

# Category Theory 101

## Graph Transformations

### Discrete Structures Day

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# Introduction

- High level approach to programming: graph rewriting based on category theory.
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- Much more difficult than term rewriting (which are just trees).
- Simulation of biological phenomenons.
- Simulation of chemical reactions.
- Study of cloning:
  - ⇒ Typically to produce a web site one starts to copy an existing one, then one modifies it accordingly to its will.
  - ⇒ Social Data Anonymization techniques rely on finely tuned cloning operations.

# Plan

- 1 Category Theory 101
- 2 Graph transformation and Categories
- 3 AGREE and Graph Generation
  - AGREE and Data Anonymization
  - Self-similar Graphs
- 4 Conclusion

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# Category Theory

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⇒ What are the fundamental structures of those two fields ?

- Results much more general than thought at first.
- Set theory is just a special case of category (Lawvere).
- In computer science E. Moggi was able to capture ideas previously thought to be outside of reach with the monads.
- In logic J.-Y. Girard and the linear logic.
- etc.

# Category Theory

## Definition

A category  $\mathcal{C}$  is made of

- A collection of object :  $Obj(\mathcal{C})$
- $\forall x, y \in Obj(\mathcal{C})$  a set  $Hom_{\mathcal{C}}(x, y)$
- $\forall x \in Obj(\mathcal{C})$  there is  $id_x \in Hom_{\mathcal{C}}(x, x)$
- $\forall x, y, z \in Obj(\mathcal{C})$  a function
  - $: Hom_{\mathcal{C}}(x, y) \times Hom_{\mathcal{C}}(y, z) \rightarrow Hom_{\mathcal{C}}(x, z)$



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such that

- 1 Identity:  $f \circ id = id \circ f = f$
- 2 Associativity:  $(h \circ g) \circ f = h \circ (g \circ f)$

## Example: Category of graphs

- Objects:  $G = (V, E, s, t)$  with  $s, t : E \rightarrow V$
- Morphisms:  $f : G \rightarrow H$  must respect source and target functions, ie:

$$\forall e \in E. f(s(e)) = s(f(e))$$

$$\forall e \in E. f(t(e)) = t(f(e))$$

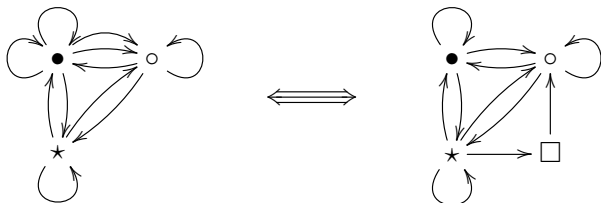
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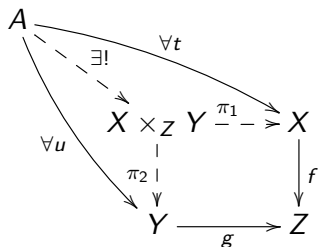
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- Exemples:



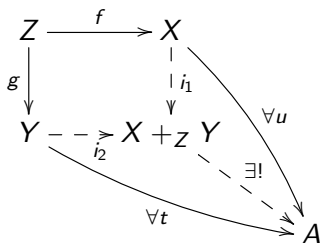
# Pullback

- Lets have :  $f : X \rightarrow Z$  and  $g : Y \rightarrow Z$
- Fiber product:  $X \times_Z Y := \{(x, w, y) \mid f(x) = w = g(y)\}$



# Pushout

- Co-construction of the pullback.
- Lets have :  $f : X \rightarrow Z$  and  $g : Y \rightarrow Z$
- disjoint sum with gluing:  $X +_Z Y := X + Y + Z / \sim$
- With  $\sim$  generated by  $f(z) \sim z \sim g(z)$



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# Rule based transformations

- Rule-based term rewriting is easy: replace a tree by another one.
- Much more difficult with graphs (multiple incident edges).
- Categorical frameworks make it clean to express graph transformations systematically.

