Modelling Public Sentiment in Twitter:

Using Linguistic Patterns to Enhance Supervised Learning

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The Task

Polarity classification of tweets

- POSITIVE vs. NEGATIVE

Hasn't this already been done before?

Most current methods ignore some very important challenges!

Challenge 1: Linguistic Patterns

Most current methods:

- "One-size-fits-all" approach
  - E.g.: Word N-grams, etc.

Issues with Linguistic Patterns:

Examples	Human	N-grams
The prose is short, but nice.	POS	POS/ NEG
The prose is nice, but short.	NEG	POS/ NEG

Challenge 1: Linguistic Patterns

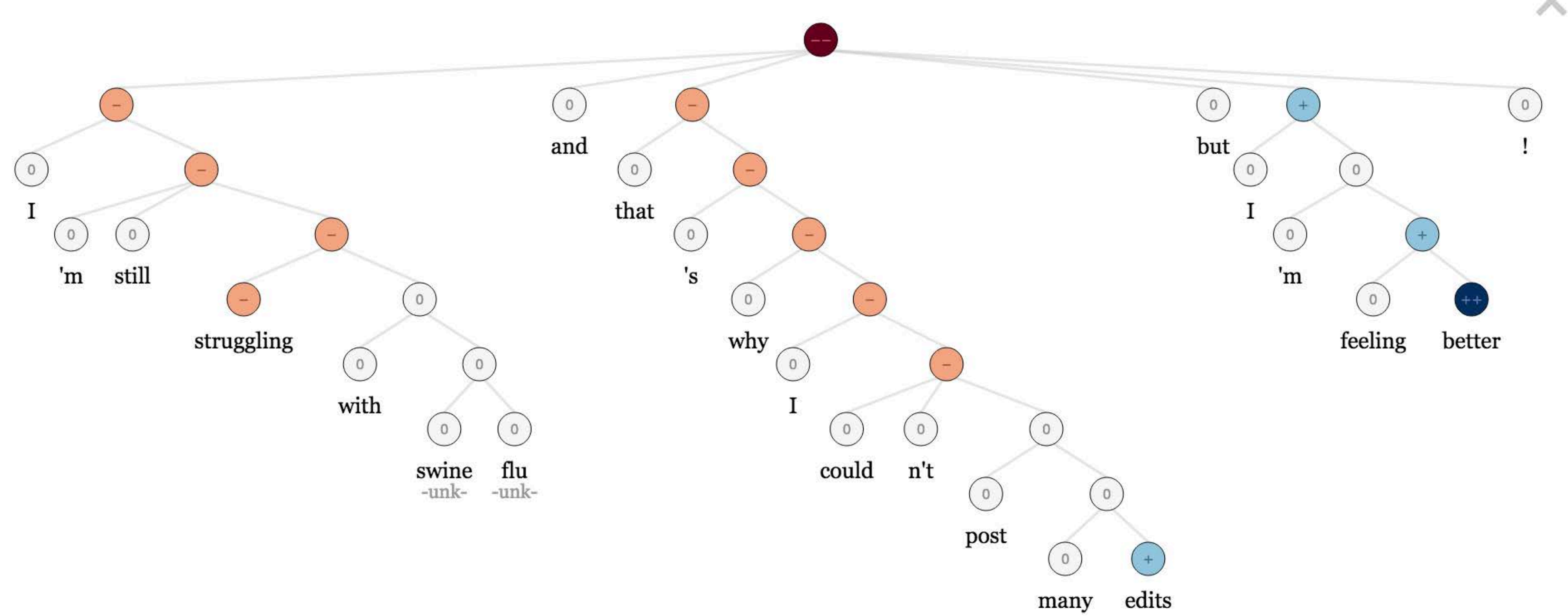
Stanford

- Deep learning, parse trees for sentences
- Tweets
  - Bad punctuation, long sentences, …
  - Doesn’t work for tweets!

I’m still struggling with swine flu and that’s why I couldn’t post many edits but I’m feeling better!

