Maximum Entropy Classifier Ensembling using Genetic Algorithm for NER in Bengali

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NER-Named Entity Recognition (NER) involves identification of proper names in texts, and classification into a set of pre-defined categories of interest as:

- Person names (names of people)
- Organization names (companies, government organizations, committees, etc.)
- Location names (cities, countries etc)
- Miscellaneous names (Date, time, number, percentage, monetary expressions, number expressions and measurement expressions)
Approaches for NER I

- **Rule-based NER**
  1. based on handcrafted set of rules
  2. suffers from adaptability to a new domain and/or languages

- **Machine learning based NER**: Supervised, Semi-supervised and Unsupervised
  1. adaptable to different domains and languages
  2. maintenance cost is less
  3. difficult to obtain large annotated corpus for resource-constrained languages

- **Hybrid NER**
  1. combination of both machine learning and rule-based
  2. maintenance of rule-based component still persists
  3. difficult to obtain large annotated corpus for resource-constrained languages
Problems for NER in Indian Languages I

- Lacks capitalization information
- Indian names are more diverse
  1. Lot of person names appear in the dictionary with other specific meanings
  2. For e.g., KabiTA (Person name vs. Common noun with meaning poem)
- High inflectional nature of Indian languages
  1. Richest and most challenging sets of linguistic and statistical features resulting in long and complex wordforms
- Scarcity of Corpus and NE annotated corpus
- Free word order nature of Indian languages
- Resource-constrained environment of Indian languages
  1. POS taggers, morphological analyzers, name lists etc. are not available in the web
- Non-availability of sufficient published works
Motivation and Contribution I

- The language - Bengali
  1. Emerged in AD 1000
  2. Spoken in West Bengal, Tripura, Assam and Jharkhand states of India (Rank 2 in India)
  3. National language of Bangladesh
  4. Rank 5th in the World in terms of native speakers
- NER in Indian languages
  1. More difficult and challenging
  2. Efforts are still in infancy
- NER system for a less computerized language
- Proposal of a generalized approach that could be applicable for many languages
- Use of Genetic Algorithm (GA) for classifier ensemble is noble
- Application of GA for solving any kind of NLP problem is new
Classifier Ensembling

- Well-known in the area of machine learning
- Concept of combining classifiers to improve the performance
- Determining the appropriate classifier combination: very crucial problem

Our proposal

- Posed the classifier ensemble selection problem under the single objective optimization framework
- Solution by genetic algorithm (GA)
Suppose, the $N$ number of available classifiers denoted by $C_1, \ldots, C_N$. Let, $A = \{C_i : i = 1; N\}$. Classifier ensemble selection problem : Find a set of classifiers $B$

- Optimize a function $F(B)$
- $B \subseteq A$
- $F$: a classification quality measure of the combined classifiers, $F \in \{\text{recall, precision, F-measure}\}$
- Here $F = \text{F-measure}$
Goal of the paper I

- Maximum Entropy: base classifier
- Depending on various feature representations, different versions of ME are made
- Features are language independent
- GA used to find appropriate classifier ensemble
- System evaluated for Bengali, a resource poor language
Genetic Algorithms:

- Randomized search and optimization techniques guided by the principles of evolution and genetics
- Evolution produced good individuals, similar principles might work for solving complex problems
- Many problems cannot be solved in polynomial amount of time using a deterministic algorithm
- Near optimal solutions requiring less time more desirable than optimal solutions with huge amount of time
- Perform search in complex, large and multimodal landscapes
Genetic Algorithm II

Genetic Algorithms \(\iff\) Nature
A solution (phenotype) \iff Individual
Representation of a solution (genotype) Chromosome
Components of the solution Genes
Set of solutions Population
Survival of the fittest (selection) Darwins theory
Search operators Crossover and mutation
Iterative procedure Generations

- Parameters of the search space encoded in the form of strings (called chromosomes)
- A collection of such chromosomes called a population
- Initial step: A random population representing different points in the search space
Genetic Algorithm III

