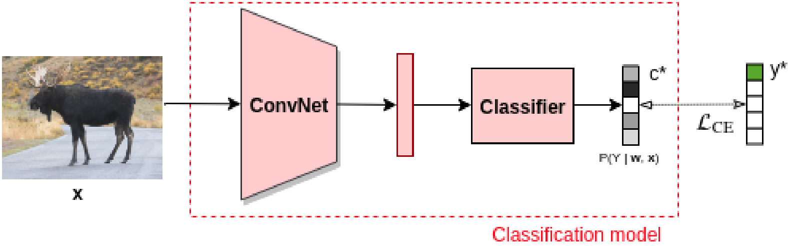
Robustness issues

Tesla's car crash back in 2016, due to a confusion between white side of trailer and brightly lit sky



⇒ **Are neural network's predictions reliable? How much is the model certain about our output? How do we account for uncertainty?**

Classification framework
$\mathcal{D} = \{(\mathrm{x}_i, y_i^*)\}_{i=1}^N$ with $\mathrm{x}_i \in \mathbb{R}^D$ and $y_i^* \in \mathcal{Y} = \{1, \ldots, K\}$.
One can infer predicted class $\hat{y} = \mathrm{argmax}_{k \in \mathcal{Y}}\, p(Y = k|\mathrm{w}, \mathrm{x})$.

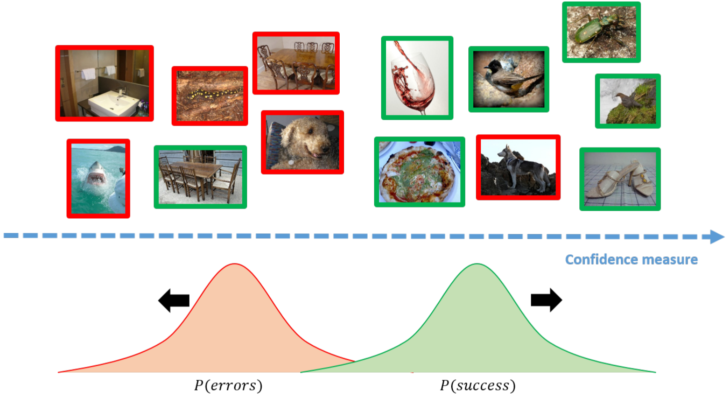


- **Maximum Class Probability** [Hendrycks and Gimpel, 2017]
A confidence measure baseline for deep neural networks:

$$\mathrm{MCP}(\mathrm{x}) = \max_{k \in \mathcal{Y}} p(Y = k|\mathrm{w}, \mathrm{x})$$

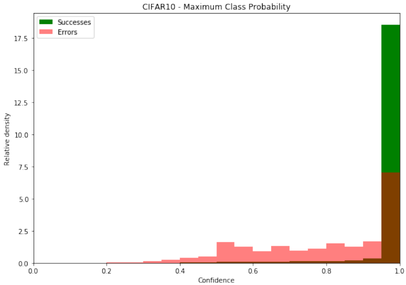
Goal

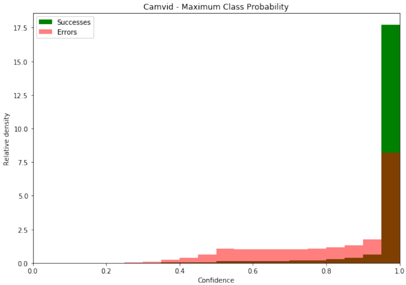
Provide **reliable confidence measures** over model's predictions whose ranking among samples enables to **distinguish correct from erroneous predictions**.



MCP, a sub-optimal ranking confidence measure

$$\mathrm{MCP}(\mathbf{x}) = \max_{k \in \mathcal{Y}} p(Y = k|\mathbf{w}, \mathbf{x})$$

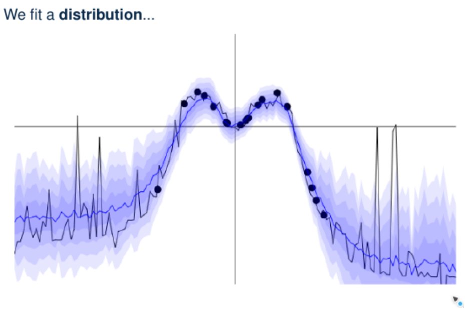


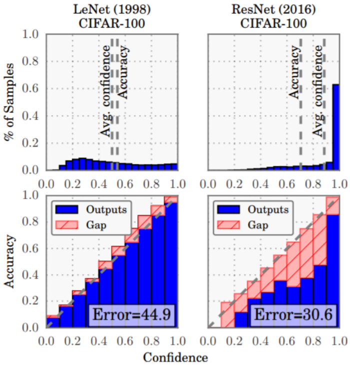


- **overlapping distributions** between successes vs. errors
  $\Rightarrow$ hard to distinguish