Human: POS

Challenge 1: Linguistic Patterns

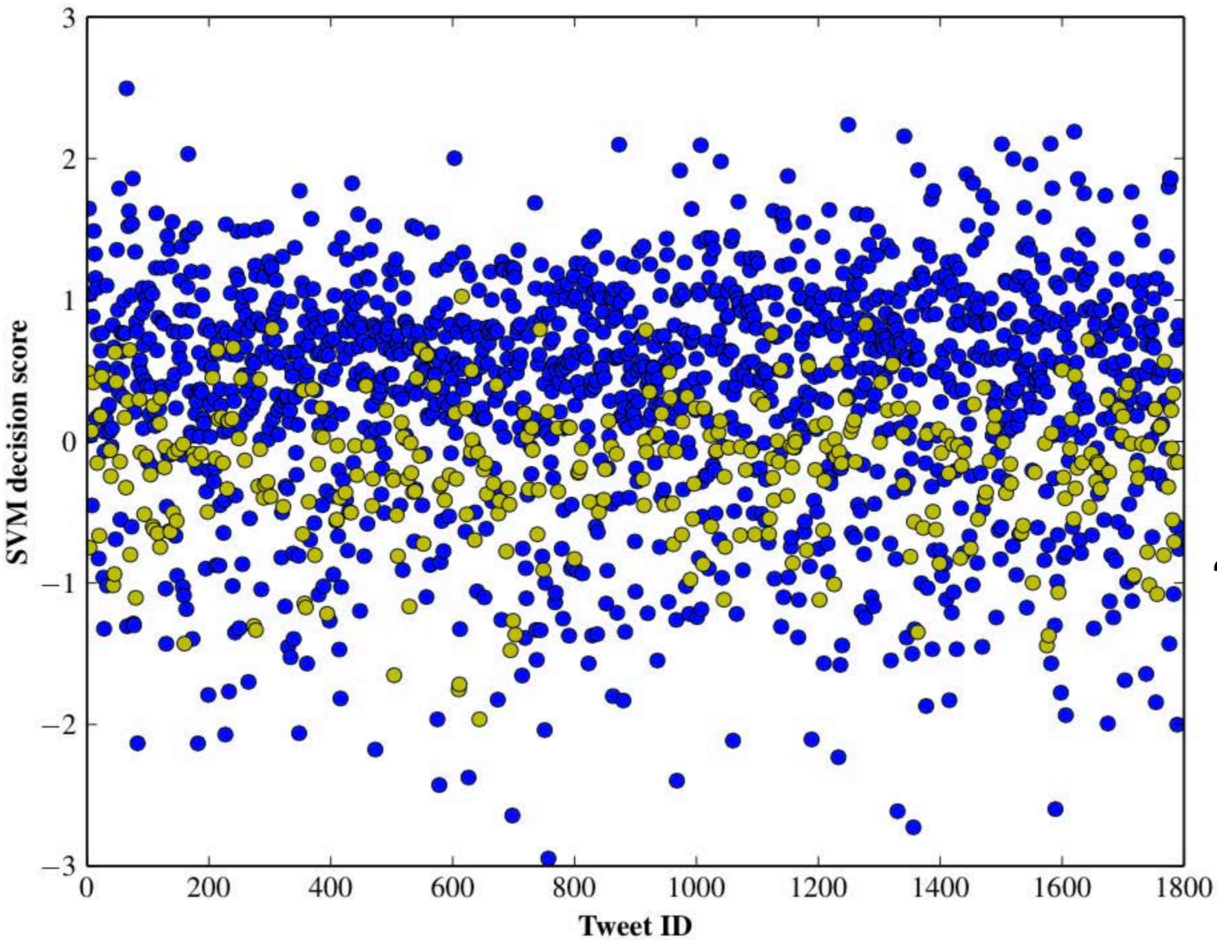


Stanford "Deep Learning for Sentiment Analysis" demo

Very Negative instead of Positive!

Socher, R., Perelygin, A., Wu, J. Y., Chuang, J., Manning, C. D., Ng, A. Y., & Potts, C. (2013, October). Recursive deep models for semantic compositionality over a sentiment treebank. In Proceedings of the conference on empirical methods in natural language processing (EMNLP) (Vol. 1631, p. 1642).