PB	PO
clone	merge
delete	add
comatch	match
global	local

# AGREE extended rule

Extension of a framework proposed by A. Corradini, D. Duval, R. Echahed, F. Prost and L. Ribeiro [ICGT15].

Definition (AGREE rules and matches)

- A *rule* is

$$\begin{array}{ccccc}
 L & \xleftarrow{l} & K & \xrightarrow{r} & R \\
 & & \downarrow t & & \\
 T_L & \xleftarrow{l'} & T_K & & 
 \end{array}$$

- A *match* of such a rule is composed of a mono  $L \xrightarrow{m} G$  and a typing morphism  $G \xrightarrow{\bar{m}} T_L$  and is such that  $l' \circ t = (\bar{m} \circ m) \circ l$ .



# AGREE rewrite step

## Definition (AGREE rewriting)

Given  $\rho = (K \xrightarrow{l} L, K \xrightarrow{r} R, K \xrightarrow{t} T_K, T_K \xrightarrow{l'} T_L)$  and a match  $L \xrightarrow{m} G, G \xrightarrow{\bar{m}} T_L : G \Rightarrow_{\rho, m} H$  is computed as follows:

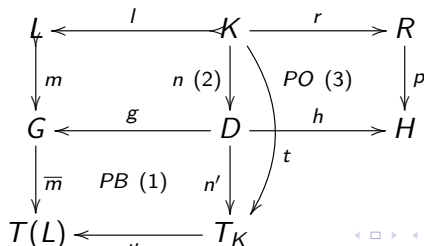
- 1  $\text{Span } G \xleftarrow{g} D \xrightarrow{n'} T_K$  is the pullback of  $G \xrightarrow{\bar{m}} T(L) \xleftarrow{l'} T_K$ . Since  $l' \circ t = \eta_L \circ l$  there is a unique  $K \xrightarrow{n} D$ .
- 2  $R \xrightarrow{p} H \xleftarrow{h} D$  is the pushout of  $D \xleftarrow{n} K \xrightarrow{r} R$ .

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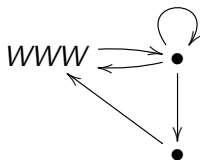


## Example : copy of web pages

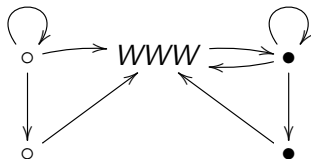
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  - Internal links: file hierarchy (indirect link)
  - External links: references pointing outside of the site.

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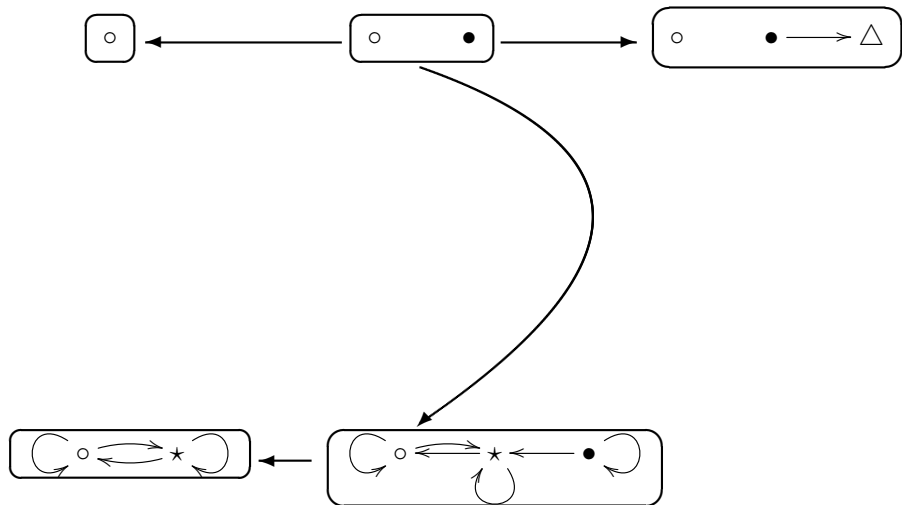
- The structure of a web site typically as two kind of links :
  - Internal links: file hierarchy (indirect link)
  - External links: references pointing outside of the site.
- The cloning of a web site consists in duplicating all local files and keeping external links shared between the two copies.



