

# LTN Examples and Code

Luciano Serafini   Michael Spranger

FBK-IRST, Trento, Italy  
Sony Computer Science Laboratories Inc., Tokyo, Japan

July 8, 2018

# Logic Tensor Networks

- ▶ <https://github.com/logictensornetworks/>
- ▶ `git clone`  
<https://github.com/logictensornetworks/logictensornetworks.git>

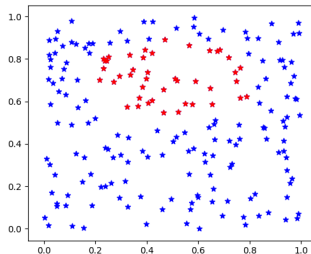
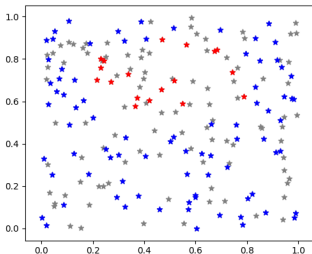
# Classification

**Domain** A set  $D$  of points in the  $[0, 1]^2$  square;

**Predicate** A unary predicate  $A$  (class)

- Supervisions**
1. **Positive examples** a set of points in  $D$ , which are known to be instances of  $A$ ;
  2. **Negative examples** a set of points in  $D$ , which are known not to be instances of  $A$ ;

**Task** For all the other point in  $D$  determine if they are instances of  $A$ .



# Classification in LTN

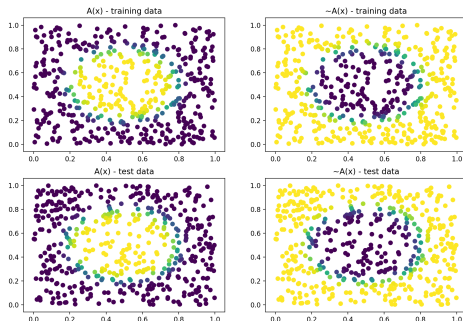
$D$  = random subset of  $[0, 1]^2$

$P = \{p \in D \mid p \text{ is a positive example of } A\}$

$N = \{p \in D \mid p \text{ is a negative example of } A\}$

$\forall x \in P : A(x)$

$\forall x \in N : \neg A(x)$



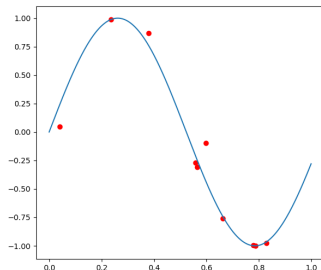
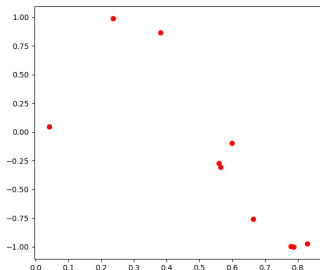
# Regression

**Domain** A set  $D = [0, 1]$

**Function** A unary function  $f : D \rightarrow D$

**Supervisions** A set of **supervision pairs**  $S = \{\langle x_1, y_1 \rangle, \dots, \langle x_n, y_n \rangle\}$  such that  $y_i = f(x_i)$

**Task** For all the other points  $x \in D$  predict  $f(x)$

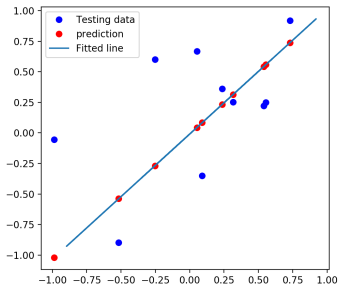
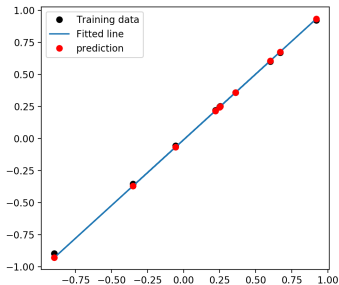


# Regression in LTN

$D$  = a uniform sampling of  $[0, 1]$

$S$  =  $\{\langle x_1, y_1 \rangle, \dots, \langle x_n, y_n \rangle\}$

$$\forall \langle x, y \rangle \in S : f(x) = y$$



# Multi-Label Classification with Label Constraints

**Domain** A set  $D$  of points in the  $[0, 1]^2$  square;

**Predicate** A set unary predicate  $A_1, \dots, A_n$  (class/labels)

**Supervisions**

1. **Positive examples for  $A_i$**  a set of points in  $D$ , which are known to be instances of  $A_i$ ;
2. **Negative examples for  $A_i$**  a set of points in  $D$ , which are known not to be instances of  $A_i$ ;

