Statistical learning theory and communication

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Bioacoustic Monitoring Workshop • James Reserve • 2008

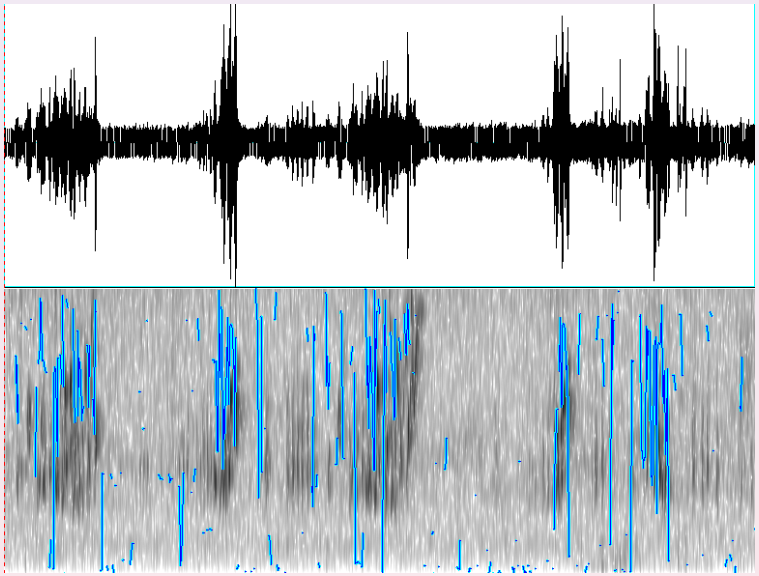
Learning from sensor data

- Models of the environment
- Individual and species identification

  (Trifa et al'08,Vallejo et al'07,Vilches et al'07)
- Organisms as situated agents. . .

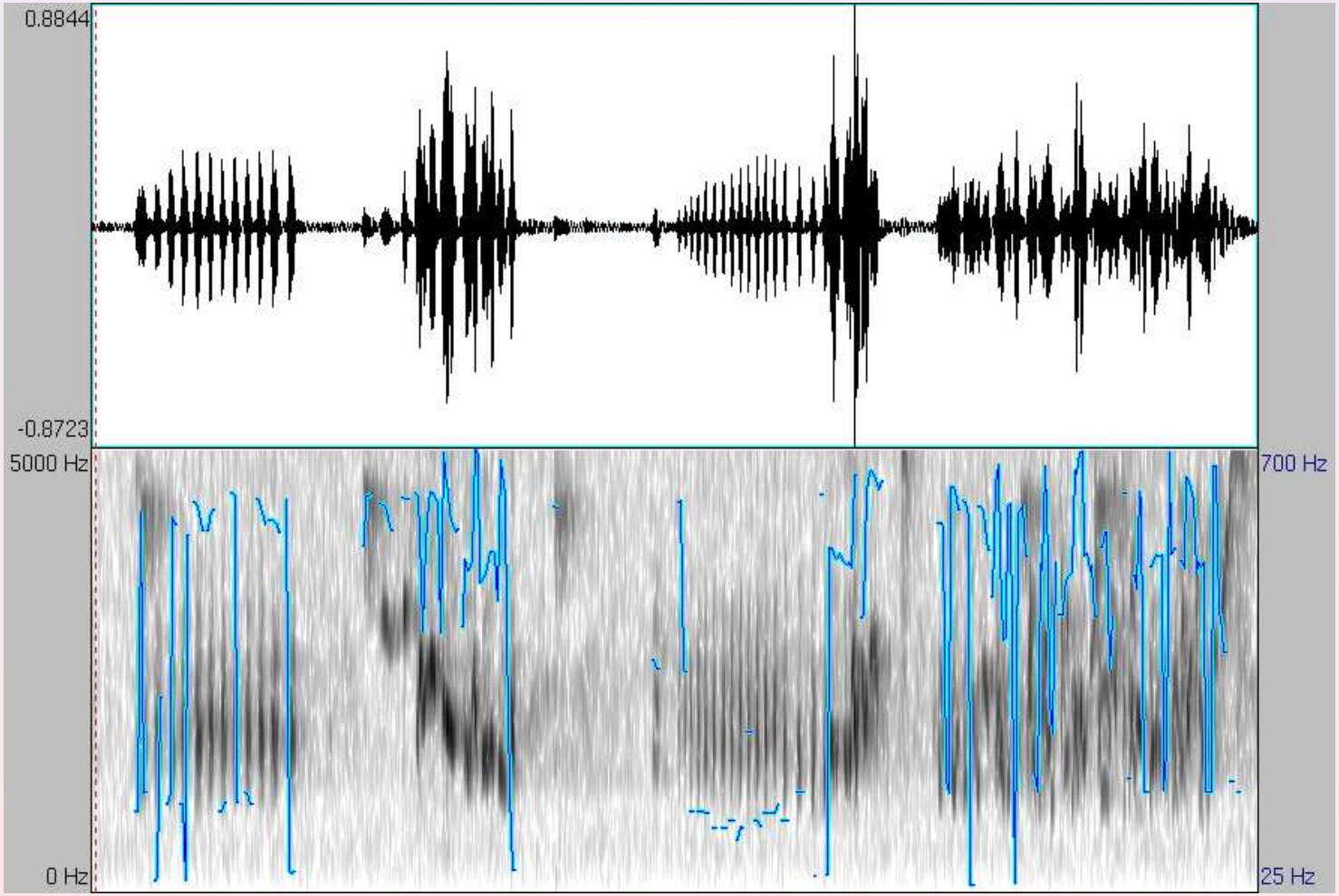
We have significant developments in data collection and computational resources, *and significant developments in modeling methods*. But we need better models!

