Learning Syntactic Structure from Examples and Applications

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Sequences and Syntactic Structure

Examples of Syntacticly Structured sequences:

- Electrocardiogram
- Chain-coded image contour
- Banded chromosome grey-level sequence
- Acoustic-phonetic sequence
- String of characters
- Natural Language sentence
- Piece of music
- DNA sequence
- etc. etc. etc. . . .

▷ ***Syntactic Structure is properly represented by Grammars and Automata***

Learning Syntactic Structure and Grammatical Inference (GI)

WHAT IS ***GRAMMATICAL INFERENCE*** (GI)?

- Theory and Methods for Learning Grammars from Training Data.
- Well established discipline dating back to the 60's [Gold,1967]: "Language Identification in the Limit". (Information & Control).
- Traditional application field: Syntactic Pattern Recognition [Fu,1982].
- Many other (potential) applications including Genetic Sequence, Speech and Natural Language processing.

Literature on Grammatical Inference

Journals:

- Information & Computation (old Information & Control)
- Theoretical Computer Science
- Journal of the ACM
- Machine Learning
- IEEE Transactions on PAMI
- IEEE Transactions on SMC
- Int. Journal on Pattern Recognition and Artificial Intelligence

Conferences and Workshops:

- International Colloquium on Grammatical Inference (ICGI) (biannual)
- Computational Learning Theory (COLT) (annual)
- Algorithmic Learning Theory (ALT) (annual)
- International Conference on Pattern Recognition (ICPR) (biannual)
- Workshop on Syntactic & Structural Pattern Recognition (biannual)

Literature on Grammatical Inference

Books:

- R.González and M.Thomason: ”Syntactic Pattern Recognition. An Introduction”. Addison-Wesley 1978.
- K.S.Fu: ”Syntactic Pattern Recognition and Applications”. PrenticeHall 1982
- Osherson Stob Weinstein: ”Systems that Learn: an Introduction to Learning Theory for Cognitive and Computer Scientists”. MIT Press 1986.

Review Papers:

- K.S.Fu: ”Grammatical Inference: Introduction and Survey”. Parts 1 & 2 IEEE Trans. System Man and Cybernetics. Vol SMC-5 No.5 pp.95-11 409-423 1975.
- D.Angluin and C.H.Smith: ”Inductive Inference: Theory and Methods”. ComputingSurveys Vol.15 N**?**3 pp.46-62 1983.
- L.Miclet: ”Grammatical Inference”. In ”Syntactic and Structural Pattern Recognition and applications”. H.Bunke A.Sanfeliu (eds.) pp.237-290. World Scientific 1990.

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Grammars

- ***Free Monoid*** Σ^****:*** Given a finite set Σ, Σ^+ is the set of all finite-length strings of elements of Σ, and $\Sigma^* = \Sigma^+ \cap \{\lambda\}$ (the empty string).

- ***Grammar:*** $G = (N, \Sigma, R, S)$
  - N: finite set of *Non-Terminals*
  - Σ: finite set of *Terminals or Primitives*
  - $S \in N$: Starting Non-Terminal or *"Axiom"*
  - $R \subset (N \cup \Sigma)^* N (N \cup \Sigma)^* \times (N \cup \Sigma)^*$: set of *Rules*.

  A rule is written as:

  $$\boldsymbol{a \longrightarrow b}, \qquad a \in (N \cup \Sigma)^* N (N \cup \Sigma)^*, \;\; b \in (N \cup \Sigma)^*$$

Grammars and Languages

- ***Elementary Derivation:*** $\underset{G}{\Longrightarrow}$***:***

  $\mu\,\alpha\,\delta \underset{G}{\Longrightarrow} \mu\,\beta\,\delta$ iff $\exists(\alpha \rightarrow \beta) \in R,\ \ \mu, \delta \in (N \cup \Sigma)^*$

- ***Derivation*** $\overset{*}{\underset{G}{\Longrightarrow}}$***:***

  Is a *finite sequence of elementary derivations*. A derivation d can be written as the corresponding sequence of rules of G.

  The *set of derivations* of $x \in \Sigma^*$ (such that $S \overset{*}{\underset{G}{\Longrightarrow}} x$) is written as $D_G(x)$.