Beyond MCP: Related Works

- Bayesian deep learning, *e.g.* MC-Dropout [Gal and Ghahramani, 2016]
- Specific confidence criterion for failure prediction, *e.g.* Trust Score [Jiang et al., 2018]
- Calibration related to overconfident prediction [Guo et al., 2017, Neumann et al., 2018]

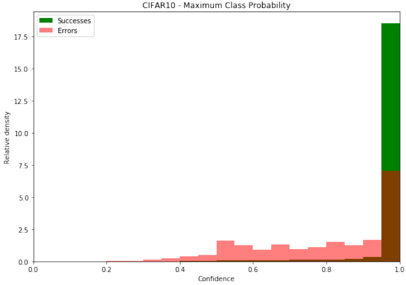


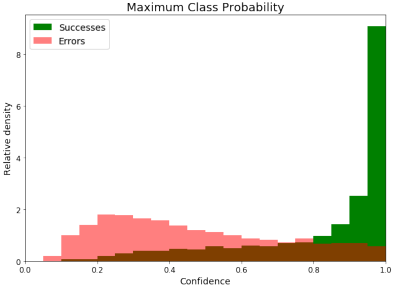


MCP, a sub-optimal ranking confidence measure

$$\mathrm{MCP}(x) = \max_{k \in \mathcal{Y}} p(Y = k | w, x)$$

- Overconfident prediction values
  $\Rightarrow$ calibration [Guo et al., 2017, Neumann et al., 2018]
- BUT: calibration does not change error/correct prediction rankings





Our Approach: True Class Probability

When missclassifying, MCP $\Leftrightarrow$ probability of the wrong class.
$\Rightarrow$ **what if we had taken the probability of the true class?**

True Class Probability

Given a sample (x, y^*) and a model parametrized by w, *True Class Probability* writes as:

$$\mathrm{TCP}(\mathrm{x}, y^*) = p(Y = y^* | \mathrm{w}, \mathrm{x})$$

Theoretical guarantees:

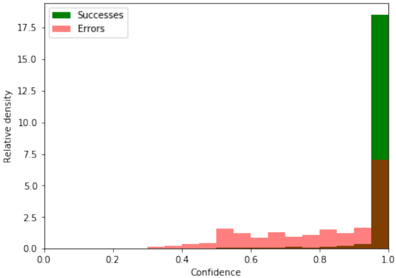
- $\mathrm{TCP}(\mathrm{x}, y^*) > 1/2 \Rightarrow \hat{y} = y^*$
- $\mathrm{TCP}(\mathrm{x}, y^*) < 1/K \Rightarrow \hat{y} \neq y^*$

N.B: a normalized variant present stronger guarantees:

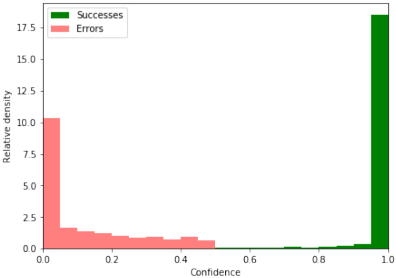
$$TCP^r(\mathrm{x}, y^*) = \frac{p(Y = y^* | \mathrm{w}, \mathrm{x})}{p(Y = \hat{y} | \mathrm{w}, \mathrm{x})}$$

TCP, a reliable confidence criterion

VGG16 on CIFAR-10



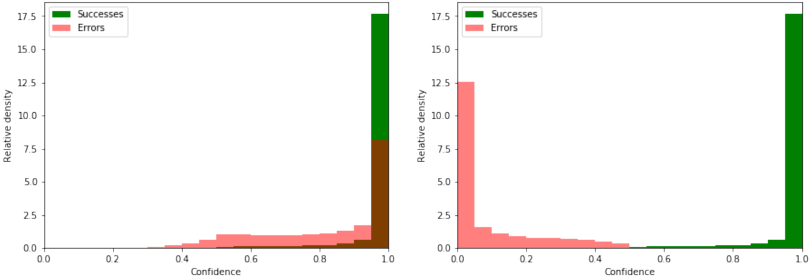
(a) Maximum Class Probability



(b) Our Proposal (True Class Probability)

