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Decision Tree Fields

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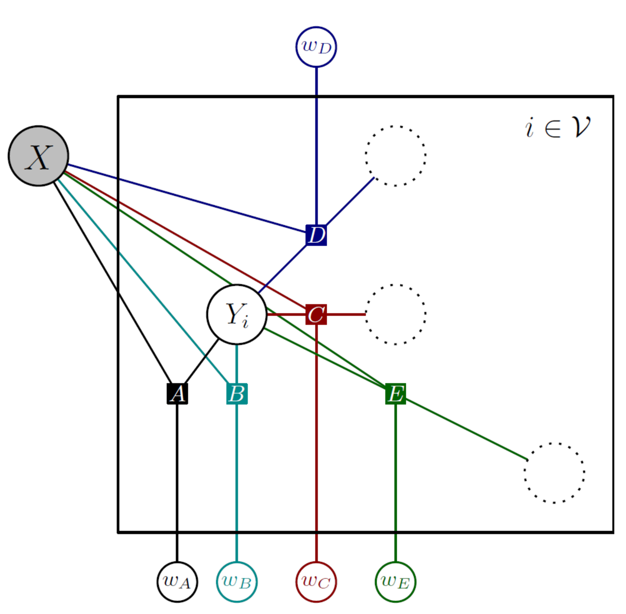
Overview

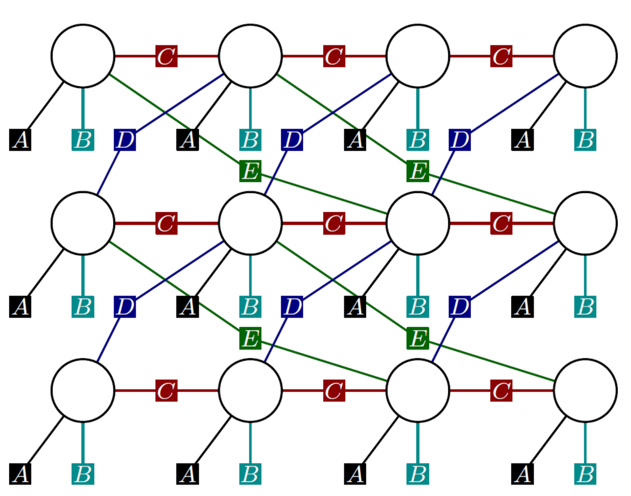
DTF = Efficiently learnable non-parametric CRFs for discrete image labelling tasks

- All factors (unary, pairwise, higher-order) are represented by decision trees
- Decision trees are *non-parametric*
- Efficient training of millions of parameters using pseudo-likelihood

Formally



Graphical Model: Factor types



Factor Graph

Energy $E(\boldsymbol{y},\boldsymbol{x},\boldsymbol{w}) = \sum_F E_{t_F}(y_F,\boldsymbol{x},w_{t_F})$

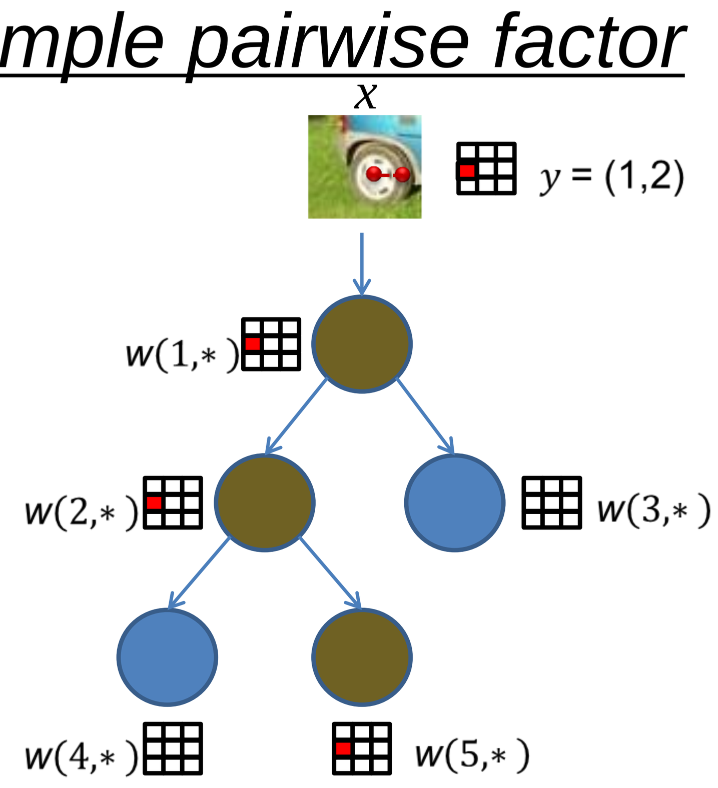
$$E_{t_F}(y_F,x,w_{t_F}) = \sum_{q \in Path(x_F)} w_{t_F}(q,y_F)$$