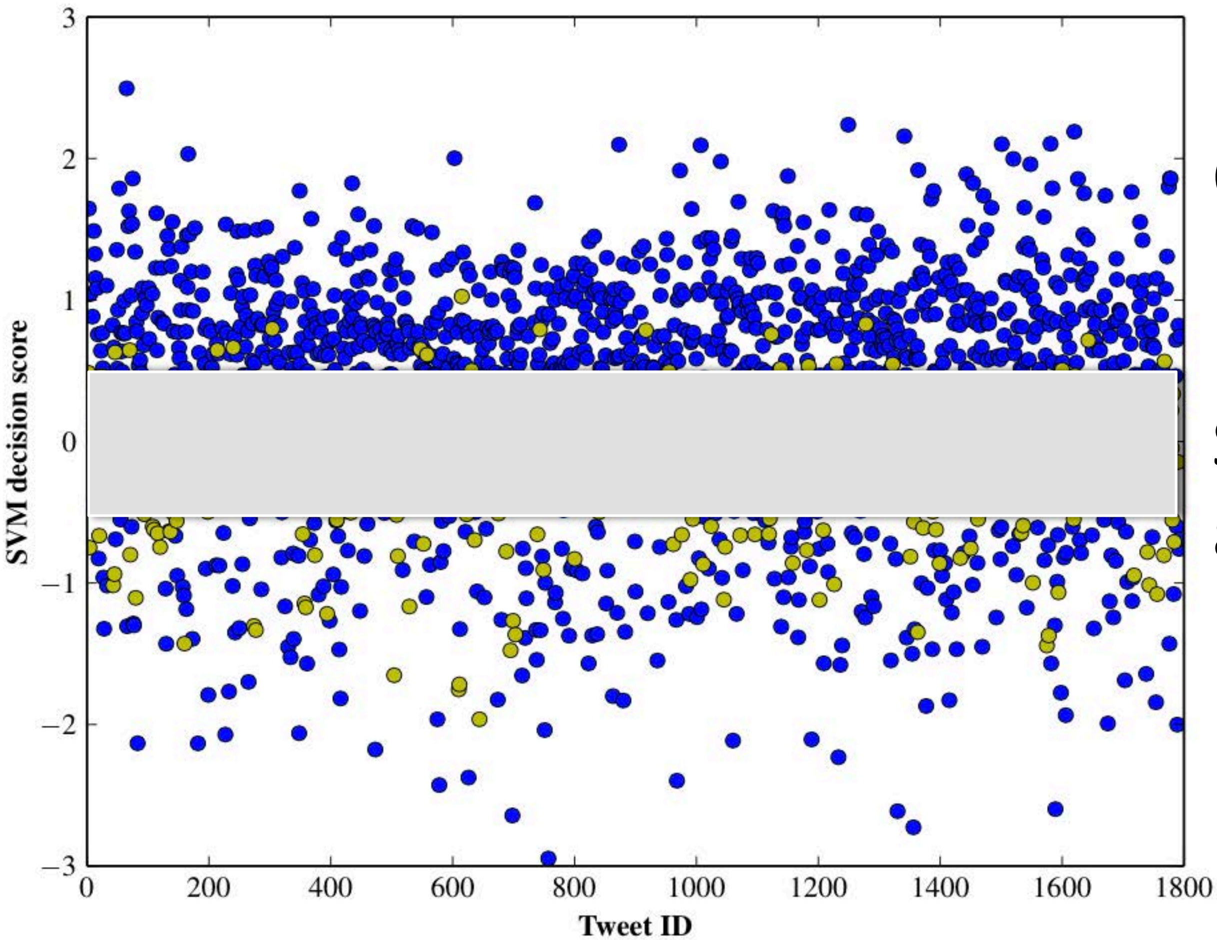
Challenge 2: SVM Decision Score



~19% misclassified

Most misclassifications occur between -0.5 and +0.5.

Challenge 2: SVM Decision Score



Only ~9.4% misclassified

So, > 90% are correct

Excluding, right or wrong, between -0.5 and +0.5.

So, we propose…

Low decision score from SVM

↓

Apply unsupervised rules

↓

Verify or change SVM label

Challenge 3: Unsupervised Polarity

Based on positive and negative *words*…

But, is bag-of-words a good representation?

Challenge 3: Unsupervised Polarity

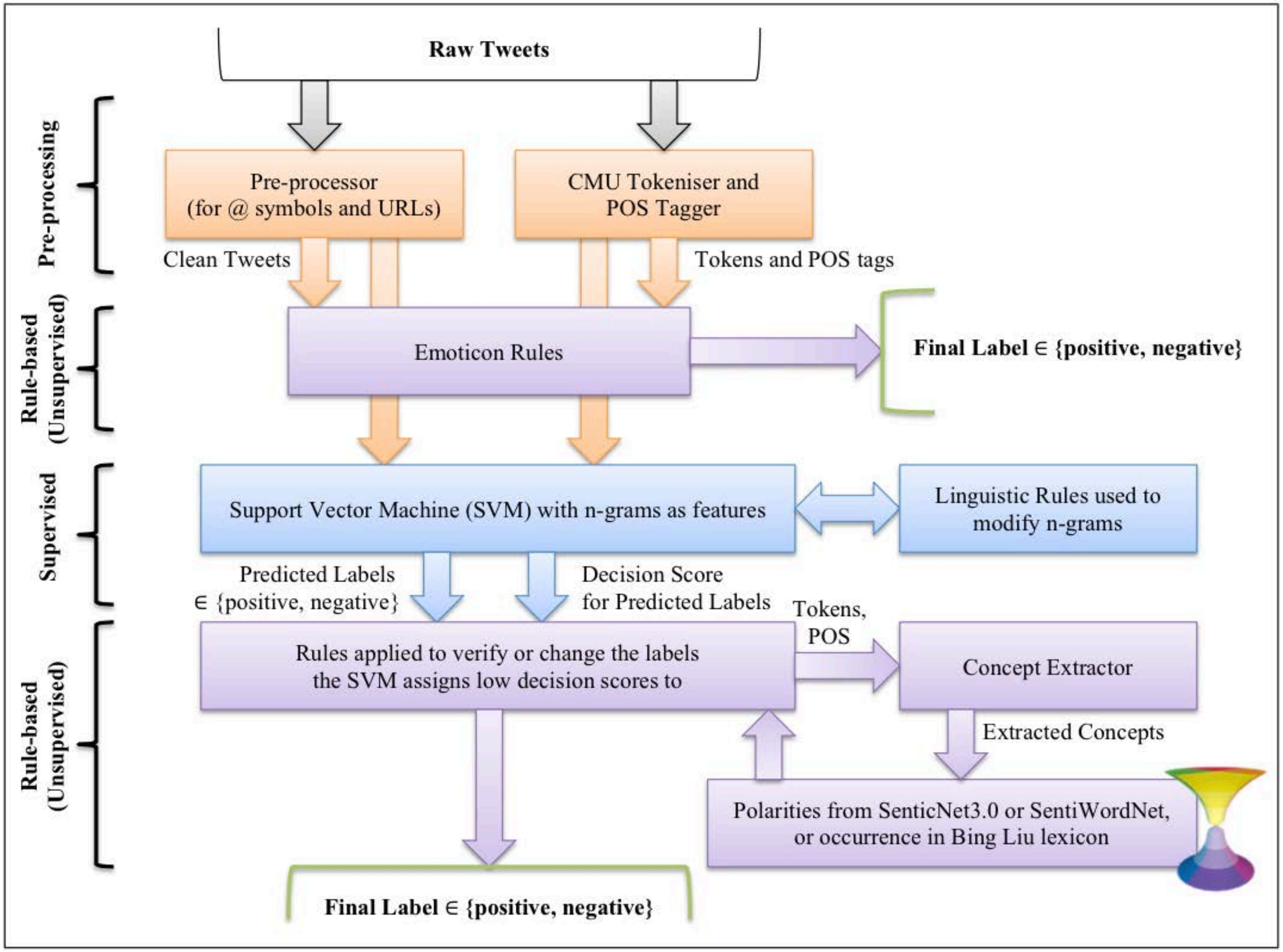
Polarity("prevent accident") !=
Polarity("prevent") + Polarity("accident")