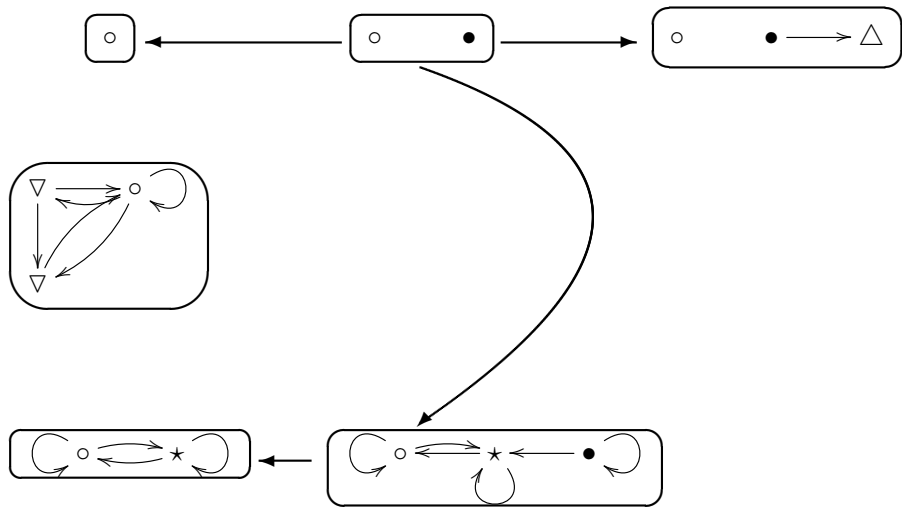
should be cloned as follows



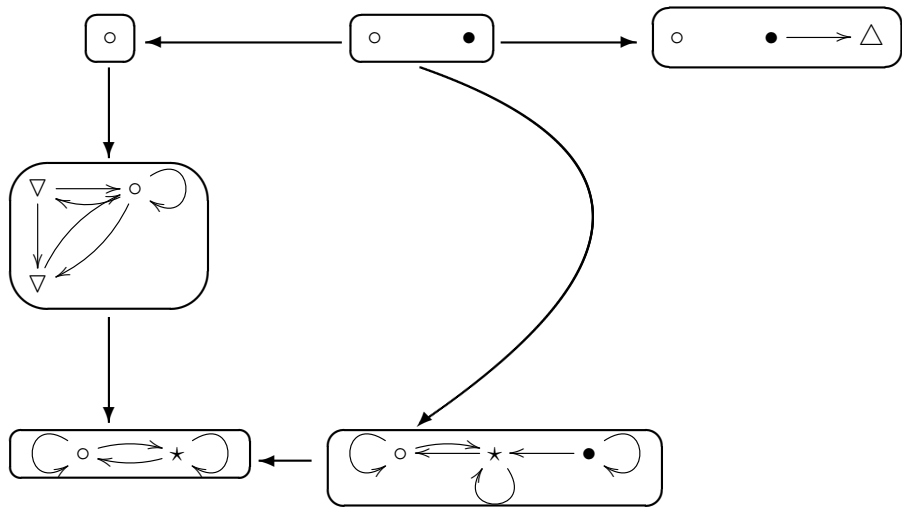
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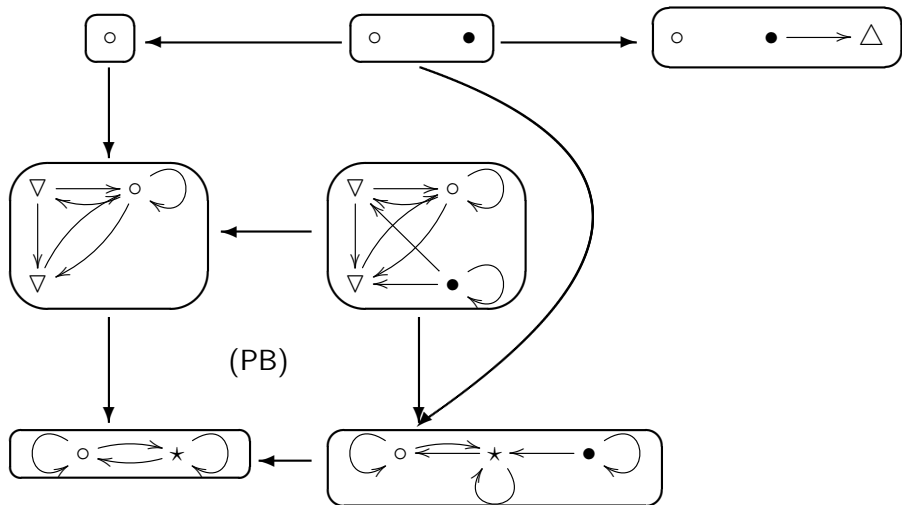