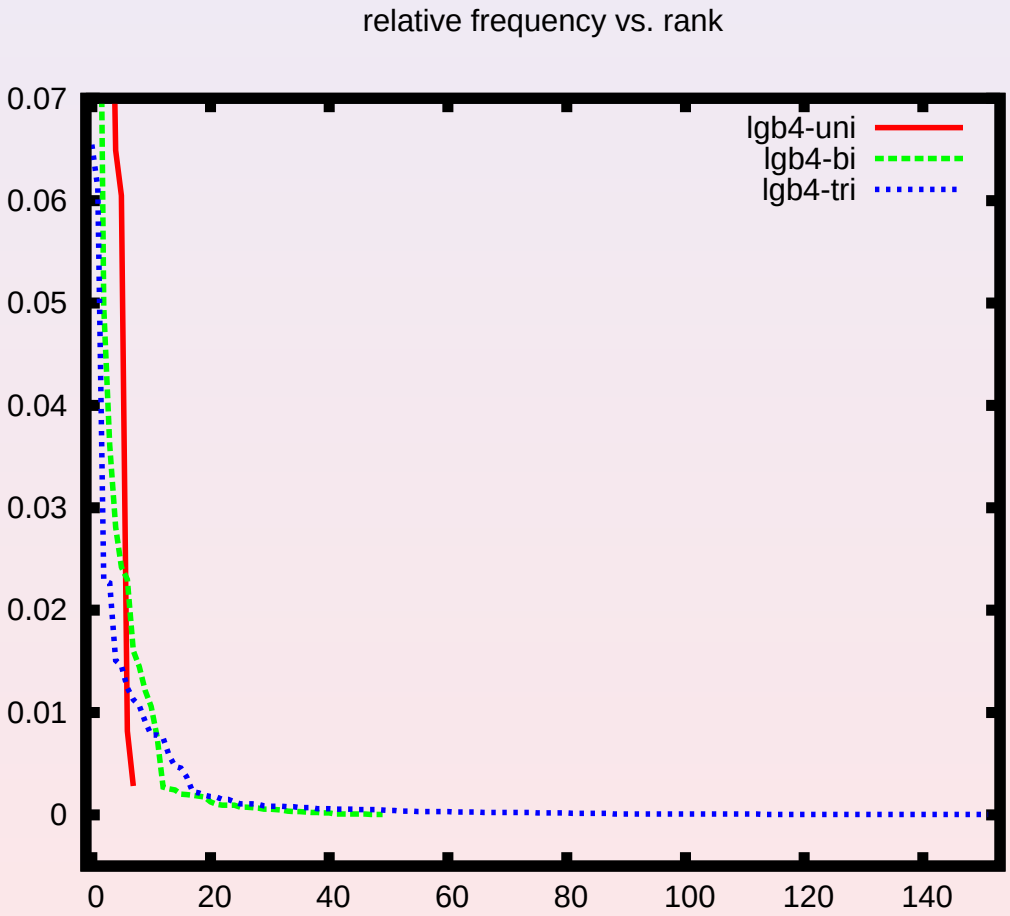
Little Greenbul:



- what is the bird doing? what sequences in these songs?
- how is the bird doing that?

>20K songs; here 4 of 6 types:



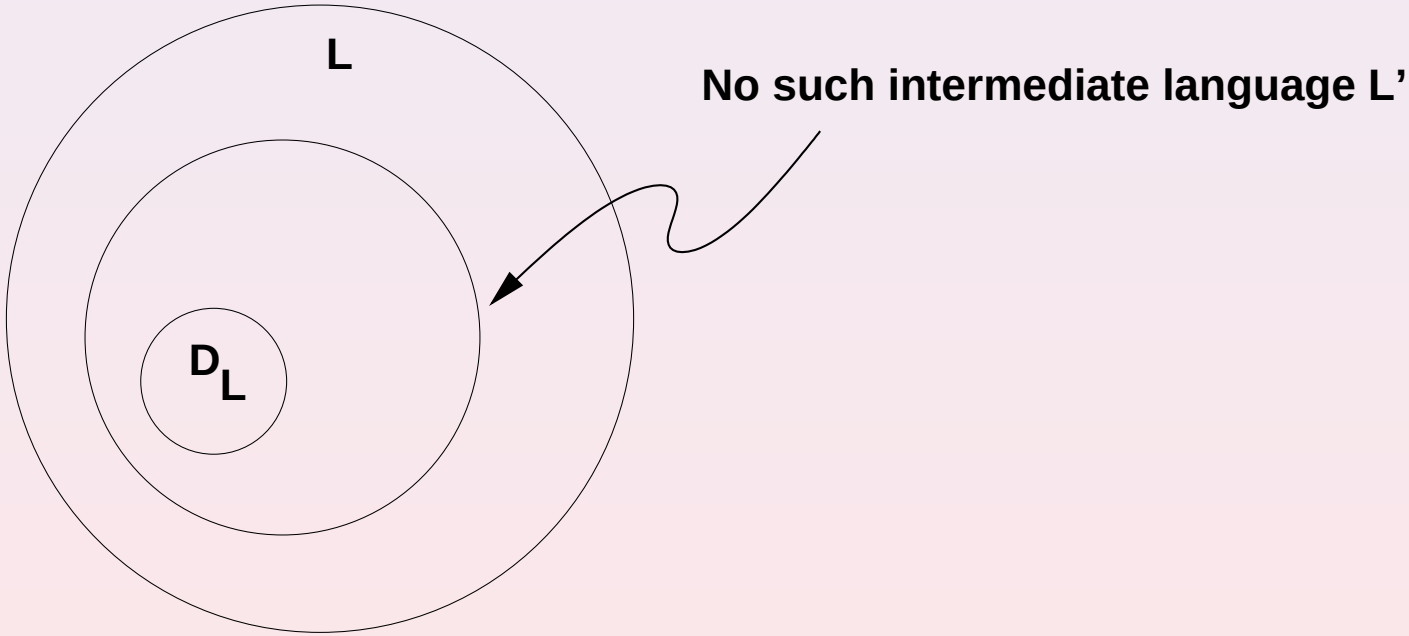


(Zipf effects: $\frac{2}{3}$ trigrams absent. 26% trigrams occur 1; 42% occur 2; >80% Ss occur 1)

learning as identification in the limit: (Gold, 1967)