  A grammar G is *ambiguous* if $\exists x \in \Sigma^*$ such that $|D_G(x)| > 1$

- ***Language generated by a grammar*** $G,\ \mathcal{L}(G)$***:***

  $$\mathcal{L}(G) \ = \ \{\, x \in \Sigma^* \ \mid \ S \overset{*}{\underset{G}{\Longrightarrow}} x \,\}$$

Types of Grammars and Languages

CHOMSKY HIERARCHY FOR RECURSIVE LANGUAGES

0: Unrestricted

1: Context Sensitive

$\alpha B \gamma \rightarrow \alpha \beta \gamma \ , \qquad \alpha, \gamma \in (N \cup \Sigma)^*, \ \ B \in N, \ \ \beta \in (N \cup \Sigma)^+$

2: ***Context Free***

$B \rightarrow \beta \ , \qquad B \in N, \ \ \beta \in (N \cup \Sigma)^*$

3: ***Regular or Finite-State***

$A \rightarrow aB$ or $A \rightarrow a \ , \quad A, B \in N, \ \ a \in \Sigma \cup \{\lambda\}^*$

Regular Grammars and Finite-State Automata

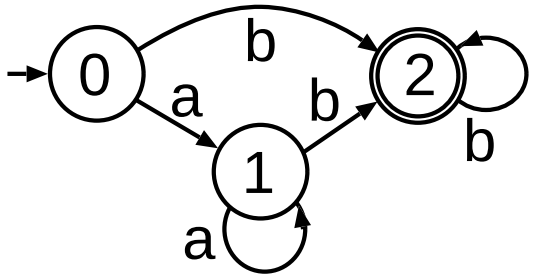
- ***Regular Grammars:*** $G = (N, \Sigma, R, S)$,
  $(A \rightarrow aB) \in R \vee (A \rightarrow a) \in R, \;\; A, B \in N, \;\; a \in \Sigma$

- ***Finite-State Automata:*** $\mathcal{A} = (Q, \Sigma, \delta, q_0, F), \quad q_0 \in Q, \;\; \delta : \; Q \times \Sigma \; \rightarrow \; 2^Q$

- ***Equivalence:*** For every Regular Grammar there exists a Finite-State Automaton that recognizes the same language. (*The converse is not always true for* **stochastic** *languages !*).

Example:

$G = (N, \Sigma, R, S);$
$\Sigma = \{a, b\}; \; N = \{S, A_1, A_2\};$
$R = \{ \; S \; \rightarrow aA_1 \mid bA_2 \mid b,$
$\quad A_1 \rightarrow aA_1 \mid bA_2 \mid b,$
$\quad A_2 \rightarrow bA_2 \mid b\}$



$\mathcal{A} = \{Q, \Sigma, \delta, q_0, F\};$
$Q = \{0, 1, 2\},$
$\Sigma = \{a, b\},$
$q_0 = 0, \; F = \{2\}$

Stochastic Grammars and Languages

- A ***Stochastic Grammar*** G' is a grammar G with probabilities associated to its rules:

$$G' = (G, p), \quad G = (N, \Sigma, R, S), \quad p : R \rightarrow [0, 1]$$

- A *context-free* (or *regular*) Grammar is ***proper*** if:

$$\forall A \in N \quad \sum_{A \rightarrow \beta \in R} p(A \rightarrow \beta) = 1$$

- ***Probability of a string*** x generated by G':

$$\forall x \in \Sigma^* \quad p(x|G') = \sum_{d \in D_G(x)} p(d), \qquad p(d) = \prod_{(A \rightarrow \beta) \in d} p(A \rightarrow \beta)$$

- A stochastic grammar G' is ***consistent*** if:

$$\sum_{x \in \Sigma^*} p(x|G') = 1$$

Estimating the Probabilities of the Rules

- ***Non-ambiguous Context-Free (or Regular) grammar G':***
  Maximum Likelihood estimation from frequencies of use of the rules in the parsing of a training set that is assumed to have been generated by G'.

  Estimates approach the true probabilities as the size of the training set $\rightarrow \infty$. [Mariansky et al., 77] [Chandhuriet al., 86].

- ***Ambiguous Context-Free (or Regular) grammars:***
  Locally optimal estimation using Backward-Forward or Inside-Outside re-estimation.