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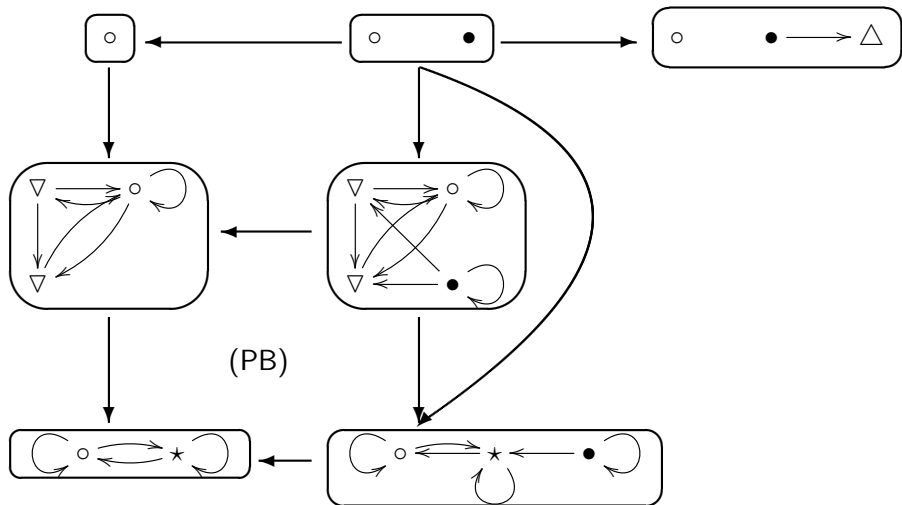


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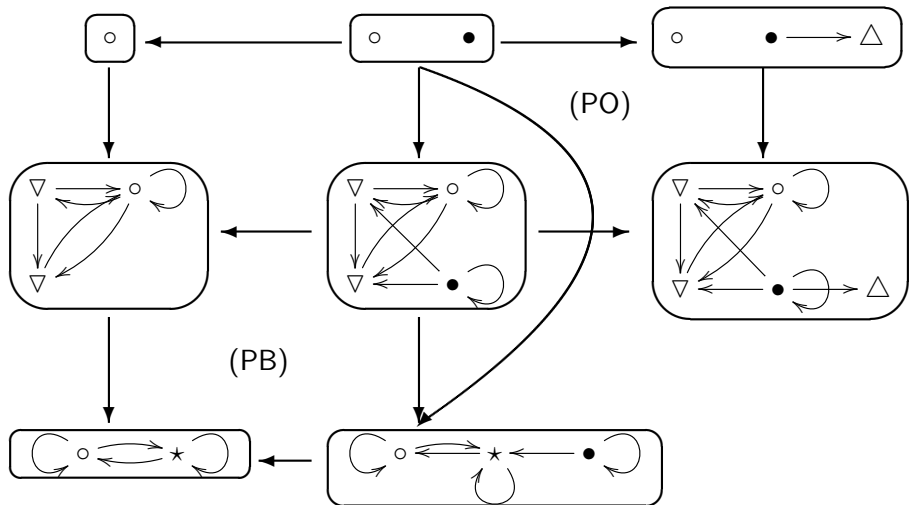




