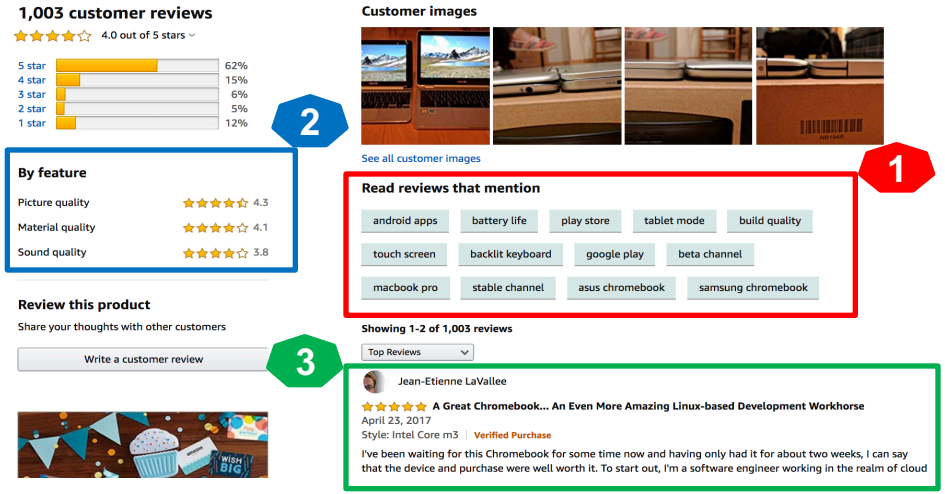
Aspect Term Extraction in Product Reviews

Subrata Ghosh

Outline

- **Project description**
- **Data: Statistics**
- **Related work**
- **Logics and results**
  - **Logic – 1:** Unsupervised approach(Rules based)
  - **Logic – 2:** Supervised approach(Extension of logic-1)
  - **Logic – 3:** CRF
  - **Logic – 4:** Ensemble
- **Future work**

Use case



General use case

Case 1: Find most important aspects.
Aspect based review filtering.

Case 2: Aspect based rating.

Case 3: Combine customer review based on aspect terms.

PMI use case

Case 1: New marketing strategy.
Case 2: Product improvement.

Problem Description

Aspect Term(AT):

- Opinionated expressions.
- Example : “I expected so as it's an Apple product.” In this sentence no AT present.

Description

- It is the task of automatically extract aspect term from product review text.
- For each word of a review, the model should predict if the word is an aspect term or not of the reviewed product.
- It is a **multi-label** classification problem. Multi-label = {**O** : not an aspect, **B** : first word of an aspect (Beginning), **I** : second, third, ... word of an aspect (Inside)}
- It is a subtask of aspect-based sentiment analysis.

What need to do?

- **Given:** Product reviews and aspect terms
- **Need to do:** Build an AT extractor model which should predict the word is a class {O, B, I} of the reviewed product.

Problem: Example

Consider the product review and aspect terms:

Review text: The **battery life** is really good and its **size** is reasonable

Aspect terms: Battery life, size.

BIO format(It will helpful for train a classifier or evaluate model):

The	battery	life	is	really	good	and	its	size	is	reasonable
O	B	I	O	O	O	O	O	B	O	O

- ATE is to assign to each word one of the three possible classes:
  - O = not an aspect (Outside)
  - B = first word of an aspect
  - I = second, third, … word of an aspect (Inside)

Challenges

Consider the Laptop reviews:

Examples:

1. I expected so as it's an **Apple product**.
2. I love India.
3. The **battery life** is really good and its size is reasonable.