TCP, a reliable confidence criterion

SegNet on CamVid



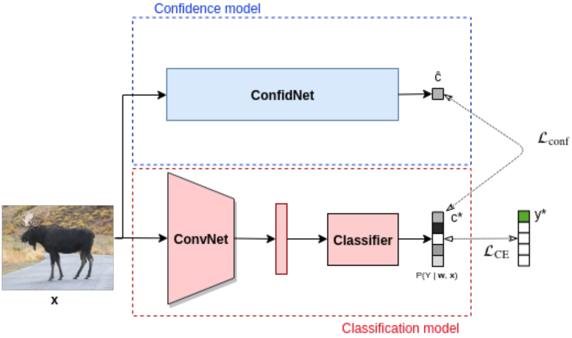
(a) Maximum Class Probability

(b) Our Proposal (True Class Probability)

ConfidNet: Learning TCP Model Confidence

However, $TCP(\mathrm{x}, y^*)$ is **unknown** at test time.

Given $\mathcal{D}_{train}$, **learn a confidence model** with parameters θ such that $\forall \mathrm{x} \in \mathcal{D}_{train}$, its scalar output $\hat{c}(\mathrm{x}, \theta)$ close to $TCP(\mathrm{x}, y^*)$

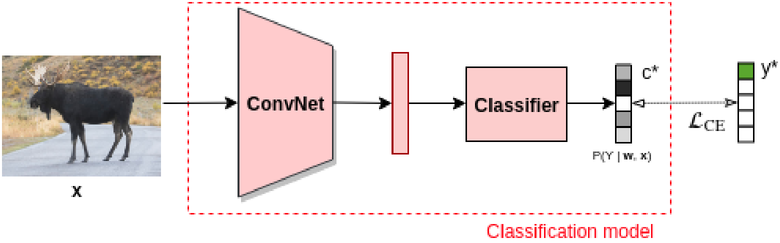


As $TCP(\mathrm{x}, y^*) \in [0, 1]$, we propose ℓ_2 loss to train ConfidNet:

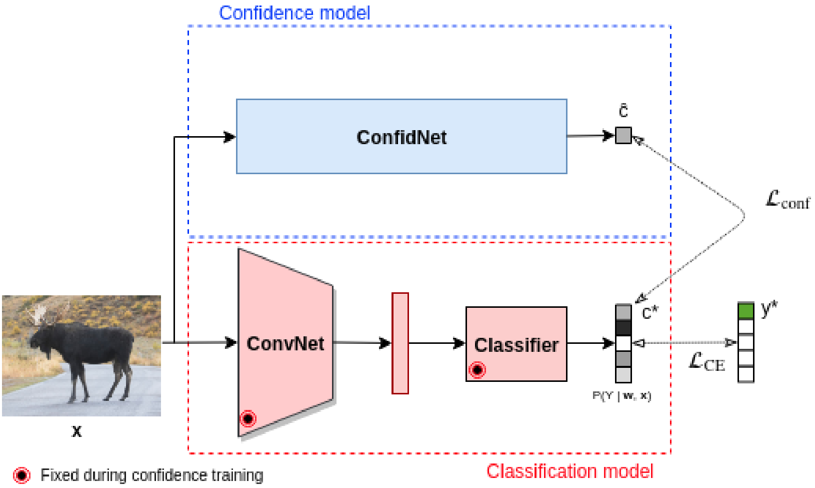
$$\mathcal{L}_{\mathrm{conf}}(\theta; \mathcal{D}) = \frac{1}{N} \sum_{i=1}^{N} \left(\hat{c}(\mathrm{x}_i, \theta) - c^*(\mathrm{x}_i, y_i^*)\right)^2$$

N.B: $c^*(\mathbf{x}, y^*) = TCP(\mathbf{x}, y^*)$ **(or** $TCP^r(\mathbf{x}, y^*)$**)**