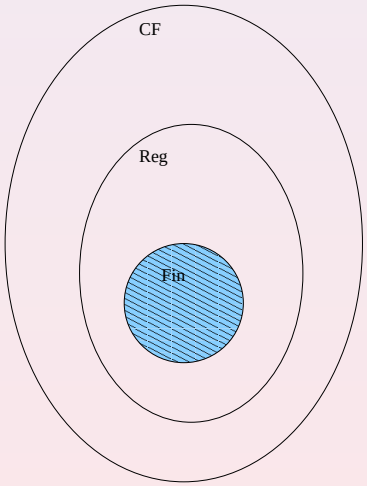
- **evidence:** an enumeration t of a dataset L
- **learner** ϕ**:** initial segments of enumerations $\longrightarrow$ model G
- ϕ **learns** t**:** iff ϕ converges to a generator G of L
- **L is learnable:** some ϕ learns every enumeration of L
- **class** $\mathcal{L}$ **is learnable** iff every L$\in \mathcal{L}$ is

(Angluin, 1980) $\mathcal{L}$ is identifiable in the limit from examples iff every L$\in \mathcal{L}$ has a finite subset D such that

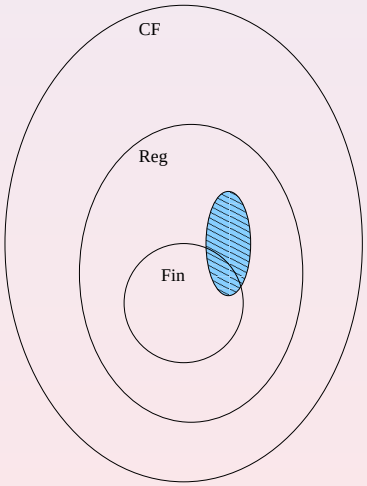


(Pitt, 1989) If $\mathcal{L}$ identifiable with $p > \frac{1}{2}$, then identifiable in the limit

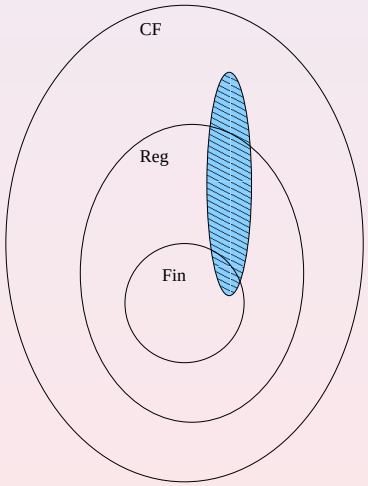
(Gold: positive results)



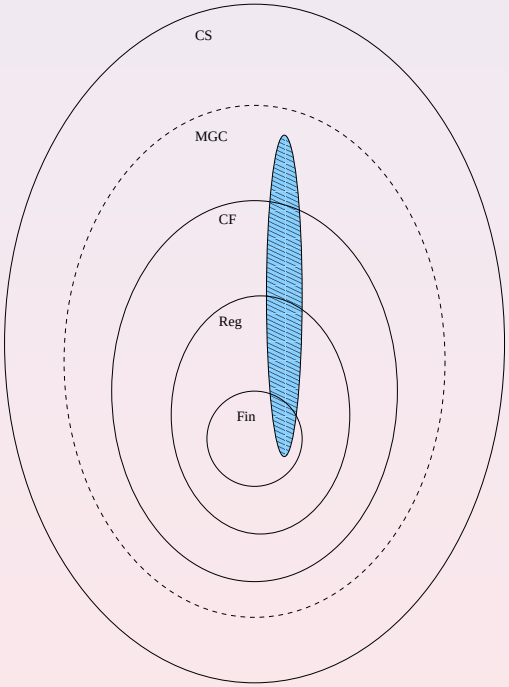
Gold 1967
finite



Angluin 1982
reversible



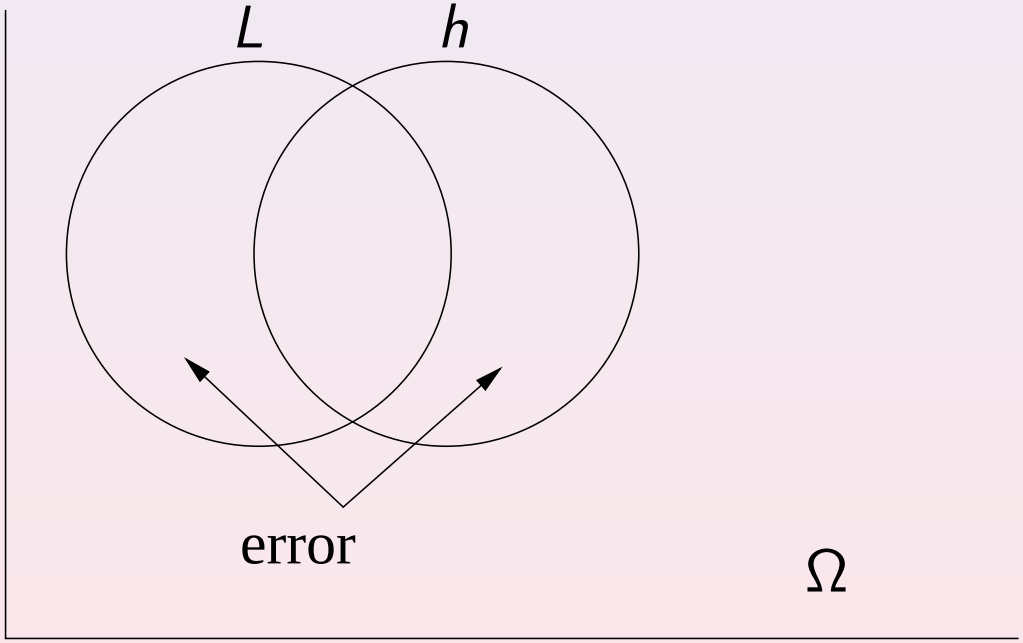
Yokomori 2003
simple CF



Stabler et al 2003
rigid PMCF

(nb: the models may be probabilistic, but the success criterion is Boolean)