$$E_{t_F}(y_F,\boldsymbol{x},w_{t_F}) = \langle w_{t_F}, B_{t_F}(y_F,x_F)\rangle$$

$$B_{t_F}(y_F,x_F) =$$

Energy linear in w

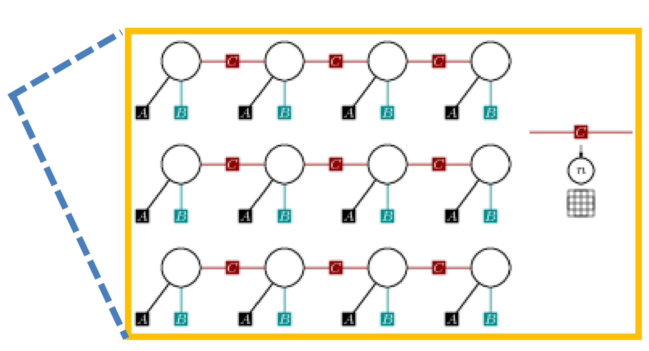
Example pairwise factor

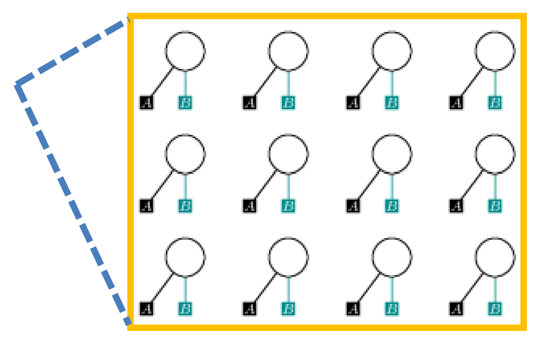


$E_{t_F}(y_F,\boldsymbol{x},\boldsymbol{w}_{t_F}) = w(1,(1,2)) + w(2,(1,2)) + w(5,(1,2))$

Special Cases

- Unary factors only = Decision Forest, with learned leaf node distributions
- Zero-depth trees (pairwise factors) = MRF
- Conditional (pairwise factors) = CRF





Algorithm - Overview

Training

1. Define connective structure (factor types)
2. Train all decision trees (split functions) separately
3. Jointly optimize all weights

Testing (2 options)

- "Unroll" factor graph:
  run: BP, TRW, QPBO, etc.
- Don't "unroll" factor graph:
  run Gibbs Sampling; Simulated Annealing

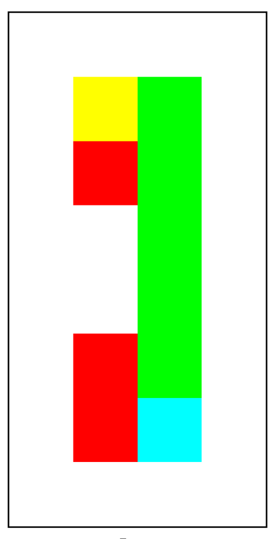
Training of weights "w"

- Maximum Pseudo-Likelihood training, convex optimization problem
- Converges in practice after 150-200 L-BFGS iterations
- Efficient even for large graphs (e.g. 12 connected, 1.47M weights, 22mins)
- Is parallel on the variable level
- Variable sub-sampling possible

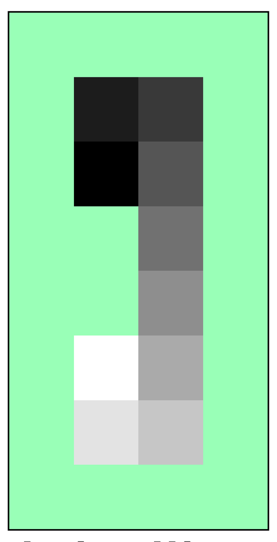
Code will be made available next month!