**Label constraints**

- **Subset constraint** if  $x$  is labelled with  $A_i$  then it is labelled with  $A_j$ ;
- **Disjoint constraint**  $x$  is labelled with  $A_i$  iff then  $x$  is labelled with  $\neg A_j$  and viceversa;

**Task** For all the points in  $D$  determine if they are labelled with  $A_i$  or  $\neg A_i$  (Notice that it is possible that  $x$  is labelled neither with  $A_i$  nor  $\neg A_i$ )

# Multi-Label Classification with Label Constraints in LTN

$$\forall x \in A_i^+ : A_i(x)$$

$$\forall x \in A_i^- : \neg A_i(x)$$

$$\forall x \in D : A_i(x) \rightarrow A_j(x)$$

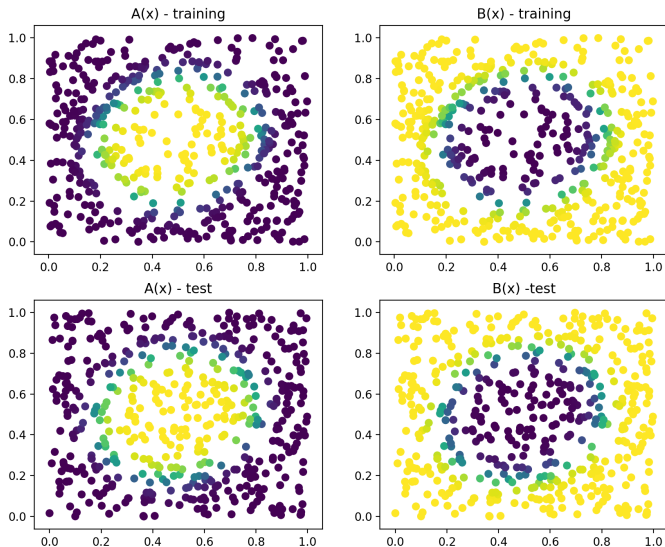
$$\forall x \in D : A_i(x) \leftrightarrow \neg A_j(x) \wedge \neg A_i(x) \leftrightarrow A_j(x)$$

Notice that FOL allows to express more general constraints between labels, as for instance

$$\forall x \in D : (A(x) \wedge B(x)) \rightarrow (C(x) \vee D(x))$$



# Multi-Label Classification with Label Constraints in LTN



# Unsupervised learning - Clustering

**Domain** A set  $D \subset [0, 1]$

**Cluster labels** A set of cluster labels  $C_1, \dots, C_n$

**Task** Put each point in some cluster  $C_i$  minimizing intra-cluster distance and maximizing inter-cluster distance

## Clustering Constraints

- ▶ Every point belongs to a cluster

$$\forall x : C_1(x) \vee \dots \vee C_n(x)$$

- ▶ Every point cannot belong to two clusters

$$\forall x : \neg(C_i(x) \wedge C_j(x)) \quad \text{for } i \neq j \in \{1, \dots, n\}$$

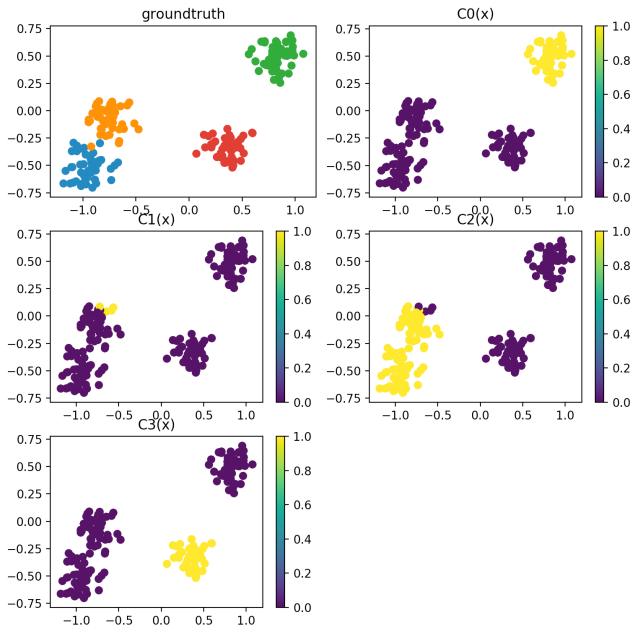
- ▶ Clusters are not empty

$$\exists x : C_i(x) \quad \text{for } i \in \{1, \dots, n\}$$

- ▶ Close points should belong to the same cluster.