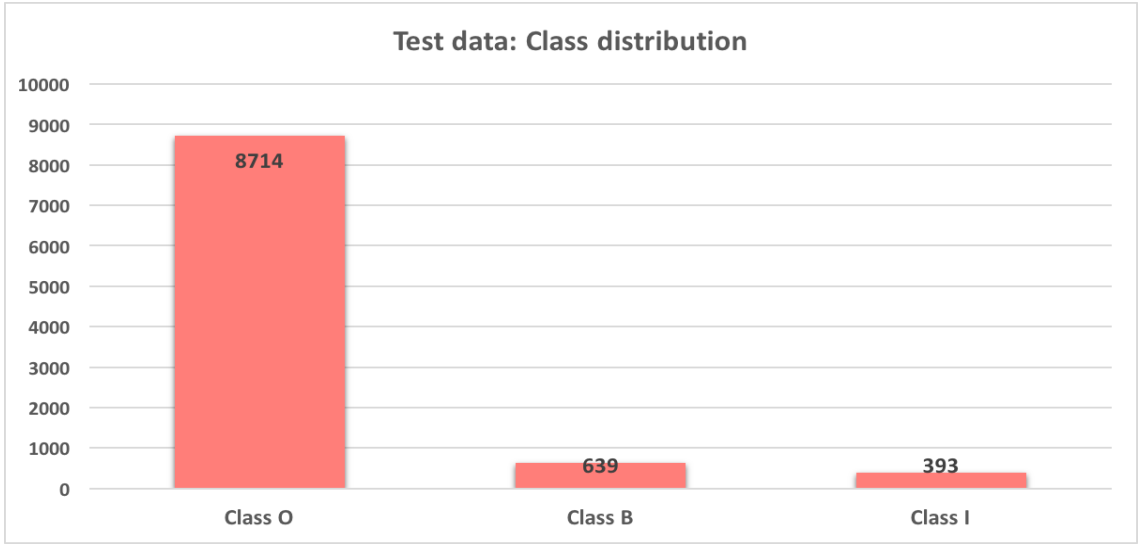
Challenge 1: AT is opinionated expression. See example 1.

Challenge 2: Domain product aspect terms. See example 2.

Challenge 3: Aspect term can be composed of more than one token. See example 3

Data: Statistics

Data type	Number of review	#aspect (single word)	#aspect (multi word)
Training	3045	365	590
Test	800	167	226



Related work

1. **Frequency and Relation based Approaches:**
   - Feature-based Summarization (Hu et al. 2004)
   - A Rule-Based Approach to Aspect Extraction from Product Reviews(my implementation)

2. **Model-based Approaches:**
   - **Supervised Learning:**
     - Naïve Bayes
     - Hidden Markov model(HMM)
       - Opinion Miner [Jin et al. 2009]
     - Conditional Random Field (CRF)
       - CRF (Li et al. 2010)
   - **Topic modeling techniques:**
     - MG-LDA (Titov et al. 2008a)

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Logic 1: Unsupervised approach

- I try to solve this problem completely unsupervised way.
- Extract aspect terms using syntactic dependencies of words in a sentence.

Workflow with example

Review text: The battery life is really good and its size is reasonable

↓

Aspect - opinion pair: [(battery, good), (size , reasonable), **(battery, life)**]

