

# Anomalous Vacillatory Learning

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- $M$  learns a set,  $A$ , if it identifies every enumeration.
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input data stream:	$a_0$	$a_1$	$a_2$	$a_3$	$a_4$	$a_5$	$a_6$	$a_7$	$a_8$	$a_9$	$\dots$
learning machine:	$\downarrow$	$\downarrow$				$\downarrow$	$\downarrow$				$\dots$
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### Examples

1.  $\{A\}$  is learnable for any c.e. set  $A$ .
2.  $\{F : F \text{ is a finite set}\}$  is learnable by  $M(\sigma) = e$  where  $W_e = \text{content}(\sigma)$ .
3.  $\{F : F \text{ is a finite set}\} \cup \{\mathbb{N}\}$  is not learnable.
4.  $\{A \cup \{x\} : x \in \mathbb{N}\}$  is not learnable for any non-computable, c.e. set  $A$ .

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Learning with errors is called anomalous learning.



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Colored hypotheses are repeated infinitely often and hypotheses of different colors code different sets.

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- In 1994, Fulk, Jain and Osherson proved that  $(\forall j \in \mathbb{N})(\text{TxtFex}_*^j \subseteq \text{TxtFext}_*^*)$ .
- Earlier this year, I proved  $\text{TxtFex}_2^* \neq \text{TxtFext}_*^*$ . This proves  $\text{TxtFex}_*^* \neq \text{TxtFext}_*^*$  in the strongest possible way.

### Theorem

*There is a u.c.e. family that is  $\text{TxtFex}_2^*$ -learnable, but not  $\text{TxtFext}_*^*$ -learnable.*

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We diagonalize against every possible machine by forcing machines to commit to a finite number of hypotheses.

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- We consider the tree of strings whose content is contained in  $L_e$ . All cones referred to subsequently will be subsets of this tree.
- Define  $\sigma$  to be an  $(e, k)$ -stabilizing sequence iff  $[e, e + k] \subseteq \text{content}(\sigma) \subset L_e$  and for  $\tau$  in the cone below  $\sigma$ 
  1.  $M_e(\tau) \leq |\sigma|$
  2.  $W_{M_e(\sigma)} \cap [0, k) = W_{M_e(\tau)} \cap [0, k)$

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- “ $\sigma$  is not an  $(e, k)$ -stabilizing sequence” is  $\Sigma_1^0$ .

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- More generally, define  $\sigma_{e,k,s}$  to be an array of strings, with  $\lim_{s \rightarrow \infty} \sigma_{e,k,s} = \sigma_{e,k}$ , if it exists, such that:
  - ▶  $\sigma_{e,k,s} \prec \sigma_{e,k+1,s}$  for all  $k, s \in \mathbb{N}$ .
  - ▶ If  $\sigma_{e,0}, \dots, \sigma_{e,n}$  are defined and there is an  $(e, n+1)$ -stabilizing sequence extending  $\sigma_{e,n}$ , then  $(\sigma_{e,n+1,s})_{s \in \mathbb{N}}$  converges to such a string.

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- Let  $a_{e,k}$  be the least even number such that  $\sigma_{e,h,s} = \sigma_{e,h,s+1}$  for  $h \leq k$  and  $s \geq a_{e,k}$ . Define  $b_{e,k} = a_{e,k} + 1$ .

- Define  $R_e = L_e \setminus \{a_{e,i} : i \in \mathbb{N}\}$  and  $R_e^* = L_e \setminus \{b_{e,i} : i \in \mathbb{N}\}$ , both of which are c.e.

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- Let  $\mathcal{L}_e = \{R_e \cup (F \cap L_e) : F \text{ is a finite set}\} \cup \{R_e^* \cup (F \cap L_e) : F \text{ is a finite set}\}$ .

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- We must prove two claims:
  1.  $\mathcal{L}_e$  is not  $\text{TxFex}_*^*$ -learnable by the fixed machine,  $M_e$ .
  2.  $\bigcup_{e \in \mathbb{N}} \mathcal{L}_e$  is  $\text{TxFex}_2^*$ -learnable.