$$\forall x, y : \text{Close}(x, y) \rightarrow (C_i(x) \leftrightarrow C_i(y)) \text{ for } i \in \{1, \dots, n\}$$

# Exemplary results



# Relations

**Domain** A set  $D$  of points in the  $[0, 1]^2$  square;

**Predicate** A set 2-ary relational predicates  $R_1, \dots, R_n$

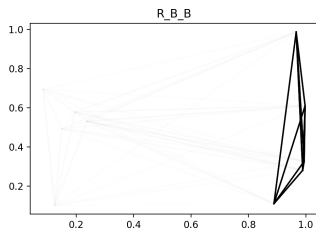
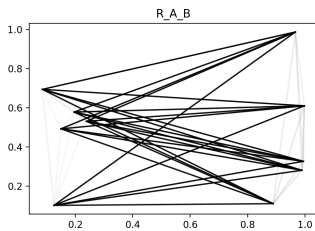
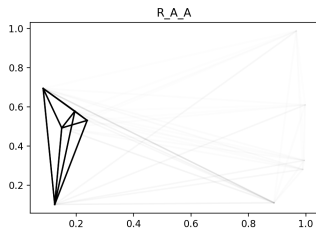
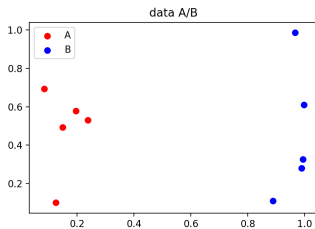
**Supervision**

1. **Positive examples for  $R_i(x, y)$**  a set of points in  $D \times D$ , which are known to be instances of  $R_i$ ;
2. **Negative examples for  $R_i(x, y)$**  a set of points in  $D \times D$ , which are known not to be instances of  $R_i$ ;

**Constraints**

- ▶ **Symmetry** if  $\forall x, y \in D \times D : R(x, y) \rightarrow R(y, x)$
- ▶ **Subset** if  $\forall (x, y) \in D \times D : R(x, y) \rightarrow R'(x, y)$
- ▶ ...

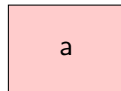
# Relations



# Learning spatial relations

## Domain

Our domain is composed of 2d rectangles on a plane; We are interested in the following 6 spatial relations.

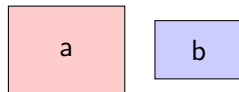


# Learning spatial relations

## Domain

Our domain is composed of 2d rectangles on a plane; We are interested in the following 6 spatial relations.

- ▶ *a* is on the left of *b*



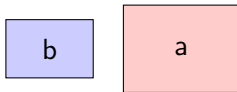


# Learning spatial relations

## Domain

Our domain is composed of 2d rectangles on a plane; We are interested in the following 6 spatial relations.

- ▶  $a$  is on the left of  $b$
- ▶  $a$  is on the right of  $b$

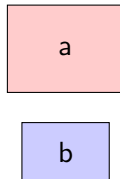


# Learning spatial relations

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- ▶  $a$  is on the left of  $b$
- ▶  $a$  is on the right of  $b$
- ▶  $a$  is above of  $b$

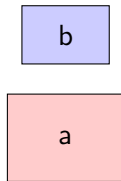


# Learning spatial relations

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- ▶  $a$  is above of  $b$
- ▶  $a$  is below of  $b$

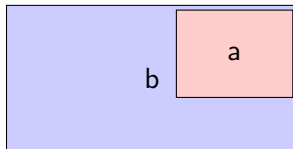


# Learning spatial relations

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Our domain is composed of 2d rectangles on a plane; We are interested in the following 6 spatial relations.

- ▶  $a$  is on the left of  $b$
- ▶  $a$  is on the right of  $b$
- ▶  $a$  is above of  $b$
- ▶  $a$  is below of  $b$
- ▶  $a$  is contained in  $b$

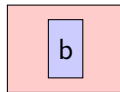


# Learning spatial relations

## Domain

Our domain is composed of 2d rectangles on a plane; We are interested in the following 6 spatial relations.