Learning as (distribution-free) approximate learning (PAC)



With any μ on Ω, learner's hypothesis h has error $\leq \epsilon$, with probability $\geq 1 - \delta$, after $m(\epsilon, \delta)$ labeled samples from Ω

Learning as (distribution-free) approximate learning (PAC)

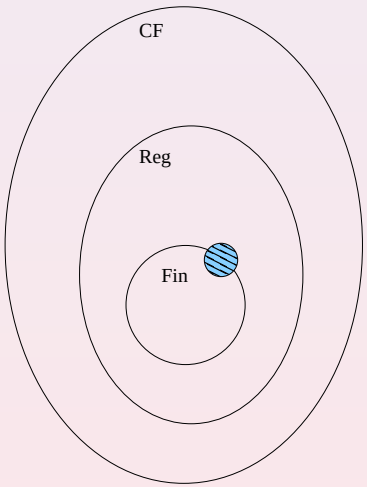
- **evidence:** $EX(L,\mu)^n$ a sample of length n drawn from Ω w.r.t. μ, labeled by target concept $L \in \mathcal{L}$
- **learner:** a function ϕ from samples to hypotheses $h \in \mathcal{H}$
- **class $\mathcal{L}$ is PAC learnable** iff $\exists\phi$ and $m : [0,1]^2 \rightarrow \mathbb{N}$ such that $\forall\mu\ \forall L \in \mathcal{L}, \forall 0 < \epsilon, \delta < 1$

$$\phi(EX(L,\mu)^{m(\epsilon,\delta)}) = h \text{ where } \mu(error_\mu(L,h) \leq \epsilon) \geq (1-\delta)$$

(Vapnik & Chervonenkis 1971, Blumer et al 1989, Alon et al. 1997, Cucker & Smale 2001, Mukherjee et al. 2004, Poggio et al. 2004,...)

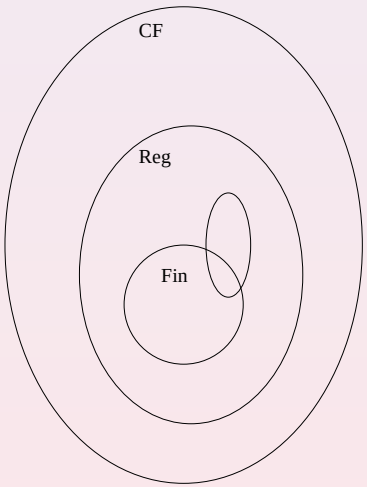
class $\mathcal{L}$ is PAC learnable
$\equiv$ ERM consistent
$\equiv$ identifiable by a 'leave-one-out stable' method
$\equiv$ $VC(\mathcal{L})$ finite
$\equiv$ uniform Glivenko-Cantelli (uGC)

(PAC, ERM and relatives: positive results)



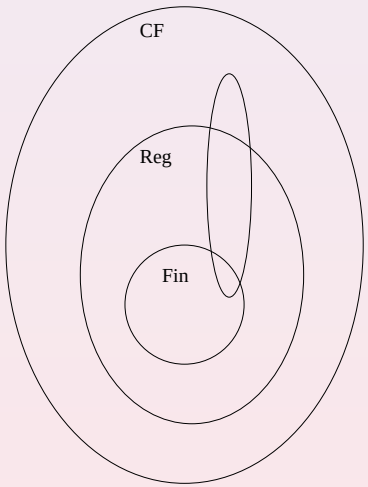
Gold 1967

~~fin~~



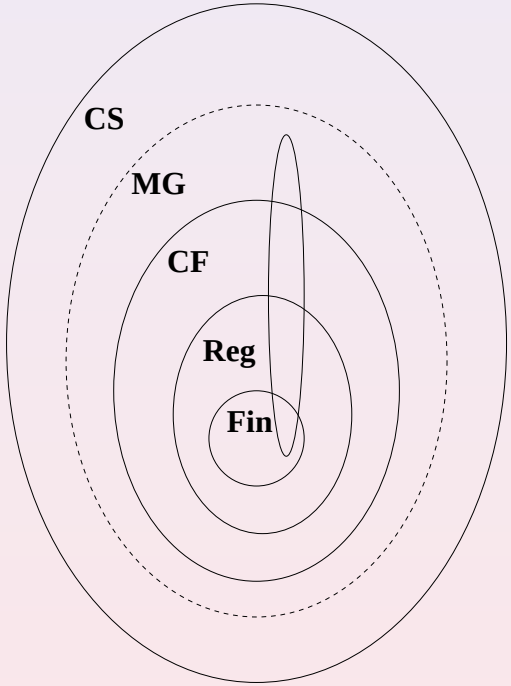
Angluin 1982

~~reversible~~



Yokomori 2003

simple CF?



Stabler et al 2003

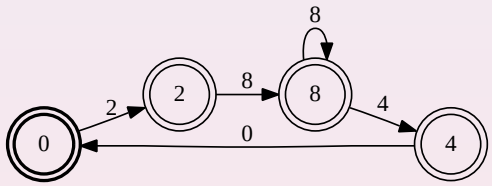
rigid PMCF?