- **objective or fitness** function: associated with each string
  - represents the degree of **goodness** of the string
- **Selection**
  - Based on the principle of survival of the fittest, a few of the strings selected
- Biologically inspired operators like **crossover** and **mutation** applied on these strings to yield a new generation of strings
- Process of selection, crossover and mutation continues for a fixed number of generations or till a termination condition satisfied
1. $t = 0$
2. initialize population $P(t)$ /* Popsize = $|P|$ */
3. for $i = 1$ to $Popsize$
   compute fitness $P(t)$
4. $t = t + 1$
5. if termination criterion achieved go to step 10
6. select (P)
7. crossover (P)
8. mutate (P)
9. go to step 3
10. output best chromosome and stop
End
String Representation I

Total number of available classifiers: $M$

Length of the chromosome: $M$

0 in the $i^{th}$ position of chromosome $\rightarrow$ $i^{th}$ classifier does not participate in ensemble

1 in the $i^{th}$ position of a chromosome $\rightarrow$ $i^{th}$ classifier participates in the classifier ensemble
Fitness Computation I

1. $N$: number of classifiers present in the ensemble represented in a particular chromosome (Total $N$ number of 1’s in that chromosome)

2. Overall average F-measure values of the 3-fold cross validation on the training data for these $N$ classifiers be $F_i$, $i = 1 \ldots N$

3. Training data divided into 3 parts

4. Each classifier trained using 2/3 of the training data and tested with the remaining 1/3 part

5. Output class label for each word in the 1/3 training data determined using the weighted voting of these $N$ classifiers’ outputs

6. The weight of the o/p label provided by the $i^{th}$ classifier = $F_i$.

7. The overall F-measure value of this ensemble classifier for the 1/3 training data calculated.
Fitness Computation II

8. Average F-measure value of the ensemble classifier used as the fitness value of that particular chromosome

Objective: Maximize F-measure using the search capability of GA
Selection I

- New generation created from a proportion of the existing population
- Individual solutions selected through a fitness-based process
  - Fitter solutions more likely to be selected
- Roulette wheel selection: Resemblance to a Roulette wheel in a casino
  - Fitness function associates a probability of selection with each individual chromosome
  - $f_i$: the fitness of individual $i$ in the population, its probability of being selected:
    $$p_i = \frac{f_i}{\sum_{j=1}^{N} f_j},$$
    where $N$: the number of individuals in the population
Crossover I

- Normal single point crossover
- Suppose, there are 8 classifiers. The two chromosomes look like:
  \[ P_1 = 0 \ 1 \ 1 \ 0 \ 0 \ 0 \ 1 \ 1 \]
  \[ P_2 = 1 \ 1 \ 1 \ 0 \ 0 \ 0 \ 1 \ 0 \]
- Consider the crossover point: 4. After single point crossover the new chromosomes will look like:
  \[ O_1 = 0 \ 1 \ 1 \ 0 \ 0 \ 0 \ 1 \ 0 \]
  \[ O_2 = 1 \ 1 \ 1 \ 0 \ 0 \ 0 \ 1 \ 1 \].
- Crossover probability selected adaptively
Mutation I

- Mutation operator applied to each entry of the chromosome
  - Entry randomly replaced by either 0 or 1
- Fitness computation, selection, crossover, and mutation executed for a maximum number of generations
- The best string seen up to the last generation provides the solution
- Elitism implemented at each generation by preserving the best string seen up to that generation in a location outside the population
- On termination, this location contains the best classifier ensemble
Feature Set Used I

1. Context Word: Preceding and succeeding words
2. Word Suffix:
   1. Not necessarily linguistic suffixes
   2. Fixed length character strings stripped from the endings of words
   3. Variable length suffix - binary valued feature
3. Word Prefix
   1. Fixed length character strings stripped from the beginning of the words
4. First Word (binary valued feature): Check whether the current token is the first word in the sentence
5. Length (binary valued): Check whether the length of the current word less than three or not (shorter words rarely NEs)
6. Position (binary valued): Position of the word in the sentence
Feature Set Used II