Polarity("pocket money") !=

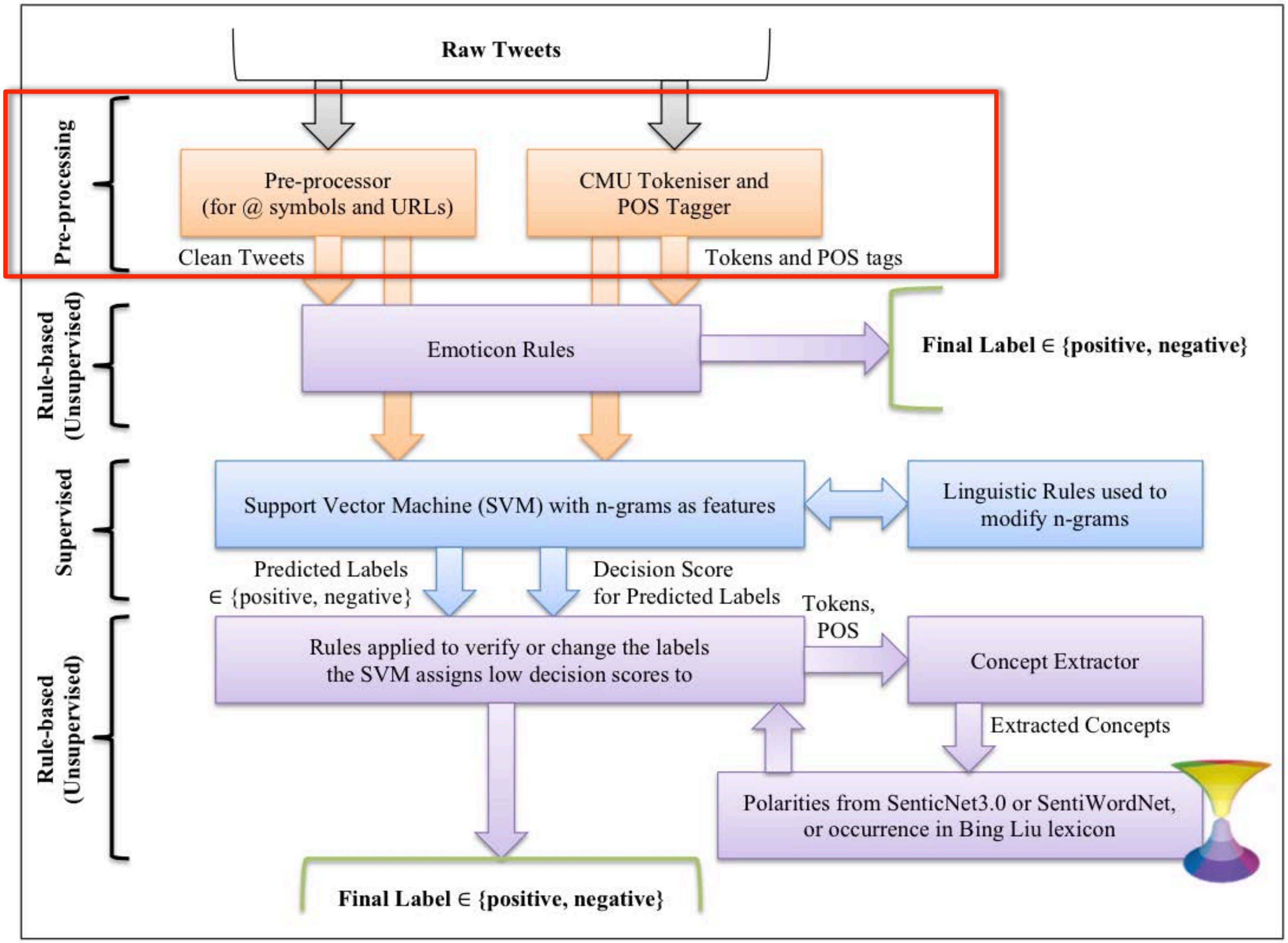
Polarity("pocket") + Polarity("money")

