Maximum Entropy Classifier Ensembling using Genetic Algorithm for NER in Bengali

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Outline

Named Entity Recognition I

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 I

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)

Single Objective Formulation of Classifier Ensemble Problem I

Suppose, the N number of available classifiers denoted by $C_1, \ldots, C_N$.
Let, $\mathcal{A} = \{C_i : i = 1; N\}$.
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, $F \in \{\text{recall}, \text{precision}, \text{F-measure}\}$
- Here $F =$ 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 Algorithm I

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 can not 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 $\Longleftrightarrow$	Nature
A solution (phenotype)	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

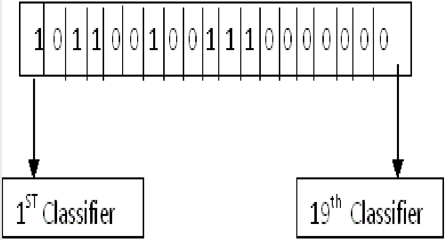
- *objective* or *fitness* function: associated with each string
  - represents the degree of *goodness* of the string
- Selection
  - Based on the principle of survival of the fittest, a few of the strings selected
- Biologically inspired operators like *crossover* and *mutation* applied on these strings 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

Basic Steps of Genetic Algorithm I

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 :

$$p_i = \frac{f_i}{\Sigma_{j=1}^{N} f_j},$$

  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 upto the last generation provides the solution
- Elitism implemented at each generation by preserving the best string seen upto 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 I

- 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$\rightarrow$ 4 NE tags)
    1. NEP $\rightarrow$ Person name
    2. NEL $\rightarrow$ Location name
    3. NEO $\rightarrow$ Organization name
    4. NEN [number], NEM [Measurement] and NETI [time]$\rightarrow$ Miscellaneous name
    5. NETO [title-object], NETE [term expression], NED [designations], NEA [abbreviations], NEB [brand names], NETP [title persons]$\rightarrow$ 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

Set	PER	LOC	ORG	MISC
Training	6,717	5,591	3,070	8,058
Test	648	670	374	1,008

Results I

Table: Feature types and parameters used for training different ME based classifiers for Bengali. X: Denotes the presence of the corresponding feature

Classifier	CW	FW	PRE-SIZE	SUF-SIZE	WL	IW	PW	DI	POS	recall	precision	F-measure
M_1	X	X						X	X	35.59	62.74	45.42
M_2	X	X	3					X	X	63.12	78.61	70.02
M_3	X	X	3	3				X	X	68.81	81.34	74.55
M_4	X	X	3	3	X			X	X	68.65	81.57	74.55
M_5	X	X	3	3	X	X		X	X	69.35	81.37	74.88
M_6	X	X	3	3	X	X	X	X	X	69.15	81.53	74.83
M_7	X	X	4					X	X	65.45	79.43	71.76
M_8	X	X	4	3				X	X	68.42	81.58	74.42
M_9	X	X	3	4				X	X	69.39	81.66	75.03
M_{10}	X	X	4	4				X	X	68.65	81.13	74.37
M_{11}	X	X	4	3	X			X	X	67.81	81.53	74.04
M_{12}	X	X	3	4	X			X	X	69.39	82.02	75.18
M_{13}	X	X	4	4	X			X	X	68.01	81.00	73.94
M_{14}	X	X	4	3	X	X		X	X	68.69	81.46	74.53
M_{15}	X	X	3	4	X	X		X	X	**69.76**	**81.75**	**75.28**
M_{16}	X	X	4	4	X	X		X	X	68.87	80.89	74.40
M_{17}	X	X	4	3	X	X	X	X	X	68.58	81.64	74.54
M_{18}	X	X	3	4	X	X	X	X	X	69.67	81.85	75.27
M_{19}	X	X	4	4	X	X	X	X	X	68.51	81.01	74.24

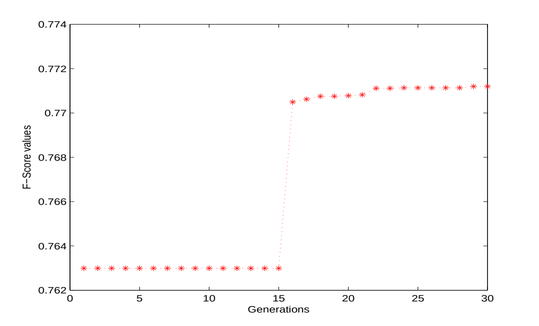
Results continued.. I

Table: Overall results for Bengali

Model	R	P	F
Best classifier	69.76	81.75	75.28
Baseline 1	69.83	82.90	75.81
Baseline 2	70.25	82.97	76.08
GA	71.14	84.07	77.11

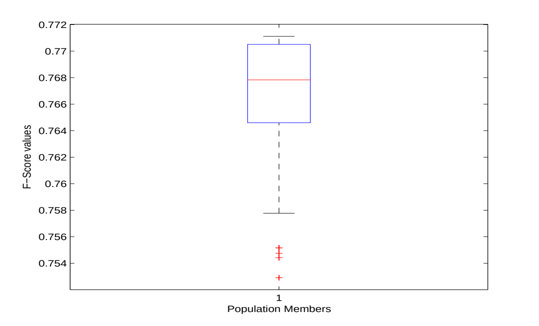
- Classifiers selected: M_2, M_3, M_4, M_5, M_7, M_9, M_{10}, M_{11}, M_{12}, M_{14}, M_{16}, M_{18} and M_{19}.

Variation of the best F-measure values over generations I



- Observation: convergence within 21 generations for this particular data set

Boxplot of the F-measure values of the solutions on the final population I



Conclusion and Future Works I

- 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

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Thank You I

Thank You For Listening