(most (all?) classes shown earlier have ∞ VC dimension; not PAC)

bounded FSA (n-grams, Markov Models, etc)

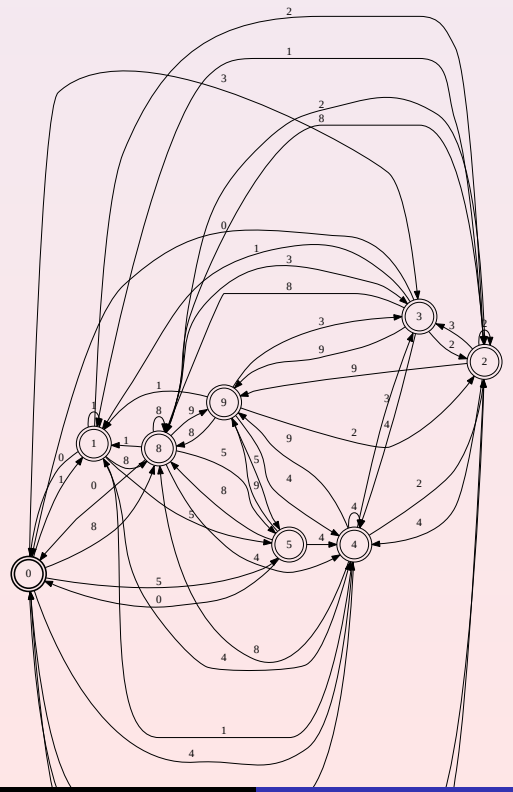
. . . (02888840,205) . . . (028888840,124) . . . (0288840,105) . . . (0288888840,36) . . . (02888888840,7) . . . (028888888840,6) . . .

	0	2	4	8
0	0.	1.	0.	0.
2	0.	0.	0.	1.
4	1.	0.	0.	0.
8	0.	0.	0.125	0.875



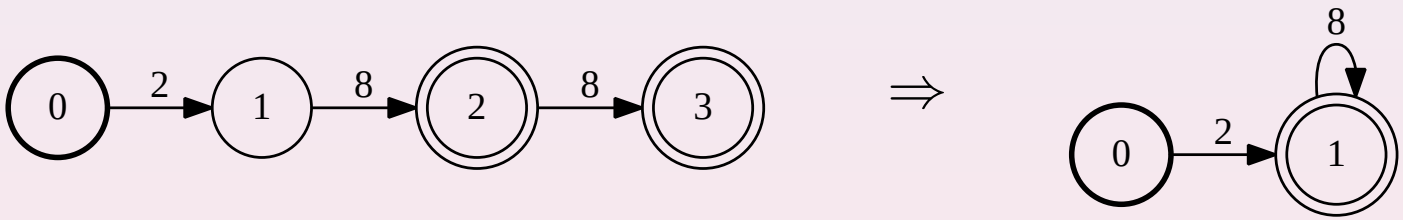
- Gold and PAC learnable
- in Greenbul song, bounds not known
- good model? decide by p(heldout) and simplicity of model

	0	1	2	3	4	5	8	9
0	0.000000	0.207968	0.330182	0.404456	0.013504	0.014855	0.029034	0.000000
1	0.013121	0.874113	0.019149	0.000000	0.091489	0.000709	0.000709	0.000709
2	0.348837	0.017054	0.009302	0.007752	0.065116	0.000000	0.528682	0.023256
3	0.225000	0.016667	0.009722	0.000000	0.022222	0.000000	0.715278	0.011111
4	0.907216	0.003436	0.017182	0.008591	0.001718	0.000000	0.012027	0.049828
5	0.363636	0.000000	0.000000	0.000000	0.030303	0.000000	0.606061	0.000000
8	0.014100	0.001356	0.010575	0.001898	0.208514	0.000542	0.761931	0.001085
9	0.000000	0.183908	0.310345	0.459770	0.022989	0.011494	0.011494	0.000000