- ▶  $a$  is on the left of  $b$
- ▶  $a$  is on the right of  $b$
- ▶  $a$  is above of  $b$
- ▶  $a$  is below of  $b$
- ▶  $a$  is contained in  $b$
- ▶  $a$  contains  $b$



# Learning spatial relations

## Problem

Given some some examples of pairs of rectangles for each specific relation, and some background knowledge about them as for instance:

- ▶ left is the inverse of right
- ▶ an object cannot be at the same time on the left and on the right of another object
- ▶ if an object  $a$  is contained in an object  $b$  and  $b$  is on the left of  $c$ , then  $a$  is on the left of  $c$

we want to be able to predict if two randomly generated rectangles, are in one of the 6 spatial relation.

# Learning spatial relations

## Domain representation

Every rectangle is represented with 4 real numbers,

$$\langle x, y, w, h \rangle$$

encoding the coordinates of the bottom-left corner, and the width and the height

## The language

The language is constituted by 6 binary relations

*left(x, y), right(x, y), above(x, y),  
below(x, y), contains(x, y), in(x, y)*

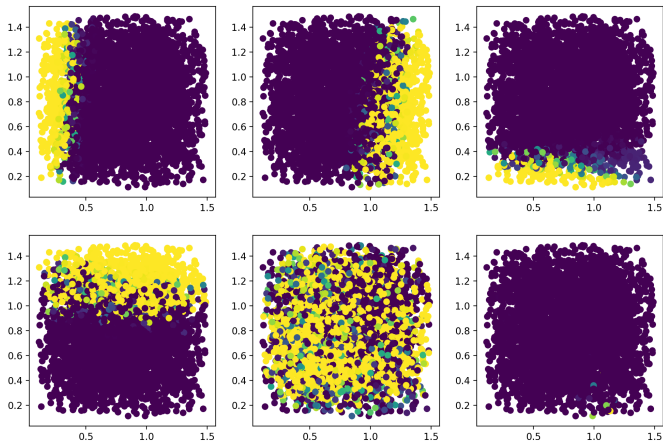
# Learning spatial relations

## The constraints

- ▶ a set of positive examples for each spatial relation:  
*left(a, b), right(c, d), above(e, f), below(h, i), contains(j, k), in(l, m), ...*
- ▶ axioms about spatial relations:
  - ▶  $\forall x, y : left(x, y) \rightarrow \neg left(y, x);$
  - ▶  $\forall x, y : left(x, y) \rightarrow right(y, x);$
  - ▶  $\forall x, y, z : in(x, y) \wedge left(y, z) \rightarrow left(x, z)$
  - ▶ ...



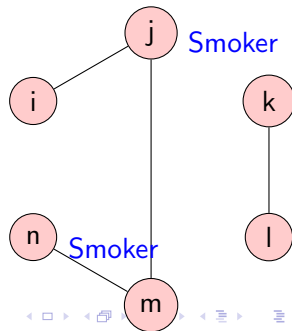
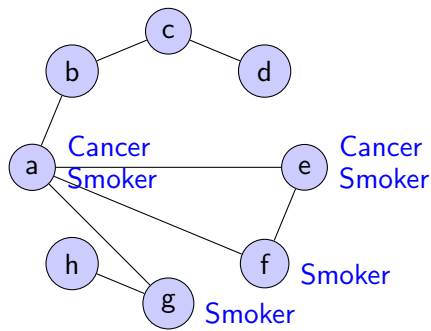
# Learning spatial relations



# Statistical relational learning

Domain: Smoking-Friends-Cancer, [?]

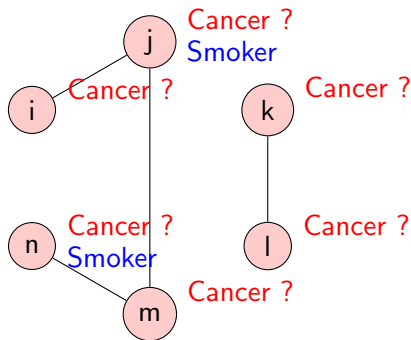
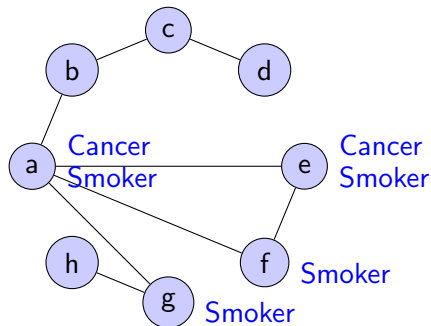
- ▶ Of two groups of people  $\{a, b, \dots, h\}$  and  $\{i, j, \dots, n\}$ ; we know if each of them smokes and the friendship relation within each group;
- ▶ for the first group we also know who has a cancer;
- ▶ we know that cancer depends on smoking
- ▶ and that smoking habits depend on the friendship relation