Lets use concepts!

System Overview



System Overview



Pre-processing

Normalization:

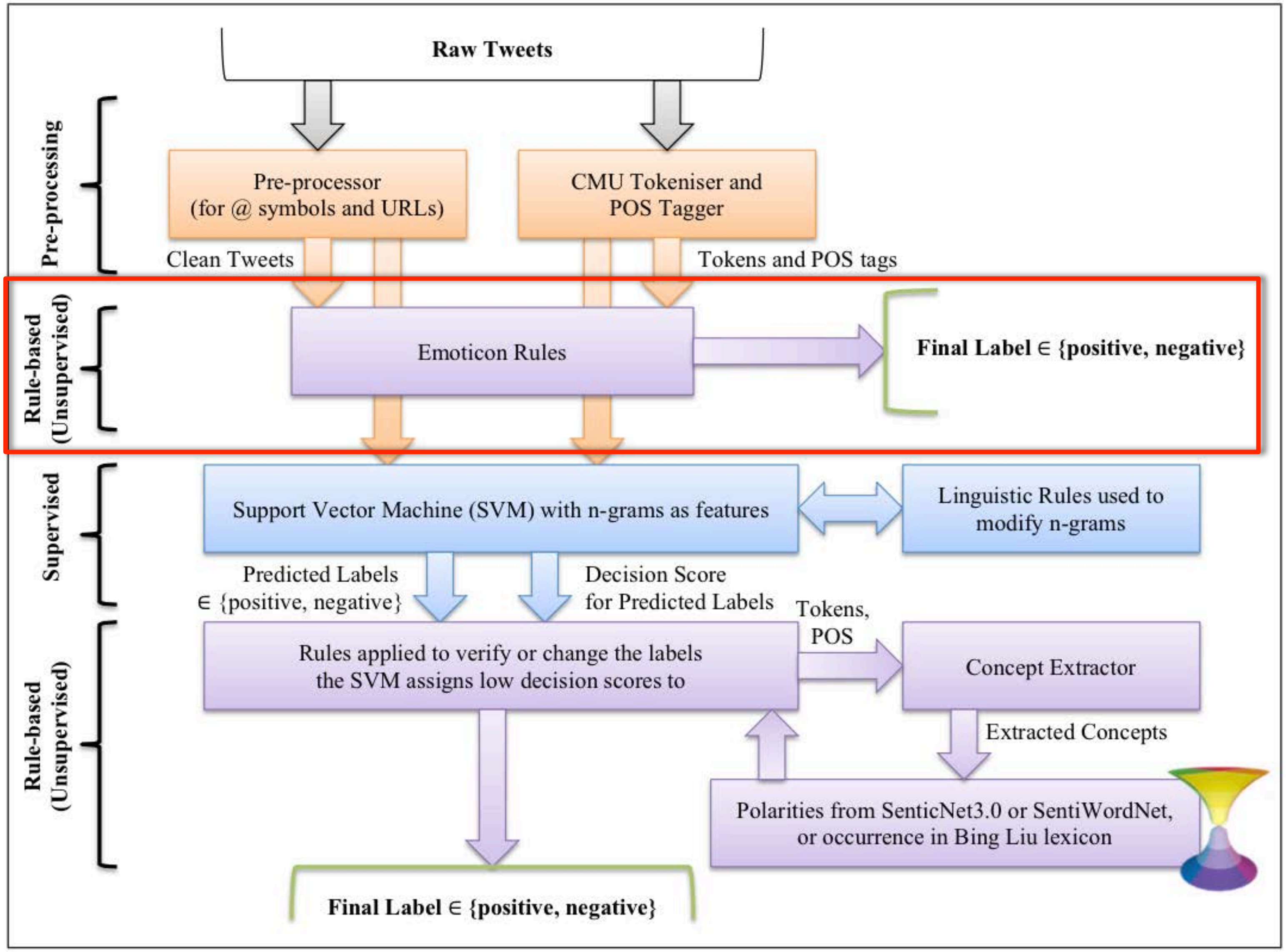
- @<username> → @USER
- URLs → http://URL.com

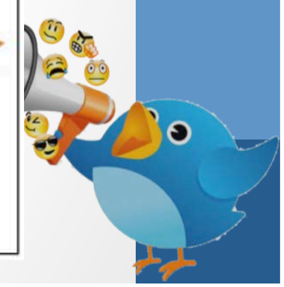
Negation:

- Tokens between negation word and next punctuation mark => appended with “_NEG”.
- Negation words: e.g. never, no, don’t, none, etc.