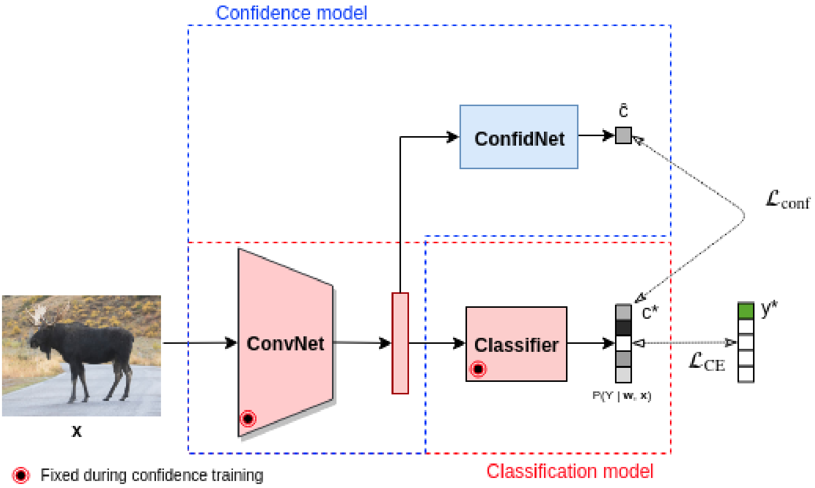
ConfidNet learning scheme



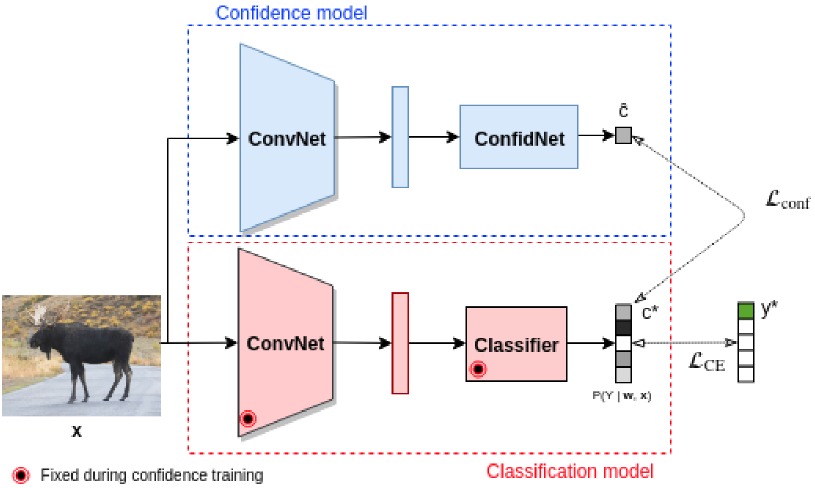
ConfidNet learning scheme



Efficient ConfidNet learning scheme (1/2)

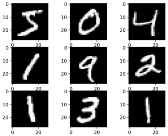


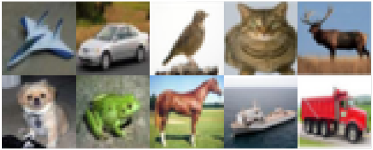
Efficient ConfidNet learning scheme (2/2)

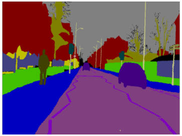


Traditional public **image classification** and **semantic segmentation** datasets

- **MNIST**: 32x32 BW, 10 classes, 60K training + 10K test
- **SVHN**: 32x32 RGB , 10 classes, 73K training + 26K test
- **CIFAR-10 & CIFAR-100**: 32x32 RGB, *10 / 100 classes*, 50K training + 10K test
- **CamVid**: *semantic segmentation* , 360x480, 11 classes







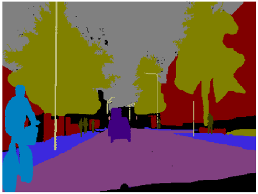
Quantitative results

Dataset	Model	FPR-95%-TPR	AUPR-Error	AUPR-Success	AUC
MNIST MLP	Baseline (MCP)	14.87	37.70	99.94	97.13
	MCDropout	15.15	38.22	99.94	97.15
	TrustScore	12.31	52.18	99.95	97.52
	ConfidNet (Ours)	**11.79**	**57.37**	**99.95**	**97.83**
MNIST Small ConvNet	Baseline (MCP)	5.56	35.05	99.99	98.63
	MCDropout	5.26	38.50	99.99	98.65
	TrustScore	10.00	35.88	99.98	98.20
	ConfidNet (Ours)	**3.33**	**45.89**	**99.99**	**98.82**
SVHN Small ConvNet	Baseline (MCP)	31.28	48.18	99.54	93.20
	MCDropout	36.60	43.87	99.52	92.85
	TrustScore	34.74	43.32	99.48	92.16
	ConfidNet (Ours)	**28.58**	**50.72**	**99.55**	**93.44**
CIFAR-10 VGG16	Baseline (MCP)	47.50	45.36	99.19	91.53
	MCDropout	49.02	46.40	**99.27**	92.08
	TrustScore	55.70	38.10	98.76	88.47
	ConfidNet (Ours)	**44.94**	**49.94**	99.24	**92.12**
CIFAR-100 VGG16	Baseline (MCP)	67.86	71.99	92.49	85.67
	MCDropout	64.68	72.59	**92.96**	86.09
	TrustScore	71.74	66.82	91.58	84.17
	ConfidNet (Ours)	**62.96**	**73.68**	92.68	**86.28**
CamVid SegNet	Baseline (MCP)	63.87	48.53	96.37	84.42
	MCDropout	62.95	49.35	96.40	84.58
	TrustScore		20.42	92.72	68.33
	ConfidNet (Ours)	**61.52**	**50.51**	**96.58**	**85.02**