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  - ▶ Inductively build an enumeration of  $L_e$  on which  $M_e$  infinitely often outputs codes for two sets that are not equal.
- Suppose  $\sigma_{e,0}$  is undefined.
  - ▶ If possible, build an enumeration as above.
  - ▶ If not, then build an enumeration on which  $M_e$  never settles upon a finite list of hypotheses.

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  - ▶ Pick  $k$  large enough so that
$$(\forall i, j \leq n)(\exists x \leq k)(W_{h_i} \neq W_{h_j} \rightarrow x \in W_{h_i} \Delta W_{h_j}).$$
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  - ▶  $A = \text{content}(\sigma_{e,k}) \cup R_e$  and  $B = \text{content}(\sigma_{e,k}) \cup R_e^*$  extend  $\sigma_{e,k}$  and have infinite symmetric difference.



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- For an input string,  $\sigma$ , we define the following:
  - ▶  $m_\sigma = \min(\text{content}(\sigma))$ .
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  - ▶  $m_\sigma = \min(\text{content}(\sigma))$ .
  - ▶  $n_\sigma = \min(\{y > m_\sigma : y \notin \text{content}(\sigma)\})$ .
- Define a learning machine,  $M$ , by

$$M(\sigma) = \begin{cases} x_e & e = m_\sigma \wedge (n_\sigma \text{ is even}) \\ x_e^* & e = m_\sigma \wedge (n_\sigma \text{ is odd}) \\ 0 & \text{otherwise} \end{cases}$$

- $M$  receives an enumeration for  $R_e \cup F$ .
- If  $R_e$  is cofinite, then both  $x_e$  and  $x_e^*$  are correct hypotheses.
- If  $R_e$  is coinfinite, then the least element of  $L_e \setminus (R_e \cup F)$  is an even number.
- Cofinitely,  $M$  will output the hypothesis  $x_e$ .



## Other Learning Criteria

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### TxtFin

Fix a symbol “?”.  $M$  TxtFin-identifies a text  $T$  if, and only if,  
 $\exists n \forall n' < n (M(T[n']) = ? \wedge M(T[n]) \neq ? \wedge W_{M(T[n])} = \text{content}(T))$ .

### TxtEx

$M$  TxtEx-identifies a text  $T$  if, and only if,  
 $\exists n (\lim_{i \rightarrow \infty} M(T[i]) \rightarrow n \wedge W_n = \text{content}(T))$ .

### TxtBC

$M$  TxtBC-identifies a text  $T$  if, and only if,  
 $\exists n \forall i > n (W_{M(T[i])} = \text{content}(T))$ .

### TxtEx\*

$M$  TxtEx\*-identifies a text  $T$  if, and only if,  
 $\exists n (\lim_{i \rightarrow \infty} M(T[i]) \rightarrow n \wedge W_n =^* \text{content}(T))$ .

### Index Sets

1. Let FINL denote the index set of all  $\Sigma_1^0$  codes for *u.c.e.* families such that  $e \in \text{FINL}$  if, and only if,  $e$  codes a TxtFin-learnable family.
2. Let EXL denote the index set of all  $\Sigma_1^0$  codes for *u.c.e.* families such that  $e \in \text{EXL}$  if, and only if,  $e$  codes a TxtEx-learnable family.
3. Let BCL denote the index set of all  $\Sigma_1^0$  codes for *u.c.e.* families such that  $e \in \text{BCL}$  if, and only if,  $e$  codes a TxtBC-learnable family.
4. Let  $\text{EXL}^*$  denote the index set of all  $\Sigma_1^0$  codes for *u.c.e.* families such that  $e \in \text{EXL}^*$  if, and only if,  $e$  codes a  $\text{TxtEx}^*$ -learnable family.

## Arithmetic Hierarchy

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Theorem

*FINL is  $\Sigma_3^0$ -complete*

Theorem

*EXL is  $\Sigma_4^0$ -complete*

Theorem

*BCL is  $\Sigma_5^0$ -complete*

Theorem

*EXL\* is  $\Sigma_5^0$ -complete*



Thank You