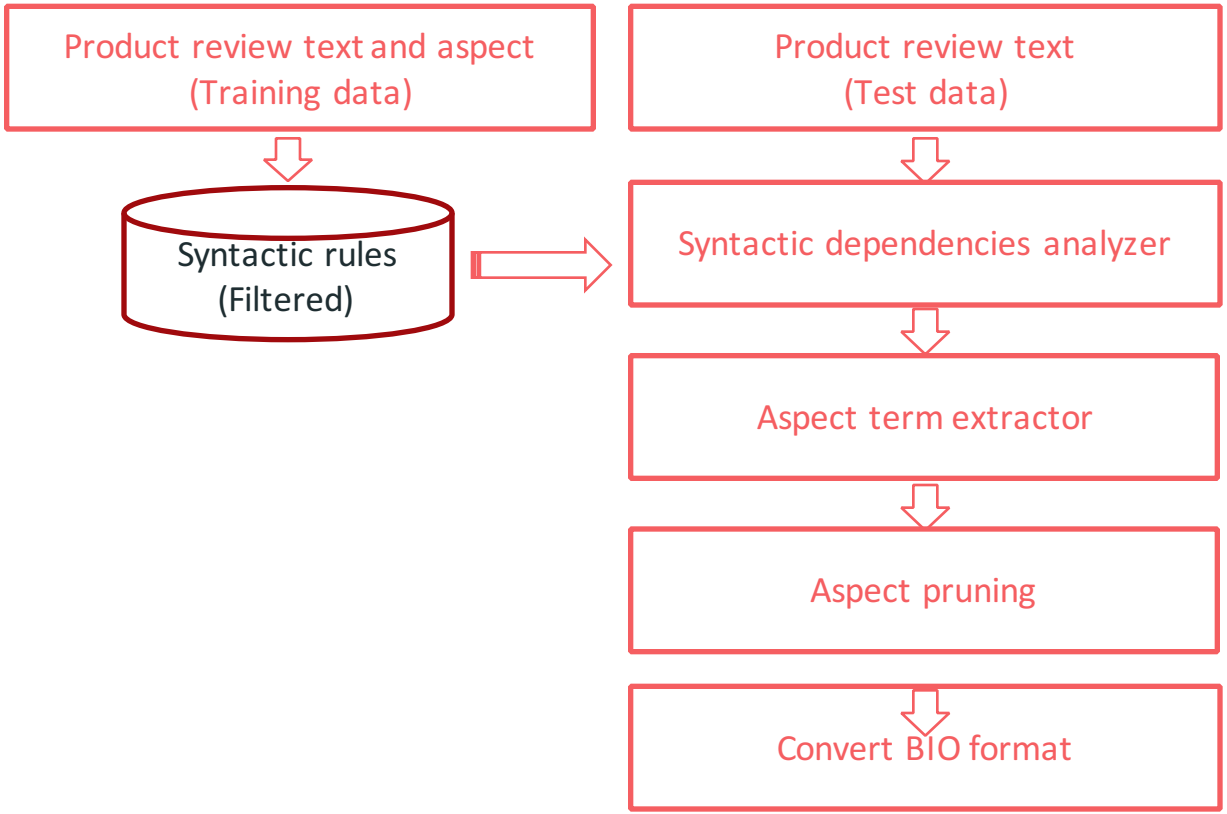
↓

Aspect terms : [battery life, size]

↓

Convert to BIO format: [(The, O), (battery, B), (life, I), (is, O), (really, O), (good, O), (and, O), (its, O), (size, B), (is, O), (reasonable, O)]

Logical workflow



Algorithm: Syntactic rules

1. **Nominal subject:** The aspect is the subject of the opinion.
2. **Noun compound modifier:** Noun that serves to modify the head noun.
3. **Adjectival modifier:** The opinion is an adjectival modifier of the aspect.
4. **Direct object:** The direct is the direct object of the opinion.

From training data, I find what syntactic rules and pattern can be useful.

Stanford Parser: In build syntactic rules tool.

Stanford Parser notation:

(('good', 'JJ'), 'nsubj', ('life', 'NN'))
(('reasonable', 'JJ'), 'nsubj', ('size', 'NN'))
(('life', 'NN'), 'compound', ('battery', 'NN'))

From above notations we an create aspect-opinion pair.

This type of several syntactic rules I use to create aspect-opinion pair.

Algorithm: Aspect terms extractor

Consider the product review and aspect terms:

Review text: The battery life is really good and its size is reasonable

Stanford Parser notation	Extracted aspect
(('good', 'JJ'), **'nsubj'**, ('life', 'NN'))	life
(('reasonable', 'JJ'), **'nsubj'**, ('size', 'NN'))	size
(('life', 'NN'), **'compound'**, ('battery', 'NN'))	battery life

Final aspect terms: {battery life, size}

In the above text **“good”** and **“reasonable”** is opinion word and **“battery life”** and **“size”** are aspects.

Algorithm: Aspect pruning

Some cases, redundant aspect could be extracted, let's consider below aspect term list:

Extracted aspect terms: [**battery life**, **life**, size]

Now, you can see “life” aspect already included in “battery life”.

After removing redundant aspect: [battery life, size]

Evaluation

Logic	Class	Precision	Recall	F1-score
Logic-1	O	0.94	0.89	0.91
Logic-1	B	0.23	0.43	0.30
Logic-1	I	0.34	0.19	0.25

- **Logic-1 F1-score(macro avg.): 0.49**

This is a class imbalance problem, as you can see in the data set almost 90% of word belongs to class O.

Class I: recall is very low, that mean this model only 19% correctly find out. Also, precision not good.

Class B: recall is not bad but precision is too low, that means wrong classification is high

Class O: Just because of class imbalance results looks good but actually it is not.

Logic 1: Pro and Cons

Pro:

1. Totally unsupervised
2. Can find low-frequency aspects.

Cons:

1. Not consider domain product aspect(challenge 2).
2. Produce many non-aspects matching with the patterns
3. Class I: recall is too low.