# Statistical relational learning

## Task 1

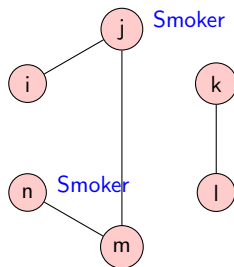
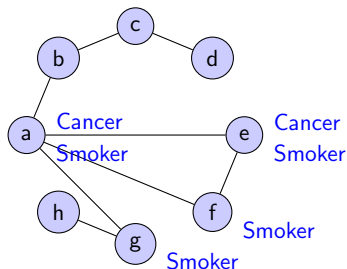
For each of the person of the second group we have to predict if he/she has a cancer or not



# Statistical relational learning

## Task 2

For each person we want to find a semantic embedding in  $\mathbb{R}^k$  consistent with the semantics and the structure. For instance:

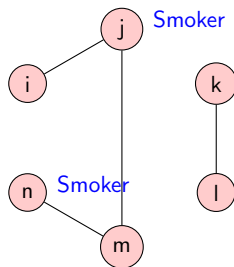
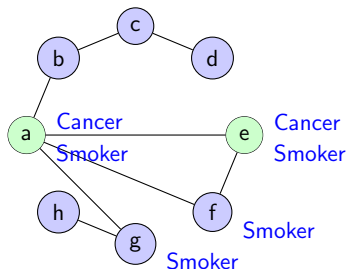


# Statistical relational learning

## Task 2

For each person we want to find a semantic embedding in  $\mathbb{R}^k$  consistent with the semantics and the structure. For instance:

- $a^{\mathcal{G}} \approx e^{\mathcal{G}}$  since both  $a$  and  $e$  smoke and have cancer, and they have two friends that smoke, one of which has a cancer

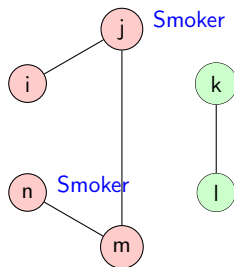
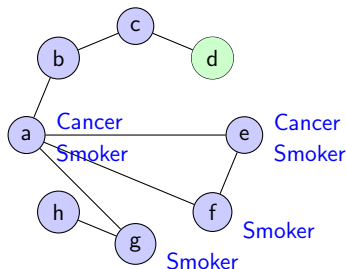


# Statistical relational learning

## Task 2

For each person we want to find a semantic embedding in  $\mathbb{R}^k$  consistent with the semantics and the structure. For instance:

- ▶  $a^{\mathcal{G}} \approx e^{\mathcal{G}}$  since both  $a$  and  $e$  smoke and have cancer, and they have two friends that smoke, one of which has a cancer
- ▶  $d^{\mathcal{G}} \approx k^{\mathcal{G}} \approx i^{\mathcal{G}}$  because they don't smoke and don't have cancer, and they have only one friend, who does not smoke and does not have a cancer

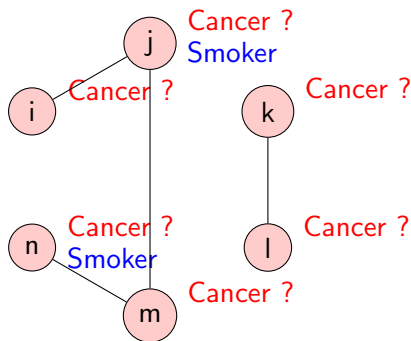
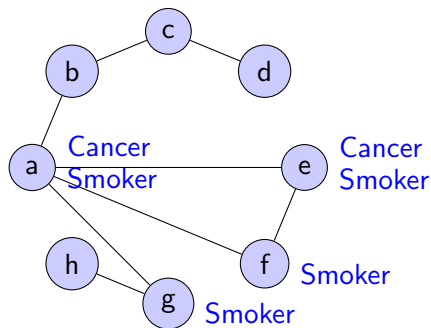


# Statistical relational learning

## Task 3

We want to know the truth value of certain formulas,

- ▶ e.g., the correlation between friendship and smoking habits;
- ▶ the correlation between smoking habits and cancer