Results: Conditional Interactions - Snake Dataset

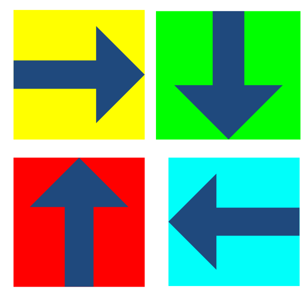
Training



Input image



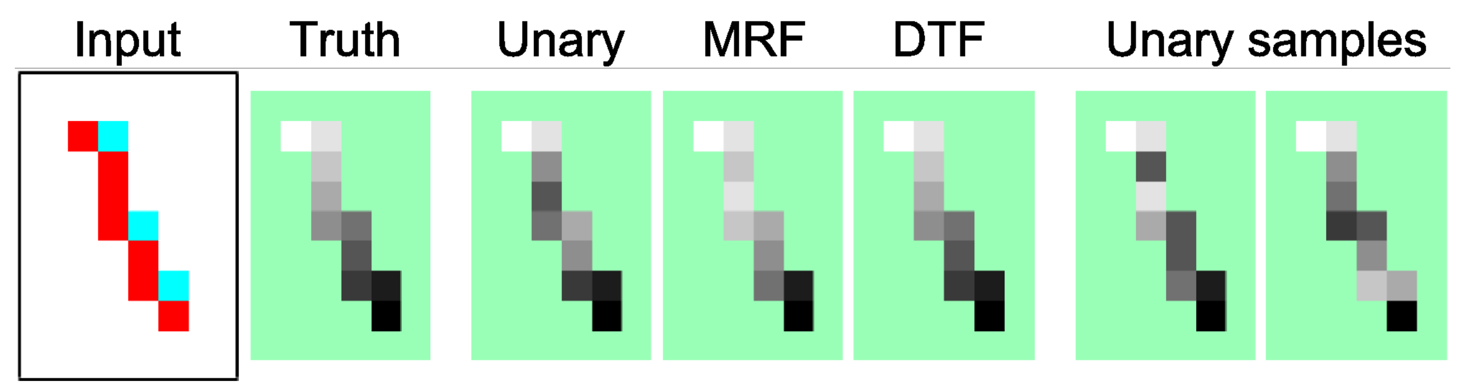
labelling



Colour encodes "direction"

