

## Erratum

L.De Raedt, *Logical settings for concept-learning*,  
Artificial Intelligence, Vol. 95, pp. 187-201, 1997.

Roni Khardon pointed out to the author that the proof of Theorem 27 on pp. 197-198 is wrong. Theorem 27, its proof, Theorem 28, and Corollary 29 should read as follows :

**Theorem 27.**  *$k$ -CNF is not efficiently PAC-learnable under entailment for  $k \geq 4$  (where  $L_e$  consists of unbounded clauses) unless  $NP \subseteq P/Poly$ .*

**Proof.** Let  $X = \{X_n\}_{n \geq 1}$  be a parametrised concept class where concepts in  $X_n$  take inputs in  $\{0, 1\}^n$ . Schapire [1] shows (in Theorem 7) that if  $X$  is learnable then there is a polynomial  $p(n)$  such that each concept in  $X_n$  has a circuit of size  $p(n)$  representing it exactly. Therefore, the evaluation problem for concepts in  $X_n$  has polynomial size circuits.

We claim that the evaluation problem for  $k$ -CNF with examples in  $L_e$  does not have polynomial size circuits unless  $NP \subseteq P/Poly$ . It then follows that  $k$ -CNF is not learnable with examples in  $L_e$  unless  $NP \subseteq P/Poly$ .

To prove the claim we present a family of concepts  $\{C_m\}_{m \geq 1}$  in 4-CNF such that if the evaluation problem for  $\{C_m\}$  with respect to  $L_e$  has polynomial size circuits then so does  $NP$ . The construction closely follows a similar proof by Selman and Kautz [3].

In order to define  $C_m$  we need to introduce some notation. Let  $V = \{p_1, \dots, p_n\}$  be  $n$  propositional variables,  $Lits = \{l \mid l \in V\} \cup \{\neg l \mid l \in V\}$  be literals over  $V$ , and define a set of auxiliary variables  $\{c_{x,y,z} \mid x, y, z \in Lits\}$ . Then,  $C_m$  is defined over the  $m = n + \binom{2n}{3}$  variables:

$$C_m = \bigwedge_{x,y,z \in Lits} (x \vee y \vee z \vee \neg c_{x,y,z})$$

Now, given a 3-CNF formula  $\phi = \bigwedge_j (l_{j1} \vee l_{j2} \vee l_{j3})$  over  $V = \{p_1, \dots, p_n\}$ ,  $\phi$  can be encoded as an example  $e_\phi$  in  $L_e$  such that  $C_m$  entails  $e_\phi$  if and only if  $\phi$  is not satisfiable. In particular, it is easy to see that this holds for

$$e_\phi = \bigvee_j \neg c_{l_{j1}, l_{j2}, l_{j3}}$$

(cf. the proof by Selman and Kautz.) It follows that if the evaluation problem for  $\{C_m\}$  with respect to  $L_e$  has polynomial size circuits then so does 3-SAT and therefore also  $NP$ . In other words if  $\{C_m\}$  has polynomial size circuits then  $NP \subseteq P/Poly$ .  $\square$

Notice that it is considered unlikely that  $NP \subseteq P/Poly$ . Indeed, if  $NP \subseteq P/Poly$  then this would e.g. imply that the polynomial-time hierarchy would collapse. It is therefore unlikely that  $k$ -CNF ( $k \geq 4$ ) is PAC-learnable under entailment. This result is also stronger than the original one because it holds for any representation of  $k$ -CNF.

Note also that the requirement in Theorem 27 that  $L_e$  is not bounded (as assumed throughout the original paper) is necessary. Indeed, Corollary 6.6 of [4] implies that if  $L_e$  includes only clauses (or even clausal theories) in  $k$ -CNF then the class of  $k$ -CNF is learnable from entailment.

**Theorem 28.**  *$jk$ -CT is not efficiently PAC-learnable under entailment for  $k \geq 4$  unless  $NP \subseteq P/Poly$ .*

**Corollary 29.**  *$k$ -CNF and  $jk$ -CT are not PAC-learnable under  $\epsilon_{int,B}$  and  $\epsilon_s$ .*

**References.**

1. Schapire, R.E., The strength of weak learnability, *Machine Learning*, Vol. 5, pp. 199-227, 1990.
2. Cohen, W.W., Page, C.D., Polynomial learnability and inductive logic programming: methods and results, *New Generation Computing*, Vol. 13, pp. 369-409, 1990.
3. Selman, B., Kautz, H., Knowledge compilation and theory approximation, *Journal of the ACM*, Vol. 43, pp. 193-224, 1996.
4. Khardon, Roth, MLJ, details to be added.