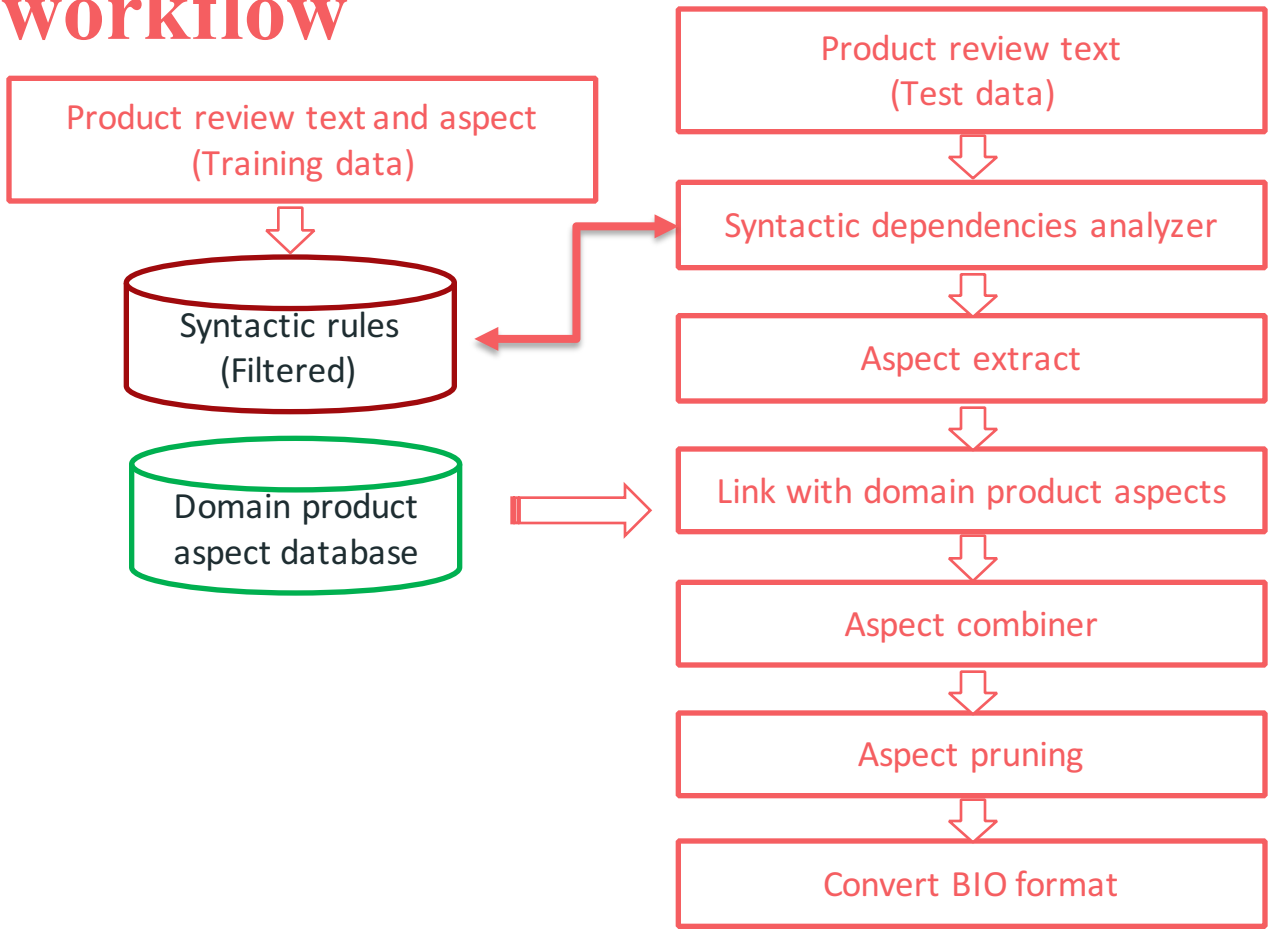
Logic 2: Extension of Logic-1

Goal:

- Remove all the cons of logic-1 and get good results.