200 randomly deforming snake images

Testing

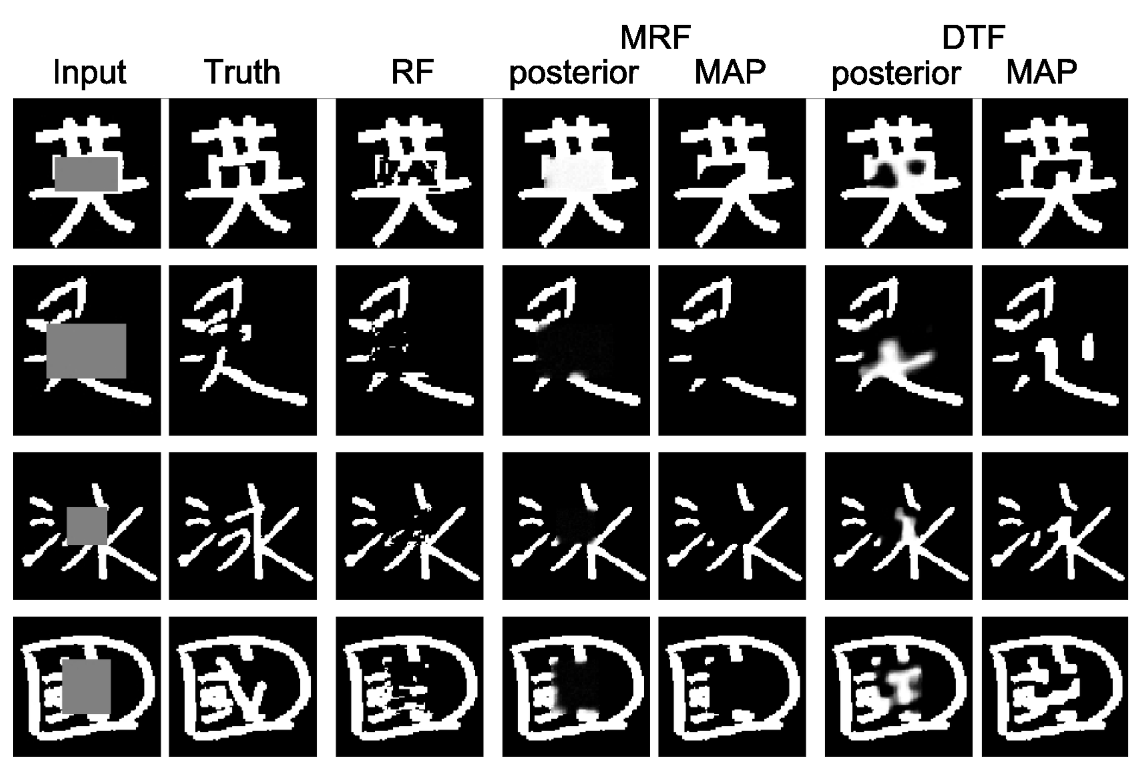


	RF	Unary	MRF	DTF
Avg. acc.	90.3%	90.9%	91.9%	**99.4%**
Tail acc.	100%	100%	100%	100%
Mid acc.	28%	28%	38%	**95%**

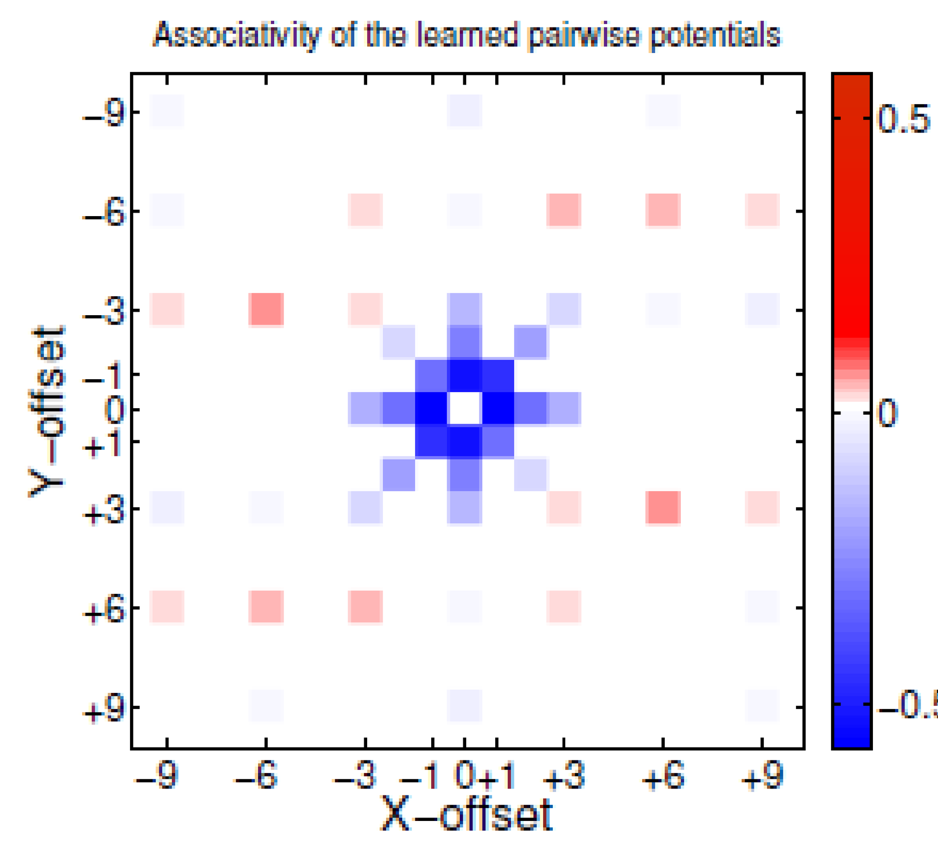
Conclusion: conditional pairwise terms are powerful