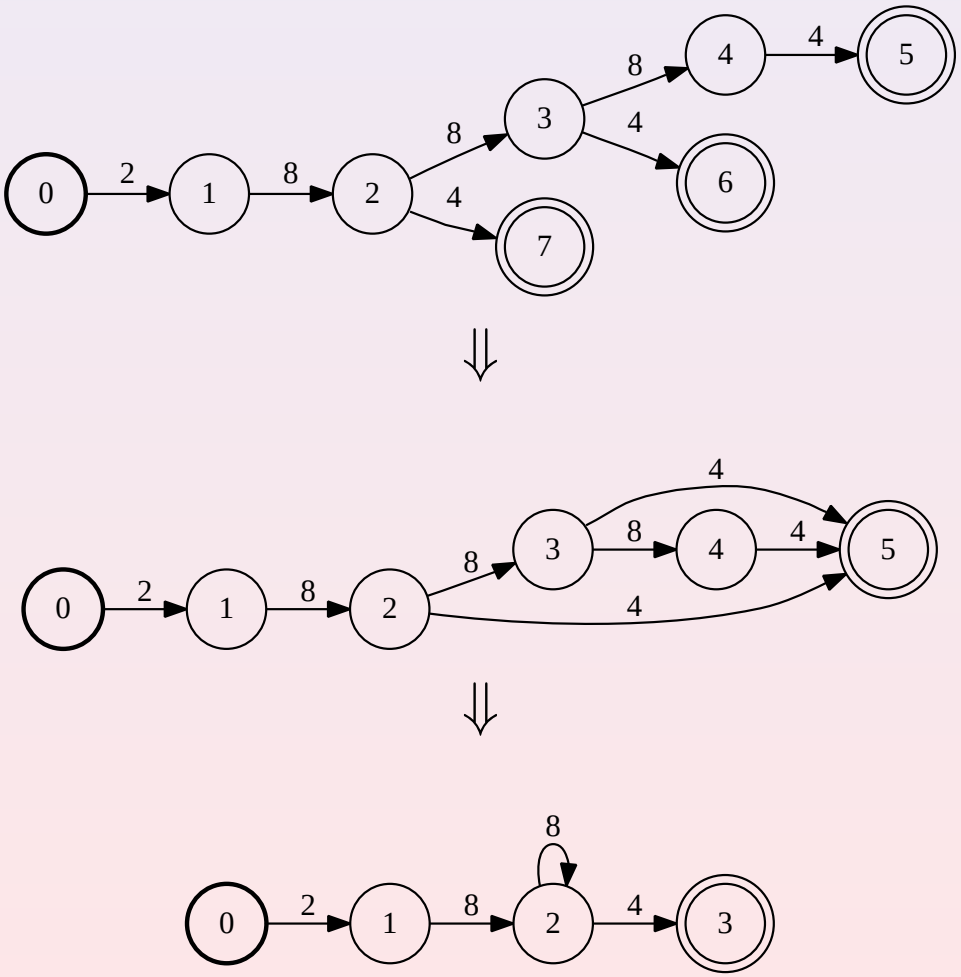


(Angluin '82)

Reversible FS (forward and backward deterministic)



- no fixed finite bound (unlike *n*-gram, Markov models), not PAC
- applied to birdsong by (Sasahara et al'06)
- good model? compare p(heldout) (hunch:no, rev unevidenced)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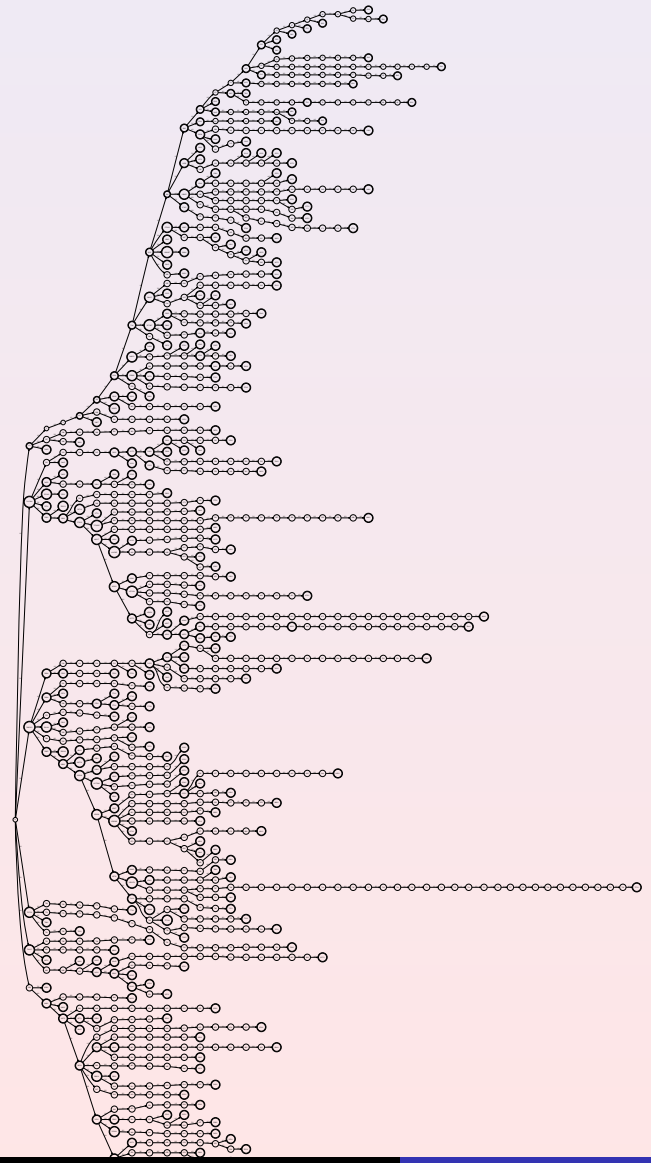
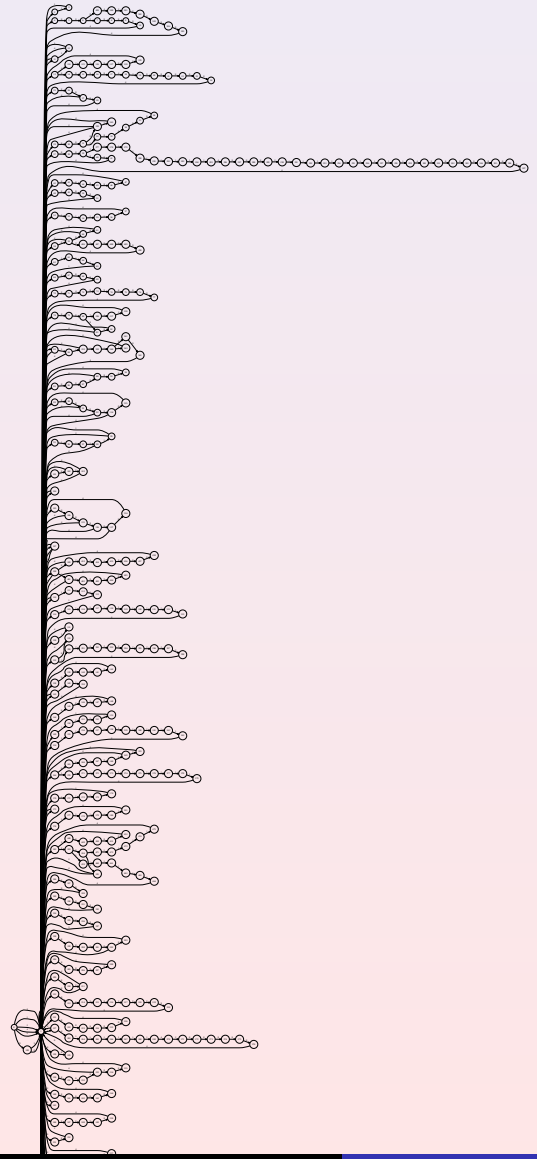
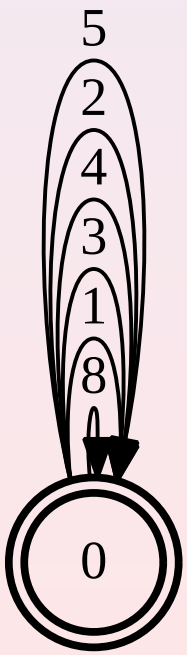