7 Infrequent (binary valued): Infrequent words in the training corpus most probably NEs

8 Digit features: Binary-valued
   1 Presence and/or the exact number of digits in a token
   2 CntDgt: Token contains digits
   3 FourDgt: Token consists of four digits
   4 TwoDgt: Token consists of two digits
   5 CnsDgt: Token consists of digits only

9 Combination of digits and punctuation symbols
   1 CntDgtCma: Token consists of digits and comma
   2 CntDgtPrd: Token consists of digits and periods

10 Combination of digits and symbols
   1 CntDgtSlsh: Token consists of digit and slash
   2 CntDgtHph: Token consists of digits and hyphen
Feature Set Used III

3 CntDgtPrctg: Token consists of digits and percentages

11 Combination of digit and special symbols
   1 CntDgtSpl: Token consists of digit and special symbol such as $, # etc.

12 Part of Speech (POS) Information: POS tag(s) of the current and/or the surrounding word(s)
   1 SVM-based POS tagger
   2 Accuracy=90.2%
Data Sets 1

- Web-based Bengali news Corpus (Ekbal and Bandyopadhyay, 2008)
  1. 34 million wordforms
  2. news data collection of 5 years

- NE annotated corpus
  1. Manually annotated 250K wordforms
  2. IJCNLP-08 Shared Task on NER for South and South East Asian Languages (available at http://ltrc.iiit.ac.in/ner-ssea-08)

- NE Tagset
  1. Person name
  2. Location name
  3. Organization name
  4. Miscellaneous name (date, time, number, percentages, monetary expressions and measurement expressions)
Data Sets II

- IJCNLP-08 NERSSEAL Shared Task Tagset: Fine-grained 12 NE tags (available at http://ltrc.iiit.ac.in/ner-ssea-08)
- Tagset Mapping (12 NE tags → 4 NE tags)
  1. NEP → Person name
  2. NEL → Location name
  3. NEO → Organization name
  4. NEN [number], NEM [Measurement] and NETI [time] → Miscellaneous name
  5. NETO [title-object], NETE [term expression], NED [designations], NEA [abbreviations], NEB [brand names], NETP [title persons] → O
Experimental Results I

- Parameters for GA:
  1. Population size = 100
  2. Number of generations = 50

- MaxEnt experiment: OpenNLP Java based ME package (http://maxent.sourceforge.net/)

- Baselines:
  - Baseline 1: Majority voting of all classifiers
  - Baseline 2
    - Weighted voting of all classifiers
    - Weight: average F-measure value of the 3-fold cross validation on the training data
Training set size: 313K wordforms Test set size: 37K wordforms

Table: Statistics of training and test sets

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<th>Set</th>
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<th>ORG</th>
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Table: Feature types and parameters used for training different ME based classifiers for Bengali. X: Denotes the presence of the corresponding feature

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<th>IW</th>
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Table: Overall results for Bengali

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<th>R</th>
<th>P</th>
<th>F</th>
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<td>GA</td>
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</table>

- Classifiers selected: $M_2, M_3, M_4, M_5, M_7, M_9, M_{10}, M_{11}, M_{12}, M_{14}, M_{16}, M_{18} \text{ and } M_{19}$.
Observation: convergence within 21 generations for this particular data set.
Boxplot of the F-measure values of the solutions on the final population 1
Conclusion and Future Works

- Proposed the use of GA to develop a classifier ensemble for NER
- Base classifier: ME framework
- Language independence
- Evaluation with a resource poor language: Bengali
  1. Recall = 71.14%, Precision = 84.07%, F-measure = 77.11%
  2. Performed better than two conventional baseline ensembles
Future Works I

- Incorporation of some more language independent (dynamic NE information etc.) as well as the language specific features to generate more classifiers
- Development of vote based classifier ensembles using some other well-known classifiers like CRF and SVM
- Use of Multiobjective optimization


References II


Thank You For Listening