Idea:

Logical workflow



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(('reasonable', 'JJ'), **'nsubj'**, ('size', 'NN'))	size
(('life', 'NN'), **'compound'**, ('battery', 'NN'))	battery life

Final aspect terms: {battery life, size}

In the above text **“good”** and **“reasonable”** is opinion word and **“battery life”** and **“size”** is aspects.

Algorithm: Link with domain aspect

- All aspects got from aspect extractor just filter it.
- Take only those aspects, also present in domain product aspects database.

Algorithm: Aspect combiner

Aspect term can be composed of more than one token so how I deal with?

Syntactic dependency rule :

- (('life', 'NN'), **'compound',** ('battery', 'NN')) ⇒ **battery life**

Sentence POS tag sequence:

1. **Noun followed by Noun:**
   - [('The', 'DT'), **('battery', 'NN'), ('life', 'NN'),** ('is', 'VBZ'),('really', 'RB'),('good', 'JJ')]. ⇒ **Battery life**
2. **Noun followed by Cardinal number:**
   - [('I', 'PRP'), ('like', 'VBP'), **('windows', 'NNS'), ('8', 'CD')**]. ⇒ **Windows 8**
3. **Noun before Noun**

Algorithm: Aspect pruning

Some cases, redundant aspect could be extract, lets consider below aspect term list:

Extracted aspect terms: [**battery life**, **life**, size]

Now, you can see “life” aspect already included in “battery life”.

After removing redundant aspect: [battery life, size]

Last: Convert to BIO format and evaluate

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Logic-1	O	0.94	0.89	0.91
Logic-1	B	0.23	0.43	0.30
Logic-1	I	0.34	0.19	0.25
Logic-2	O	0.96	0.99	0.97
Logic-2	B	0.72	0.64	0.68
Logic-2	I	0.79	0.43	0.56

- **Logic-2 F1-score(macro avg.): 0.74**

Class I: Now recall is reasonable and precision is good.

Class B: recall is good and precision also better then logic-1

Evaluation Metrics: SemEval 2014 Task-4

$$Precision = \frac{|ExtractedAspects \bigcap GoldStandardAspects|}{|ExtractedAspects|}$$

$$Recall = \frac{|ExtractedAspects \bigcap GoldStandardAspects|}{|GoldStandardAspects|}$$

$$F - measure = \frac{2 \times Recall \times Precision}{(Recall + Precision)}$$

Results: SemEval 2014 Task-4

No.	Team	F1-score
1	HIS_RD.	74.55
2	DLIREC	73.78
3	DLIREC	70.4
4	NRC-Can.	68.56
5	UNITOR	67.95
6	XRCE	67.24
7	SAP_RI	66.6
8	IITP	66.55
9	UNITOR	66.08
10	SeemGo	65.99
11	ECNU	65.88
12	SNAP	62.4

No.	Team	F1-score
13	Logic-2	62.01
14	DMIS	60.59
15	UWB	60.39
16	JU_CSE.	59.37
17	Isis_lif	56.97
17	USF	52.58
19	Blinov	52.07
20	UFAL	48.98
21	UBham	47.49
22	UBham	47.26
23	SINAI	45.28
24	EBDG	41.52

Logic 3: Conditional Random Fields(CRF)

CRF:

- A type of Discriminative classifier, and as such, they model the decision boundary between the different classes.
- We'll first need to decide on a set of feature functions ***fi***

Feature Functions in a CRF:

In a CRF, each **feature function** is a function that takes in as input:

- a sentence s
- the position i of a word in the sentence
- the label l_i of the current word
- the label l_{i-1} of the previous word

and outputs a real-valued number (though the numbers are often just either 0 or 1).

Logic 3: CRF

Features to Probabilities:

- Assign each feature function ***fj*** a weight ***λj.***
- Given a sentence **s**, we can now score a labeling ***l*** of ***s*** by adding up the weighted features over all words in the sentence:

$$score(l|s) = \sum_{j=1}^{m} \sum_{i=1}^{n} \lambda_j f_j(s, i, l_i, l_{i-1})$$

Finally, we can transform these scores into probabilities $p(l|s)$ between 0 and 1 by exponentiating and normalizing:

$$p(l|s) = \frac{exp[score(l|s)]}{\sum_{l'} exp[score(l'|s)]} = \frac{exp[\sum_{j=1}^{m} \sum_{i=1}^{n} \lambda_j f_j(s,i,l_i,l_{i-1})]}{\sum_{l'} exp[\sum_{j=1}^{m} \sum_{i=1}^{n} \lambda_j f_j(s,i,l'_i,l'_{i-1})]}$$

Logic 3: CRF

Learning Weights: Gradient descent

$\lambda_i = \lambda_i + \alpha[\sum_{j=1}^{m} f_i(s, j, l_j, l_{j-1}) - \sum_{l'} p(l'|s) \sum_{j=1}^{m} f_i(s, j, l'_j, l'_{j-1})]$ where α is some learning rate.