# Statistical relational learning

## Representation of the domain in $\mathbb{R}^k$

For each individual of the domain  $\{a, \dots, n\}$  we don't provide an explicit mapping to  $\mathbb{R}^k$ , which instead is generated, as the result of the constraint optimization. We only provide the dimension of the domain (i.e.,  $k$ )

## The language

- ▶ unary predicates  $S(x)$  and  $C(x)$  for “ $x$  smokes” and “ $x$  has a cancer” and a binary predicate  $F(x, y)$  for “ $y$  is a friend of  $x$ ”

## Constraints

- ▶  $S(a), \neg S(b), \neg S(c), \neg S(d), S(e), \dots, \neg S(i), \dots, S(n)$ ;
- ▶  $C(a), \neg C(b), \neg C(c), \dots, \neg C(h)$ ;
- ▶  $\forall x : \neg F(x, x)$
- ▶  $\forall xy : F(x, y) \rightarrow F(y, x)$



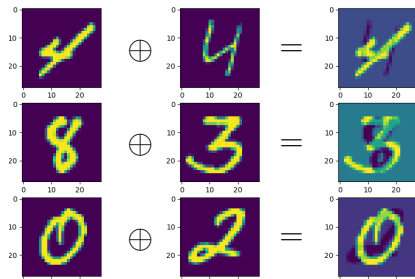
# Mnist with constraints

## Dataset

Contains pictures resulting from overlaying two MNIST digit pictures, where the smaller digit is in black-on-white and the smallest in white-on-black. I.e.,  $d_x$  and  $d_y$  are the pixel matrices of the digits  $x$  and  $y$ , then the pixel matrix  $d_{xy} = d_x \oplus d_y$  is defined as

$$d_x \oplus d_y = \begin{cases} d_x - w \cdot d_y & \text{if } x \leq y \\ d_y - w \cdot d_x & \text{Otherwise} \end{cases}$$

where  $w$  is randomly generated number in  $[0, 1]$

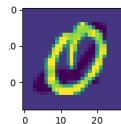
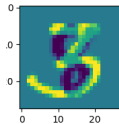
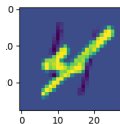


# Mnist with constraints

## The Task

Given an image  $d_{xy} = d_x \oplus d_y$  we have to predict  $x$  and  $y$ .

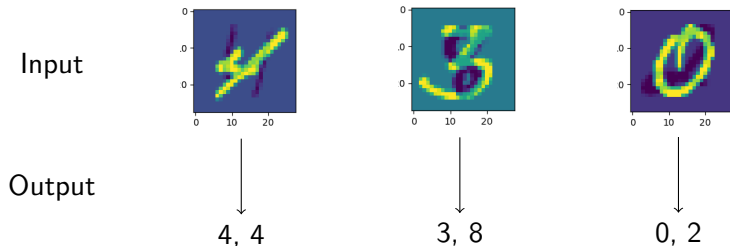
Input



# Mnist with constraints

## The Task

Given an image  $d_{xy} = d_x \oplus d_y$  we have to predict  $x$  and  $y$ .



# Mnist with constraints

## The language

20 unary predicates, two for every digit;

$$\begin{array}{llll} zero_1(x) & one_1(x) & \dots & nine_1(x) \\ zero_2(x) & one_2(x) & \dots & nine_2(x) \end{array}$$

$zero_1(x)$  (resp.  $zero_2(x)$ ) means: “the smaller (resp the larger) digit of  $x$  is a 0

## Constraints

- ▶  $four_1 \left( \begin{array}{c} \text{[Handwritten 4]} \\ \text{0 10 20} \end{array} \right), three_1 \left( \begin{array}{c} \text{[Handwritten 3]} \\ \text{0 10 20} \end{array} \right), zero_1 \left( \begin{array}{c} \text{[Handwritten 0]} \\ \text{0 10 20} \end{array} \right),$   
 $four_2 \left( \begin{array}{c} \text{[Handwritten 4]} \\ \text{0 10 20} \end{array} \right), eight_2 \left( \begin{array}{c} \text{[Handwritten 8]} \\ \text{0 10 20} \end{array} \right), two_2 \left( \begin{array}{c} \text{[Handwritten 2]} \\ \text{0 10 20} \end{array} \right), \dots$
- ▶  $\forall x : zero_1(x) \rightarrow \neg one_1(x), \dots$
- ▶  $\forall x : \neg(one_1(x) \wedge zero_2(x)), \dots$