Results: Learning Calligraphy - Chinese Characters

300 Training images



100 Test images



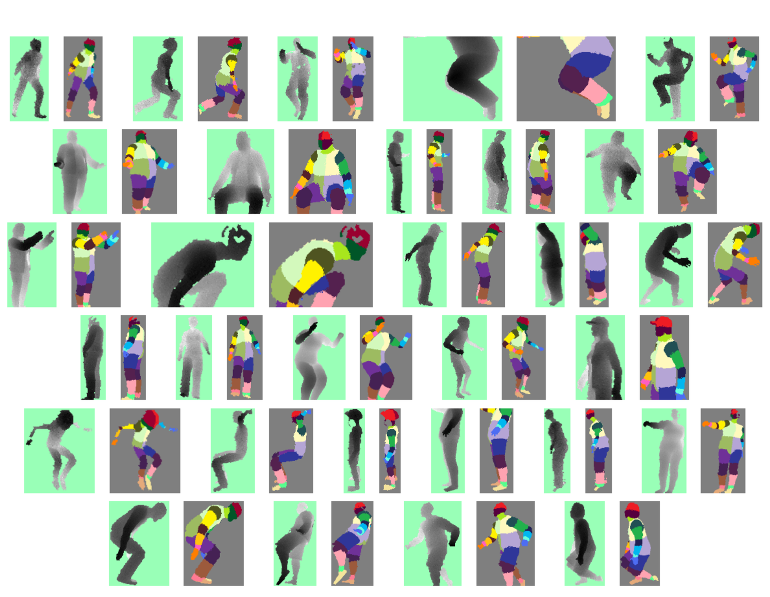
MRF weights

(blue attractive; red repulsive)

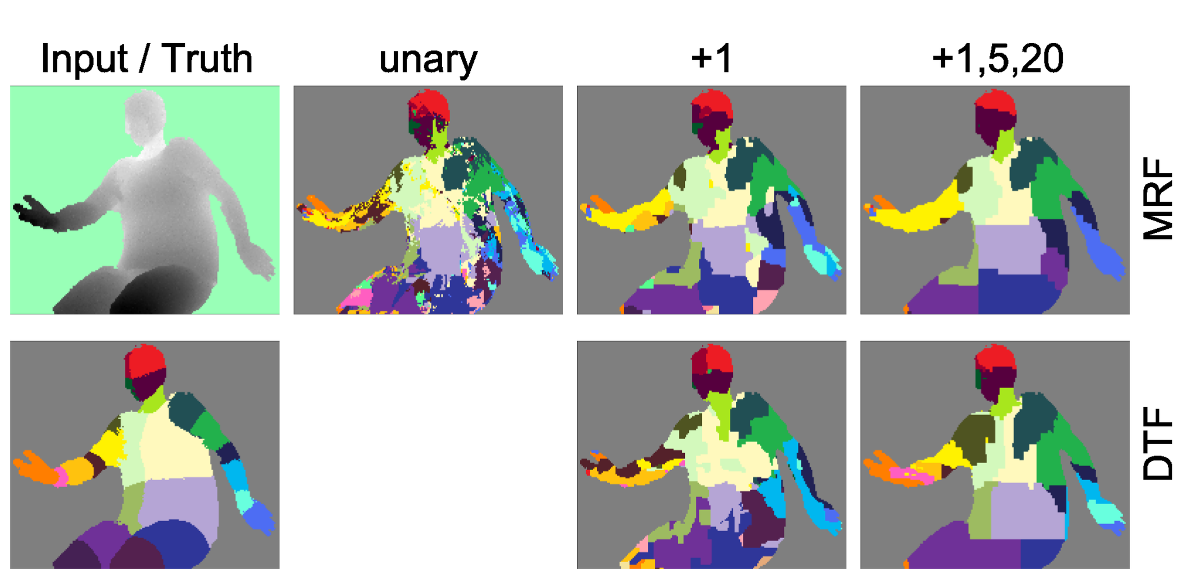
- **Densely connected pairwise DTF:**
  ~64 neighbours per variable, ~10k variables, ~300k factors, ~11k learned parameters
- **Test-time inference with simulated annealing (Gibbs chain)**
- **Hard energy minimization instances of this task are online:**
  http://www.nowozin.net/sebastian/papers/DTF_CIP_instances.zip