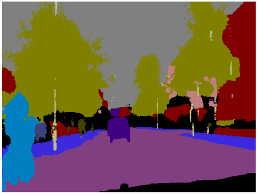
Qualitative results

Failure detection for **semantic segmentation** on CamVid dataset

(a) Input Image

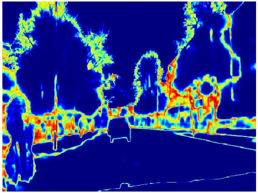


(b) Ground truth

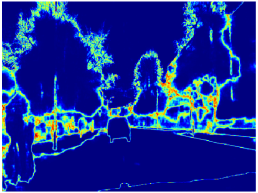


(c) Prediction

(d) Model Errors



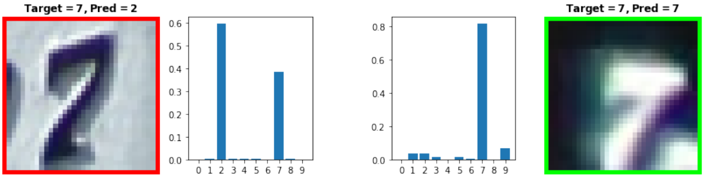
(e) ConfidNet



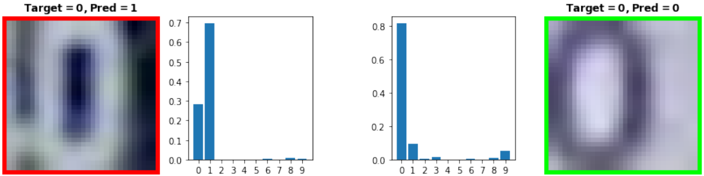
(f) MCP

Qualitative results

Entropy as a confident estimate, such as in MC-Dropout [Gal and Ghahramani, 2016], may not always be adequate



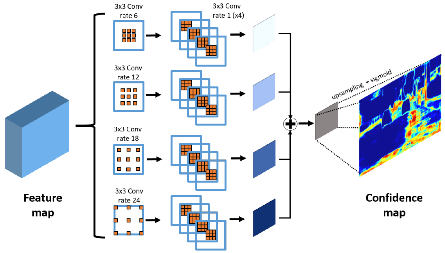
(a) MCP=0.596, MCDropout=-0.787, *ConfidNet*=0.449 (b) MCP=0.816, MCDropout=-0.786, *ConfidNet*=0.894

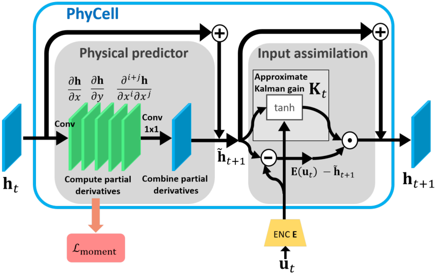


(c) MCP=0.696, MCDropout=-0.726, *ConfidNet*=0.436 (d) MCP=0.814, MCDropout=-0.725, *ConfidNet*=0.886

Conclusion

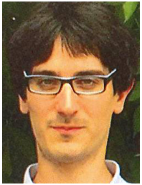
- **DILATE & ConfidNet**: new loss & confidence for deep neural networks
  - Agnostic to model archi, data and tasks
- ConfidNet perspectives:
  - Application to Unsupervised Domain Adaptation (UDA)
  - Relative *vs* absolute confidence, out-of-distributions
- DILATE perspectives:
  - Deep archi with physical priors
  - Weakly-supervised predictions

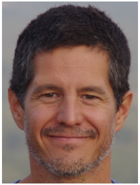
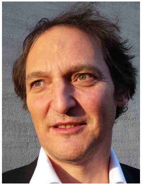
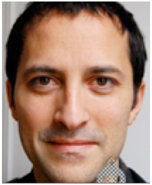




Thank your for your attention!

- **DILATE: Vincent Le Guen, Nicolas Thome**
  - **NeurIPS'19 paper**: Shape and Time Distortion Loss for Training Deep Time Series Forecasting Models
  - **GitHub code:** `https://github.com/vincent-leguen/DILATE`
- **ConfidNet: Charles Corbière, Nicolas Thome, Avner Bar-Hen, Matthieu Cord, Patrick Pérez**
  - **NeurIPS'19 paper**: Addressing Failure Prediction by Learning Model Confidence
  - **GitHub code:** `https://github.com/valeoai/ConfidNet`

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