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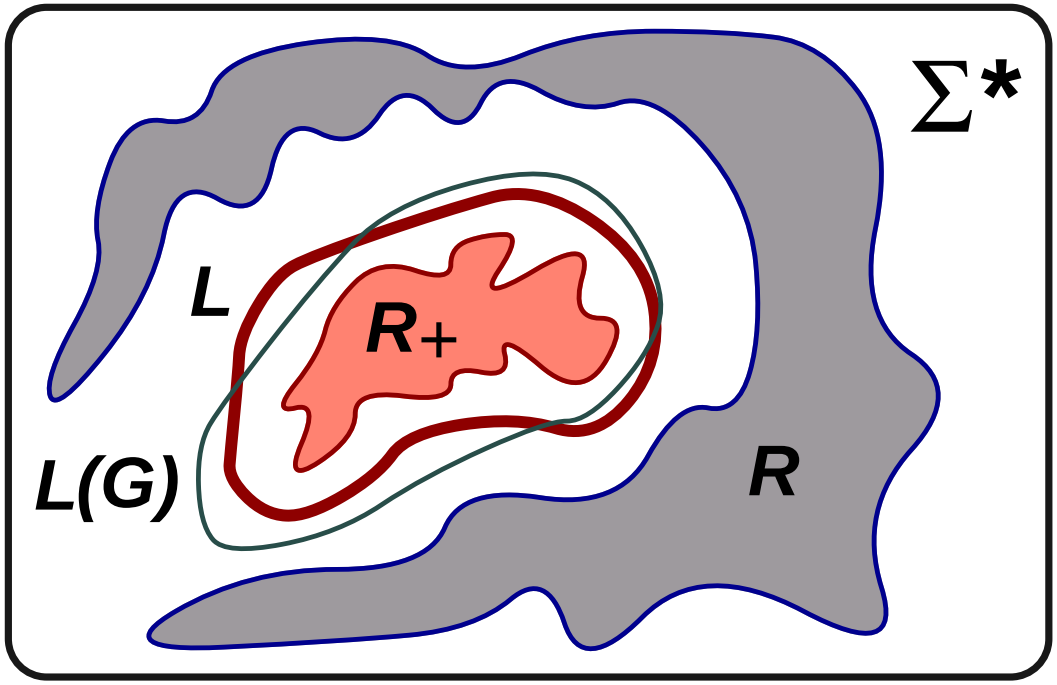
Language Identification in the Limit

- Given a *positive training set of an unknown language* L: $S_+ \subset L$
- [And possibly a *negative training set*: $S_- \subset \Sigma^* - L$]
- find a grammar G such that: $S_+ \subset \mathcal{L}(G)$ [and $S_- \cap \mathcal{L}(G) = \emptyset$]
- and, in the limit, for sufficiently large, $|S_+ \cup S_-|$: $\mathcal{L}(G) = L$



Computability Results

+ Any class of *recursively enumerable languages can be identified in the limit from* ***complete presentation*** (both positive and negative samples) [Gold,67].

However: Negative samples are not always available and also their use can lead to probably intractable problems [Angluin,78] [Gold,78].

– *No superfinite class of languages can be identified in the limit from only* ***positive presentation*** [Gold,67].

Therefore: Not even the class of Regular Languages is identifiable in the limit from only positive samples.

Possible escape: *use only positive samples* and:

- infer non-superfinite classes of languages: (***"characterizable" methods***)
  ... or
- supply adequate a-priori knowledge: (***"heuristic" methods***)

Using Positive Examples only

- Undecidability results strictly apply to superfinite classes. But many non-superfinite classes may exist that are identifiable with just positive information. E.g. undecidability does not apply to classes that do not contain all finite languages.

- The danger is *over-generalization*: if in a given inference step a language is produced that is larger than the unknown target language, this is irreversible since no positive sample could ever supply information to detect this error.

- By allowing only ***"conservative" generalizations*** over-generalization can be avoided for non-trivial classes of languages.

  An explicit characterization of these classes is given in [Angluin,80]

Design of GI Algorithms using Positive Data only

- ***Heuristic***: Rely on a *priori knowledge* on each application domain to avoid improper generalizations for this application.

  Examples:

  - K-Tails [Biermann & Feldman, 72]
  - Tail Clustering [Miclet,80]
  - Error Correcting Grammatical Inference (ECGI) [Rulot & Vidal, 87]
  - etc. . . .

- ***Characterizable***: Consider *specific classes of languages* which are identifiable in the limit.

  Examples:

  - K-Reversible Languages [Angluin,82]
  - Terminal Deterministic Languages [Radhakrishnan & Nagaraja, 88]
  - K-Testable Languages [García & Vidal, 90]
  - etc. . . .

  The (practical) problem consists of how to establish a relation between each considered application and a convenient class of (inferable) languages.

- ***A methodological tradeoff (MGGI):*** *techniques based on symbol relabeling functions (morphismes) [García Vidal & Casacuberta, 87*]

Other Learning Paradigms with more Optimistic Computational Results

- ***Approximate Identification*** in the limit is possible for ”dense” classes of Languages using only positive presentation [Wharton,74].

  An example is the identification of ***Stochastic Regular Languages*** [Carrasco & Oncina, 99].

- ***Other Helpful Learning Environments*** [Parekh & Hanovar, 2000]
  - *Probably Approximately Correct Identification (PAC)*
  - Learning from *Example Based Queries*
  - Using *Teaching and Characteristic Sets*
  - Learning from *Simple Examples*

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