- First term in the gradient is the contribution of feature *fi* under the true label
- Second term in the gradient is the expected contribution of feature *fi* under the current model.

Features

Features list:

- Word
- POS tag
- Previous word
- Previous word POS tag
- Previous previous word
- Previous previous word POS tag
- Next word
- Next word POS tag
- Next next word
- Next next word POS tag
- Is first
- Is last
- Is capitalized
- Is all caps
- Is all lower
- prefix-1
- prefix-2
- prefix-3
- suffix-1
- suffix-2
- suffix-3
- Has hyphen
- Is numeric
- Capitals inside

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Logic-1	I	0.34	0.19	0.25
Logic-2	O	0.96	0.99	0.97
Logic-2	B	0.72	0.64	0.68
Logic-2	I	0.79	0.43	0.56
Logic-3	O	0.96	0.99	0.97
Logic-3	B	0.79	0.61	0.69
Logic-3	I	0.84	0.50	0.62

- **Logic-3 F1-score(macro avg.): 0.76**

Class I: Now recall and precision is good.

Class B: recall is good and precision also better then logic-2

Results: SemEval 2014 Task-4

No.	Team	F1-score
1	HIS_RD.	74.55
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3	DLIREC	70.4
4	NRC-Can.	68.56
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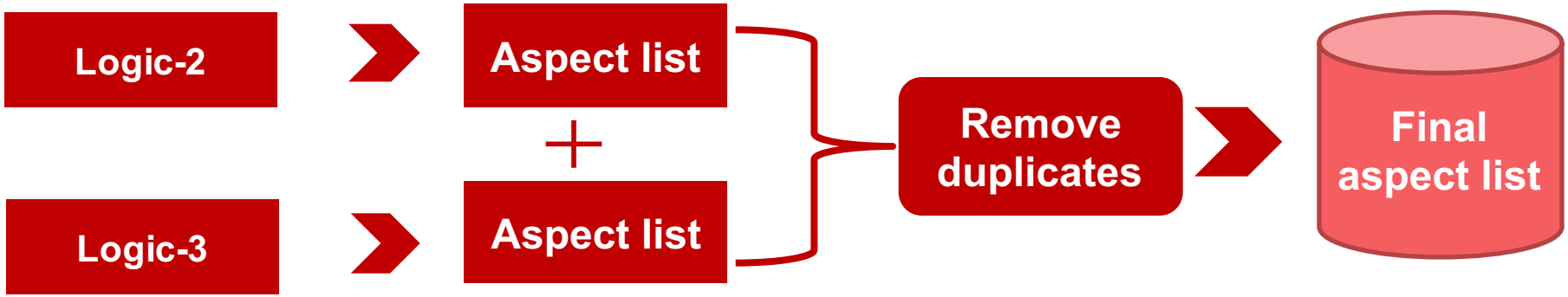
8	IITP	66.55
9	UNITOR	66.08
10	SeemGo	65.99
11	ECNU	65.88
12	SNAP	62.4

No.	Team	F1-score
13	Logic-2	62.01
14	Logic-3(crf)	61.51
15	DMIS	60.59
16	UWB	60.39
17	JU_CSE.	59.37
18	Isis_lif	56.97
19	USF	52.58
20	Blinov	52.07
21	UFAL	48.98
22	UBham	47.49
23	UBham	47.26
24	SINAI	45.28

Logic 4: Ensemble logic-2 and logic-3



Results: SemEval 2014 Task-4

No.	Team	F1-score
1	Logic-4	75.64
2	HIS_RD.	74.55
3	DLIREC	73.78
4	DLIREC	70.4
5	NRC-Can.	68.56
6	UNITOR	67.95
7	XRCE	67.24
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Features work: Rules based approach

1. **Syntactical relations:**
   - Can be improved further on by looking up more combined patterns and I have a gut feeling there are more combined patterns out there.
2. **Aspect term with multiple token:**
   - Yes, this part also we can improve by adding more POS tag pattern.
3. **Increase domain product aspects :**
   - WordNet.