CMU Twitter Tokenizer and POS Tagger

System Overview





Emoticon Rules

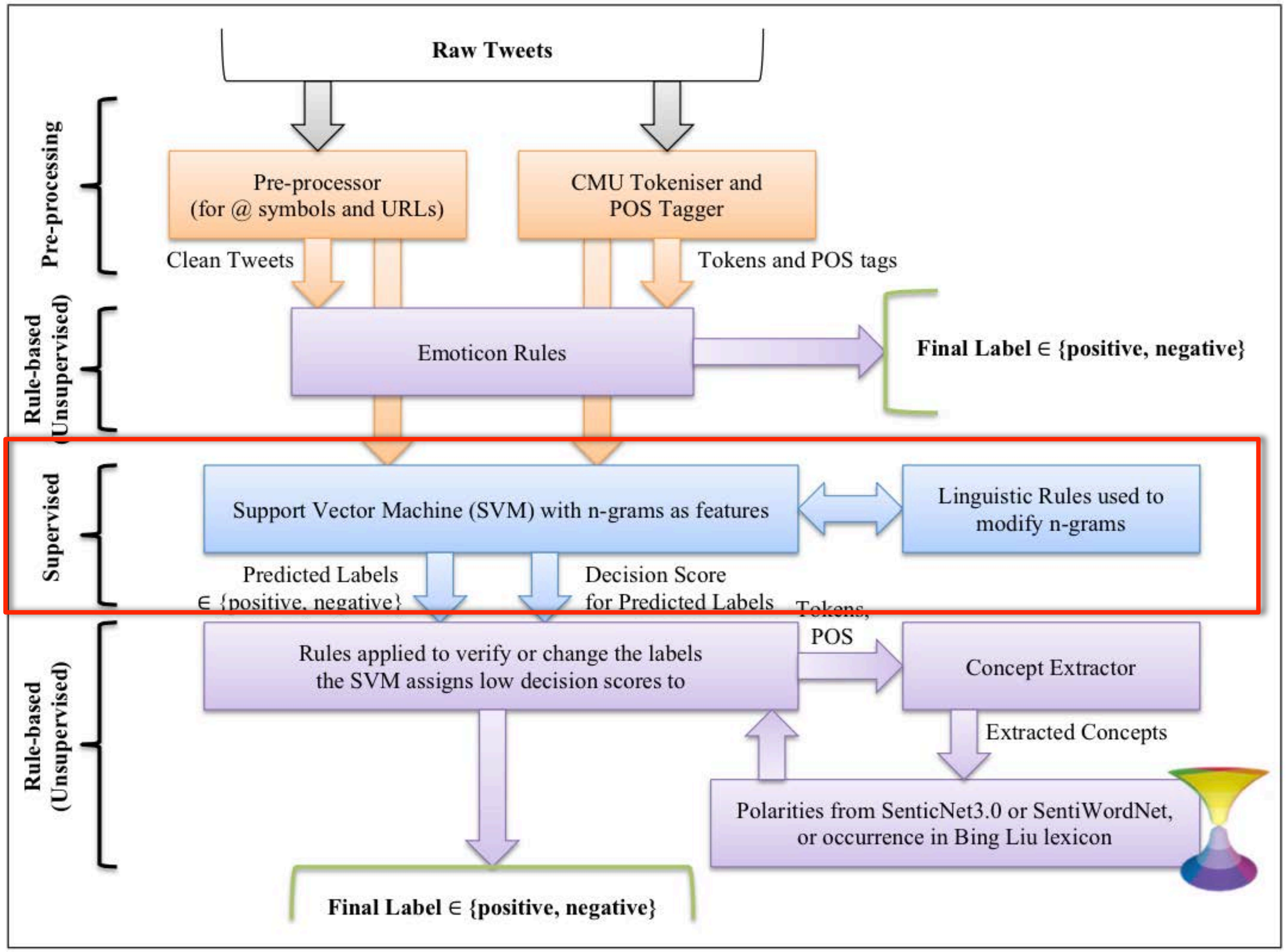
If a tweet contains a simple POS or NEG emoticon, the final label is assigned using emoticon rules.