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- Raw problem: given a graph  $G$  we would like to produce  $G'$  such that
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  - It is not possible to reidentify nodes (or edges) of  $G$  from knowing  $G'$  (and some extra informations...).
- Naïve approach doesn't work : Netflix [NarayanShmatikov06].
- Anonymization is an active research field ... rather artistic at the time: approaches validated through experiments.

# Social Data Anonymization: Dimensions and Principles

- Problem more down to the earth than non-interference:
  - Partial knowledge of the graph by the opponent.
  - Active attacker (embedding fake sub graphs to re-identify them).
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  - Object of interests vary from one data set to another.
- Hence three important points to consider:
  - 1 Background Knowledge: What does the opponent know ? Model of the opponent.
  - 2 Privacy: what is attacked ?
  - 3 Usage: How the data is going to be analyzed ?

⇒ Anonymizing techniques



# Social Data Anonymization: Techniques

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  - Clustering: group together edges and nodes.
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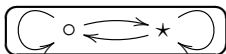
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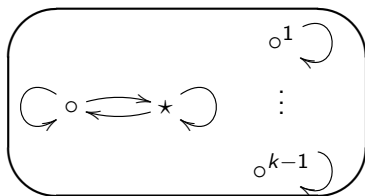
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- It is NP-hard to find graph transformations minimizing the editing distance between a graph and a  $k$ -isomorphic graph.
- One solution: select  $1/k$  nodes randomly, create  $k$  clones, link the clones together easy to program with *AGREE* approach.

# Using *AGREE* for $k$ -anonymity

- Programming with types !
- $L$  is just a cloud of nodes, and  $K$  is made of  $k$  clones of  $L$ .
- Standard  $T_L$  is :



- Simplest  $T_K$  is :

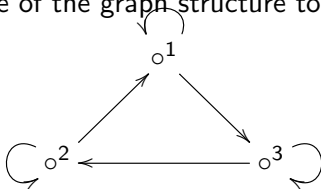


# Types and structural graph properties

- The simplest  $k$ -clones are not connected to each others.

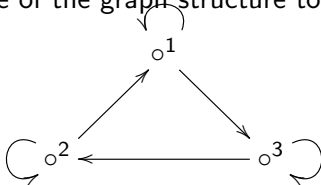
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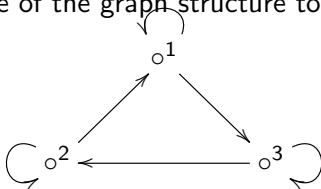


- Degree problems (nodes of degree 1).

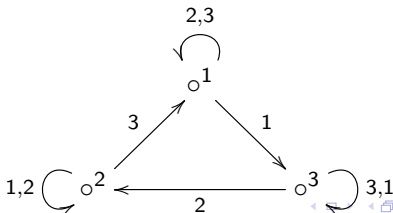


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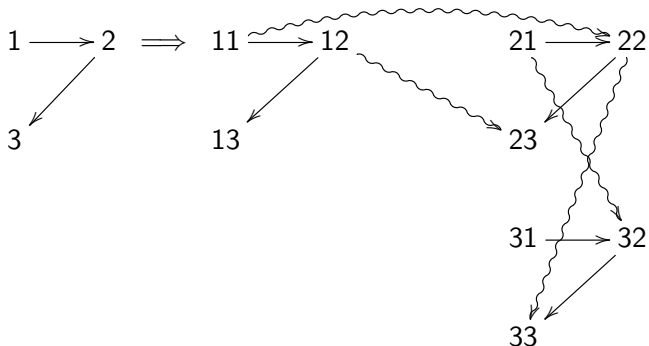