$\Rightarrow$



$\Rightarrow$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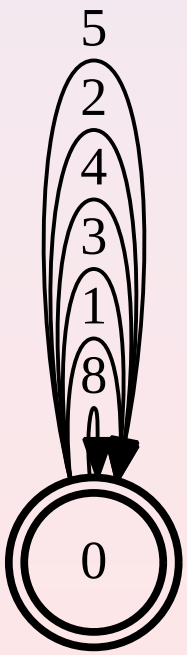


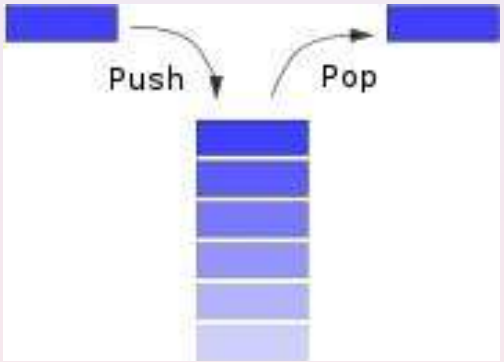
Sasahara et al propose relaxing reversibility to 'k-reversibility'...

We will look at more radical strategies...

(Yokomori'03)

Simple CF: $A \to a\alpha$ **for** $a \in \Sigma, \alpha \in N^*$**, at most one per** $a \in \Sigma$

N → * N N
N → + N N
N → - N
N → 0|1|2|...



S → 0 T E
T → 2
E → 8 E
E → 4

- Gentner et al'06: starlings recognize CF pattern (aabb)
- good model of Greenbul song?

...(0288884,205) ...(02888884,124) ...(028884,105) ...(028888884,36) ...(0288888884,7) ...(02888888884,6) ...

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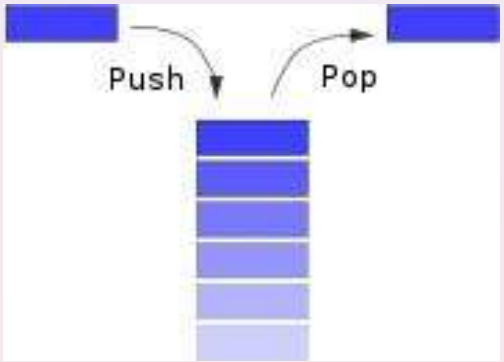

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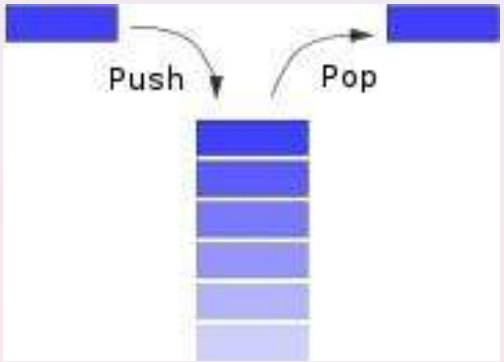
N → 0|1|2|...



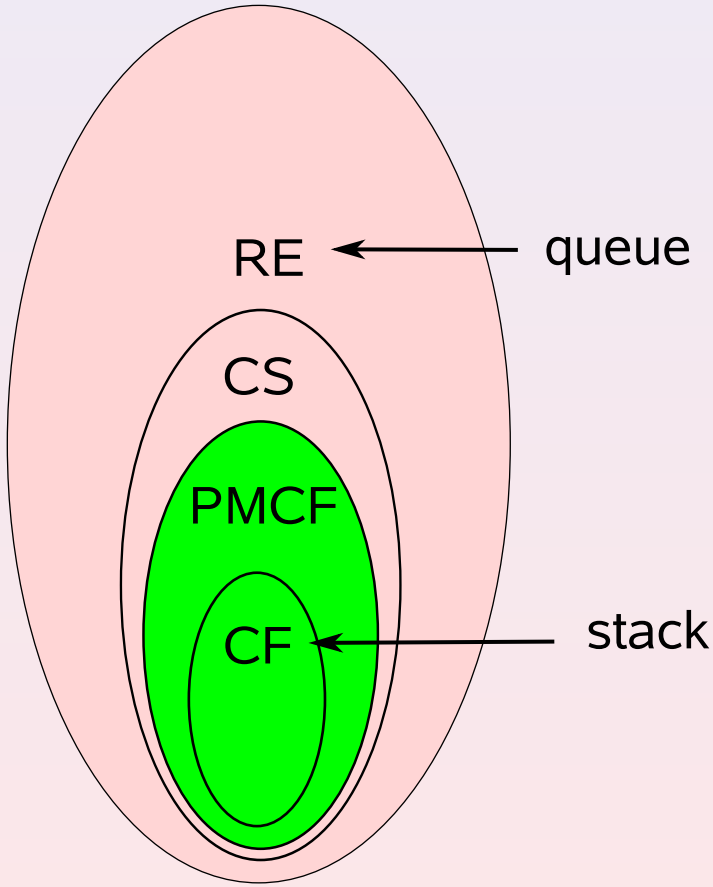
S → 0 T E
T → 2
E → 8 E
E → 4

- Gentner et al'06: starlings recognize CF pattern (aabb)
- good model of Greenbul song? (no: data not generable!, and misses repetition)

How can we get all the data and increase p(repetitions)?