POS :), :D, ^_^, etc

NEG :(, :’(, </3, etc

Ignore ;), :O, etc => ambiguous sentiment

System Overview



Modifying n-grams using Linguistic Patterns

“But” conjunction rules:

Most are of the form,

You didn’t win ABC but <u>you won over my heart.</u> You may not know but <u>you are quite good.</u>

Salient part => after “but” kept

Everything else removed

Modifying n-grams using Linguistic Patterns

You didn't win ABC but you won over my heart. You may not know but you are quite good.

Becomes

you won over my heart. you are quite good.

Modifying n-grams using Linguistic Patterns

Conditional rules:

For “if”, “in case”, “until”, and “unless”:

- Remove the conditional clause
- Consequent clause remains

May not always work… but works for most cases.

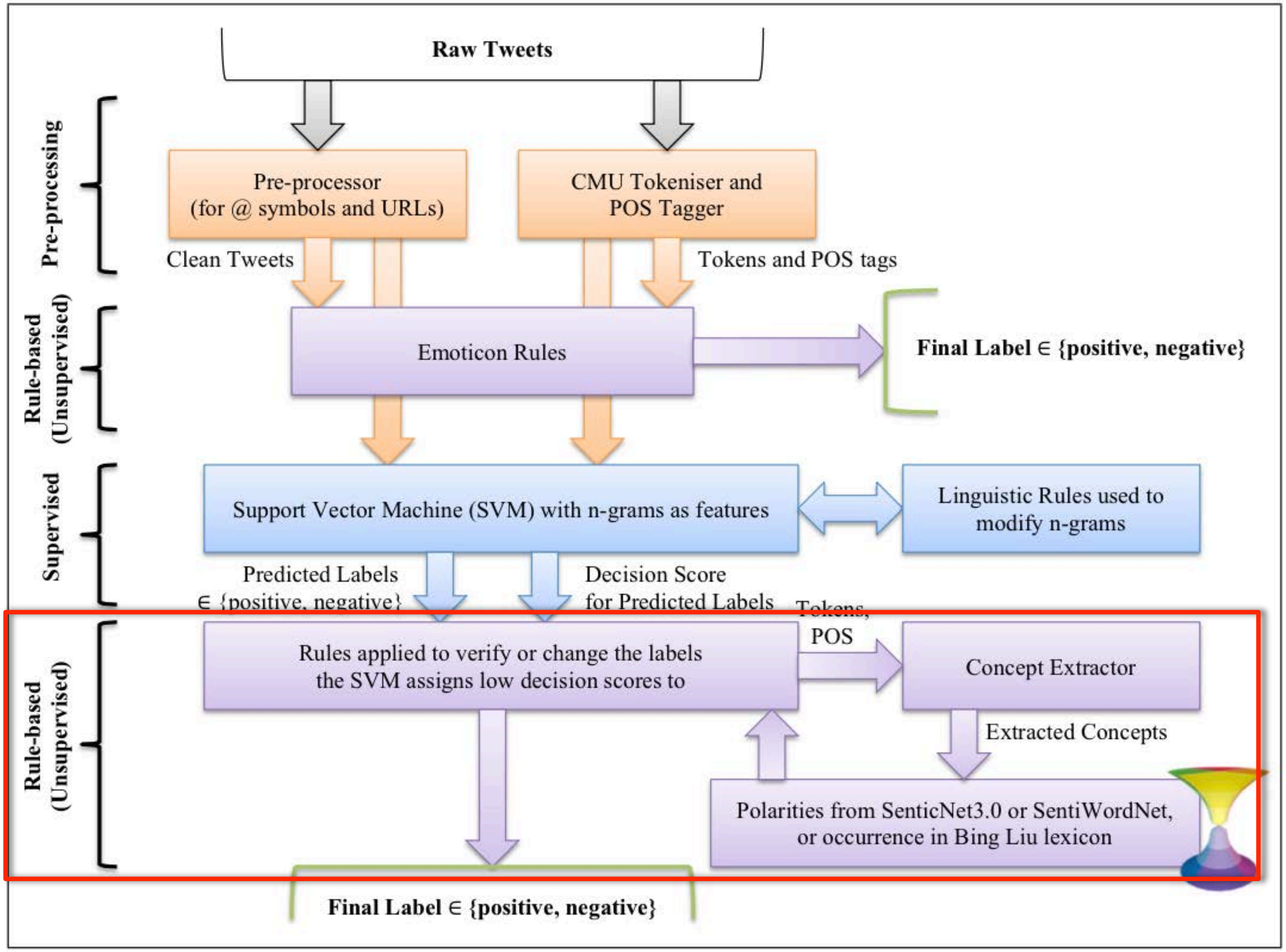
Modifying n-grams using Linguistic Patterns

If you work hard, <u>you will get good grades.</u>

Becomes:

you will get good grades.

System Overview



Tweaking SVM Predictions using Linguistic Rules and Sentic Computing

Decision score between -0.5 and +0.5

=> Unsupervised rules are applied

What are these rules?