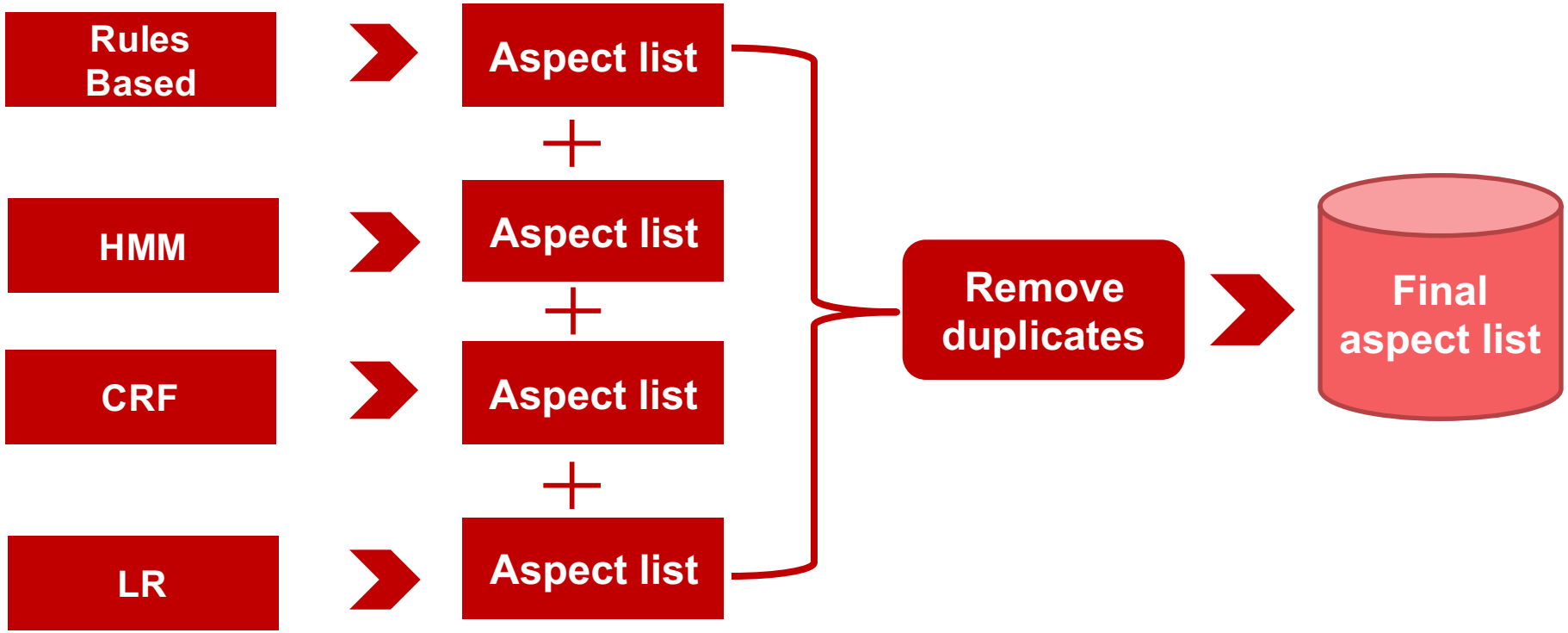
Features work: CRF

1. **More features:**

Word Feature:
Word token
Word lemma
Word part of speech
Previous word token, lemma, part of speech
Next word token, lemma, part of speech
Negation word appears in previous 4 words
Is superlative degree
Is comparative degree
Dictionary Feature
WordNet Synonym
WordNet Antonym
SentiWordNet Prior Polarity
Sentence Feature
Num of positive words in SentiWordNet
Num of negative words in SentiWordNet
Num of Negation word
Syntactic Features:
Parent word
Parent SentiWordnet Prior Polarity
In subject
In copular
In object
Edge Feature
Conjunction word
Syntactic relationship

- **CRF (Li et al. 2010)**

Features Workflow



- Bagging approach for supervised classifiers

Thank You