Results: Kinect-based bodypart detection

- **Body part recognition from depth images (Shotton et al., CVPR 2011)**
- **DTF: 4 unary factor types, 20 pairwise (+1,+5,+20)**
- **1500 training images, 150 test images**
- **Test-time inference with TRW (unrolled)**



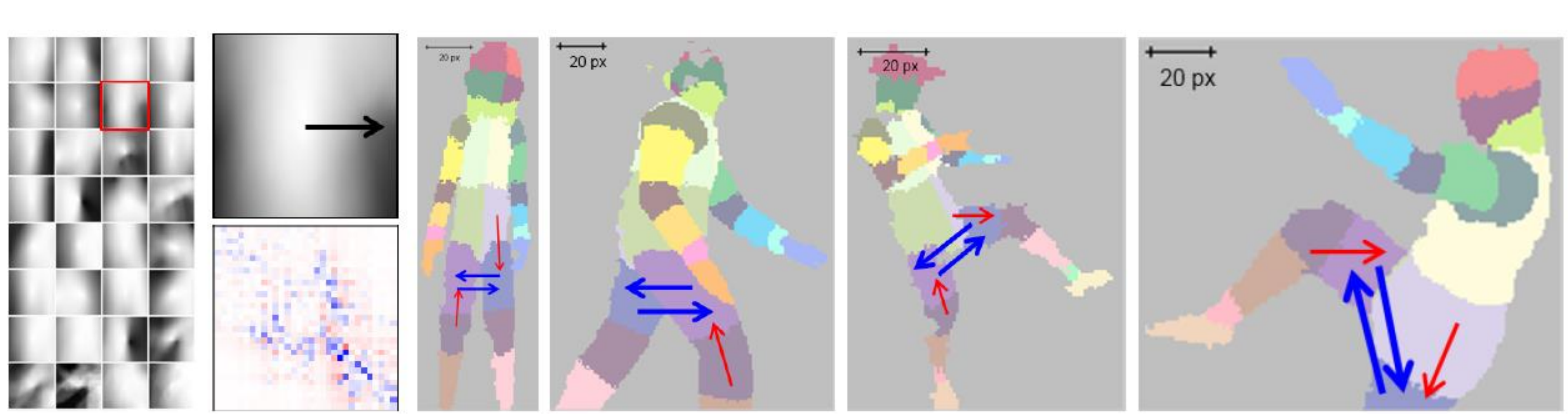
Example training images



Example test images

Model	Measure	[27]	unary	+1	+1,20	+1,5,20
MRF	avg-acc	14.8	21.36	21.96	23.64	24.05
30	runtime	1m	3m18	3m38	10m	10m
	weights	-	176k	178k	183k	187k
DTF	avg-acc	-	-	23.71	25.72	**27.35**
30	runtime	-	-	5m16	17m	22m
	weights	-	-	438k	951k	1.47M
MRF	avg-acc	34.4	36.15	37.82	38.00	39.30
1500	runtime	6h34	*	*	*	$(30h)*$
	weights	-	6.3M	6.2M	6.2M	6.3M
DTF	avg-acc	-	-	39.59	40.26	**41.42**
1500	runtime	-	-	*	*	$(40h)*$
	weights	-	-	6.8M	7.8M	8.8M

Test performance



Illustrating one learned horizontal interaction (20 pixels apart)