Tweaking SVM Predictions using Linguistic Rules and Sentic Computing

1. Extract concepts from tweets

   Concepts = single-word + multi-word

Single-word Concept Extraction:

a) Remove stop words

b) All single-words left are concepts

Tweaking SVM Predictions using Linguistic Rules and Sentic Computing

Multi-word Concept Extraction:

a) Remove stopwords

b) Adjacent tokens with tags:

<N N>, <N V>, <V N>, <A N>, <R N>, <P, N>, <P V>

E.g.:

RT @USER what a beautiful day what a beautiful life http://URL.com

⇒“beautiful”, “day”, “life”,
“beautiful day”, “beautiful life”, …

Tweaking SVM Predictions using Linguistic Rules and Sentic Computing

Query concepts in **SenticNet**.

Not found => SentiWordNet.

Not found => Bing Liu lexicon.

If #positive concepts > #negative concepts and max positive polarity is > +0.6 => POS

If #negative concepts > #positive concepts and max negative polarity is < -0.6 => NEG

Results

Trained supervised classifier on ~1.6 million positive and negative tweets.

Evaluated on 2 publicly available datasets:

SemEval 2013 Test Data

SemEval 2014 Test Data

(ignored “neutral” tweets)

Results (SemEval 2013)

Method	F_{avg}
N-grams (uni+bi+tri)	77.43
N-grams and Emoticon Rules	78.00
Modified N-grams	77.70
Modified N-grams, and Emoticon Rules	78.27
Modified N-grams, Emoticon Rules, and Word-level Unsupervised Rules	80.98
Modified N-grams, Emoticon Rules, and Concept-level Unsupervised Rules	81.90

SemEval 2013 – 1794 tweets

Overall, 4.47 units increase

Results (SemEval 2014)

Method	F_{avg}
N-grams (uni+bi+tri)	76.69
N-grams and Emoticon Rules	77.19
Modified N-grams	76.73
Modified N-grams, and Emoticon Rules	77.21
Modified N-grams, Emoticon Rules, and Word-level Unsupervised Rules	79.64
Modified N-grams, Emoticon Rules, and Concept-level Unsupervised Rules	79.81

SemEval 2014 – 3584 tweets

Overall, 3.12 units increase

Results (Online System)

Manually annotated 1000 tweets

F_{avg} = 78.82

Conclusion

- Unsupervised emoticon rules and modified n-grams for supervised learning

  => Handle special linguistic characteristics

- Verifying of changing low-confidence predictions of SVM using a secondary rule-based classifier

  => Helps improve results also

Future Work

- Linguistic rules:
  - Works for majority of tweets
  - Can define more complex rules.
    for other conjunctions and conditionals,
    modal verbs, modifiers, etc.
- Unsupervised rule-based classifier:
  - Expanding commonsense KBs like SenticNet
- Subjectivity detection
- Spam removal from online system using social features of tweets.

Any questions?

SemEval 2013

Method	Positive			Negative			Average		
	P	R	F	P	R	F	P	R	F
N-grams	90.48	82.67	86.40	61.98	76.45	68.46	76.23	79.56	77.43
N-grams and Emoticon Rules	90.62	83.36	86.84	62.99	76.65	69.15	76.80	80.00	78.00
Modified N-grams	89.95	84.05	86.90	63.33	74.59	68.50	76.64	79.32	77.70
Modified N-grams, and Emoticon Rules	90.10	84.73	87.33	64.41	74.79	69.22	77.26	79.76	78.27
Modified N-grams, Emoticon Rules, and Word-level Unsupervised Rules	91.40	86.79	89.04	68.55	77.89	72.92	79.97	82.34	80.98
Modified N-grams, Emoticon Rules, and Concept-level Unsupervised Rules	92.42	86.56	89.40	68.96	80.79	74.41	80.69	83.68	81.90

Table 2. Results obtained on 1794 positive/negative tweets from the SemEval 2013 dataset.

SemEval 2014

Method	Positive			Negative			Average		
	P	R	F	P	R	F	P	R	F
N-grams	89.92	81.90	85.72	61.20	75.66	67.67	75.56	78.78	76.69
N-grams and Emoticon Rules	89.74	83.05	86.27	62.50	74.85	68.11	76.12	78.95	77.19
Modified N-grams	89.39	82.90	86.02	62.00	73.93	67.44	75.69	78.41	76.73
Modified N-grams, and Emoticon Rules	89.25	83.97	86.53	63.29	73.22	67.89	76.27	78.60	77.21
Modified N-grams, Emoticon Rules, and Word-level Unsupervised Rules	90.22	86.24	88.19	67.37	75.25	71.09	78.80	80.75	79.64
Modified N-grams, Emoticon Rules, and Concept-level Unsupervised Rules	90.41	86.20	88.25	67.45	75.76	71.37	78.93	80.98	79.81

Table 3. Results obtained on 3584 positive/negative tweets from the SemEval 2014 dataset.