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One possibility is to type differently the edges, eg:

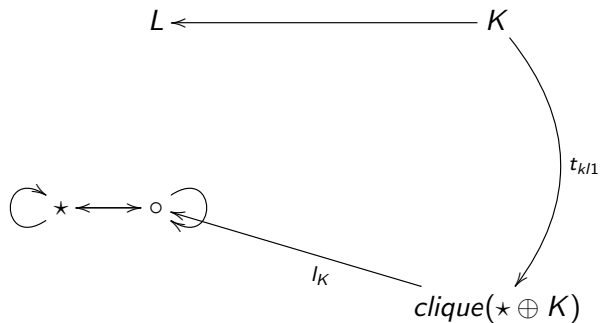


# Self-similar graphs

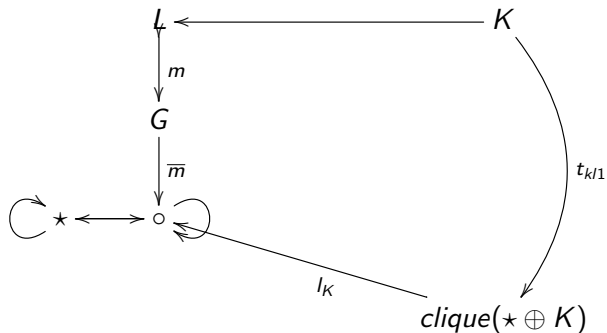
- Every vertex is replaced by a copy of the graph.
- Interconnections between copies of the original “mimic” the ones in the target graph.



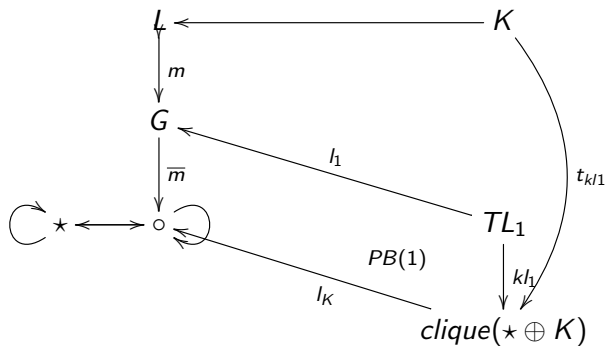
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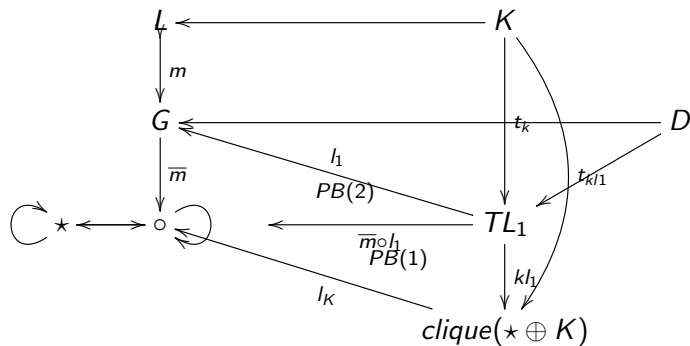


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# Conclusion

- Categorical frameworks allow simple and mathematically workable definition of complex transformations.
- Only basic constructs are needed: pushouts, pullbacks.
- An very generic implementation is scheduled.
- Open questions:
  - matching ? (random match does not lead to scale-free networks)
  - What statistics can be interesting (Ramsey-like theory) ?
  - What kind of certificate can be produced ?