...(0288884,205) ...(02888884,124) ...(028884,105) ...(028888884,36) ...(0288888884,7) ...(02888888884,6) ...

the power of the queue

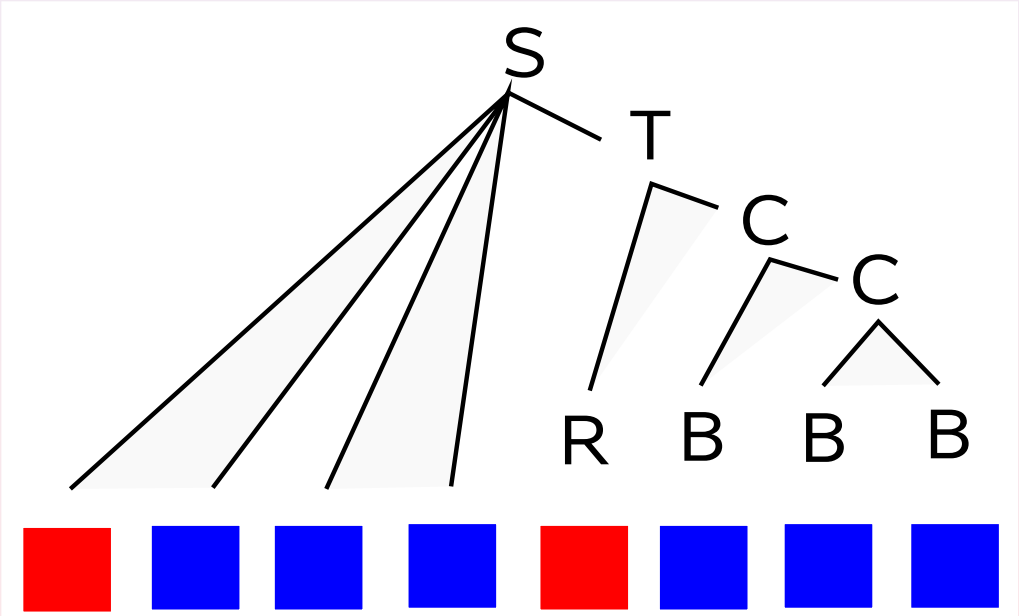


- with a queue, we have turing machine power (e.g. Li et al '93)
- idea: stack for computation + memory for input (PMCF)

(Seki et al'91,Stabler et al'03,Kobele'06)

Unambiguous PMCF

$$\begin{matrix} x \\ S \end{matrix} \longrightarrow \begin{matrix} x \\ T \end{matrix}, \quad \begin{matrix} xx \\ S \end{matrix} \longrightarrow \begin{matrix} x \\ T \end{matrix}$$

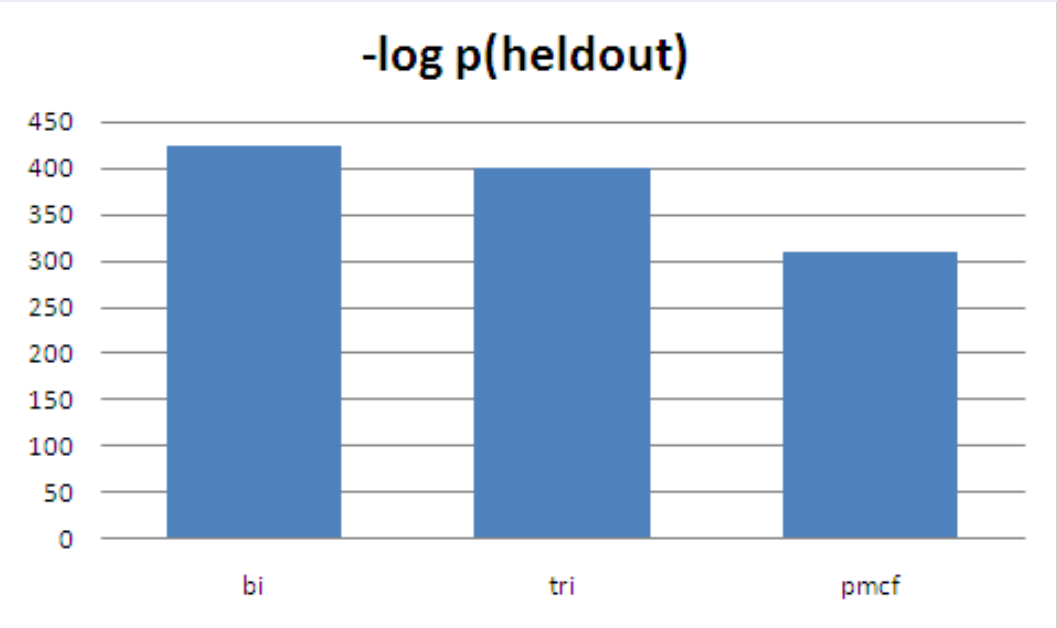


- rules allow copying, so p(copies)↑
- good model?

(hunch: maybe)

Comparison:

	-log p(heldout)
bigram	423.615064
trigram	398.922888
pmcf	308.870379



- not easy to keep such comparisons fair since the models differ in many ways,

  but these preliminary results confirm that small models with copying can fit the data very well

Prospects and future work:

- *n*-gram,Markov,PAC models to weak; too few other models
- H: birds produce and notice repetition in song sequences
  - Confirmed by our first comparison of Greenbul models

    (cf Mennill&Vehrencamp'08; Mann et al'06; Hill'04; Trainer&McDonald'95)
  - Interesting models of gestural iteration & timing

    (cf Nam et al'08; Port'03; Beek et al'02; Saltzman&Byrd'00; Wallenstein et al'95)
- Many questions we would like to answer
  - How much individual variation among birds in same locale?
  - What kinds of information are communicated by birdsong?
  - What neural mechanisms recognize/produce iteration?

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