



# Informal sentiment analysis in multiple domains for English and Spanish

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# Introduction - sentiment analysis

- Computational study of opinions, sentiment, evaluations, attitudes, views, emotions, subjectivity, etc. in text
- Also known as ‘opinion mining’





# Motivation

- “Opinions” are important influencers of human behavior:
- To a large extent, our perception of reality is condition on how others see the world
- When we are making decisions, we often look for opinions of others





# Domains

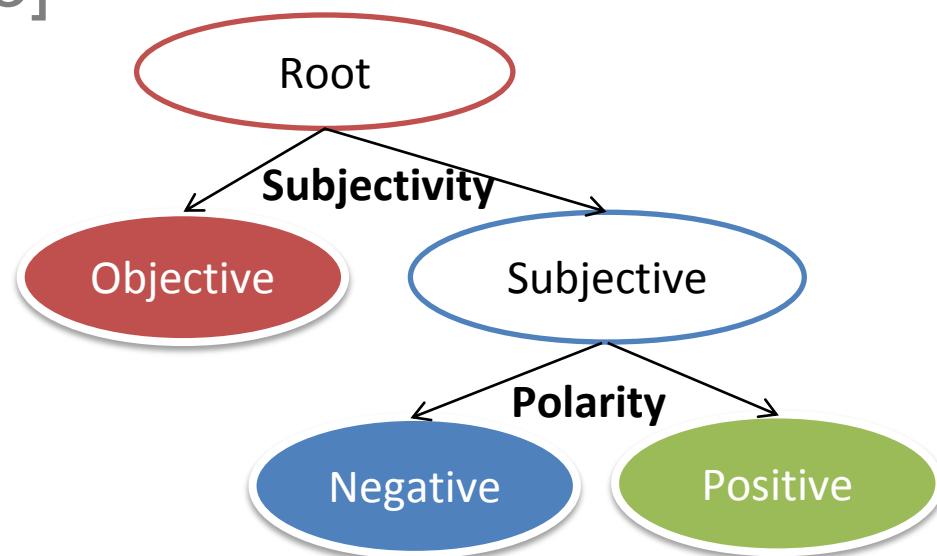
- Where can we find these opinions?
  - On the web, via word of mouth
    - Social media
    - Product, movie reviews
  - News
  - Internal data (customer feedback)
- Do different domains exhibit different properties?





# Related work

- Early work focused on predicting movie review polarity as a text mining task [Pang & Lee, 2004]
  - Only positive vs. negative
- In some domains, separating subjective from objective is an important subproblem [Wiebe & Riloff, 2005]





## Related work

- An interesting ground for testing various machine learning approaches, such as domain adaptation [Mejova & Srinivasan, 2012] or deep learning [Glorot et al, 2011].
- Integration of external and domain knowledge using sentiment lexicons
  - SentiWordNet [Esuli & Sebastiani, 2006]
  - SenticNet [Cambria et al., 2012]





# Problem formulation

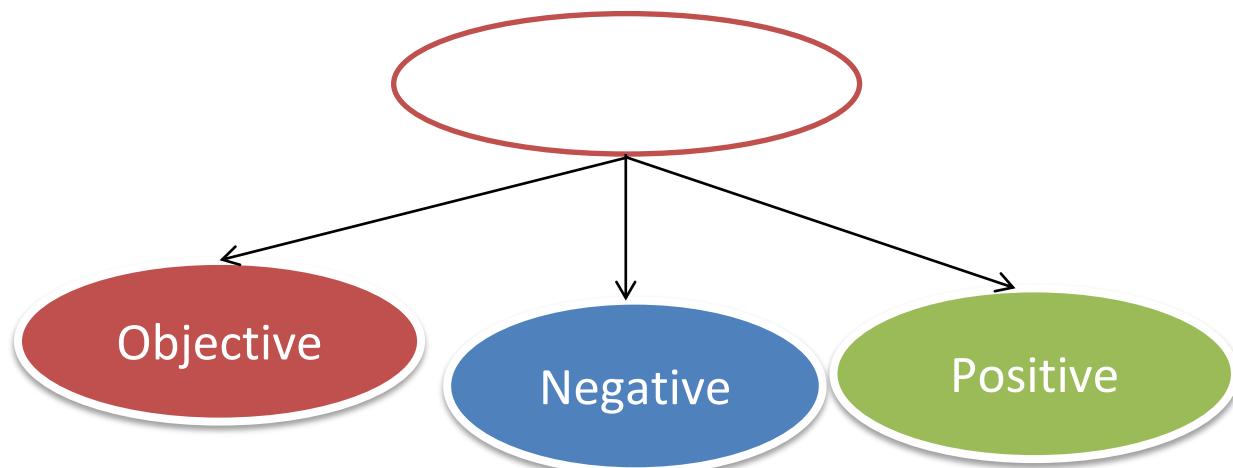
- General definition of opinion:
  - Opinion =  
(Holder, Target, Aspect, Orientation, Time)
- Some of these can be interesting sub-problems:
  - **Holder, Target** - named entity extraction
  - **Aspect** – target property extraction
  - **Orientation** – what is the strength and orientation of the opinion, if any (positive, negative, objective)?





# Problem formulation

- This work focuses mainly on **orientation**, determining whether the opinion is positive, negative or objective





# Goals

- Do external sources of information increase performance?
- What is the best way to model this additional knowledge?
- Which lexicon resources work best?
- What are the differences across domains and languages?





# Data description

- 5 datasets (2 Spanish, 3 English)

Dataset	Domain	Language	Size
JRC-ES [Balahur et al. 2010]	news	Spanish (translated from english)	1281 examples (pos, neg, obj)
RenderES	social media	Spanish	891 examples (pos, neg, obj)
PangLee [Pang and Lee, 2002]	reviews	English	2000 examples (pos, neg)
JRC-EN [Balahur et al. 2010]	news	English	1281 examples (pos, neg, obj)
RenderEN	social media	English	134 examples (pos, neg)





# Feature representation

- Three main sources of knowledge:
  - Content
    - counting preprocessed word tokens
  - Sentiment lexicons
    - is there a global sentiment score assigned to a particular word?
  - Surface patterns
    - How is the text phrased, written, expressed?





# Content features

- Goal: bag of words representation
- Preprocessing steps:
  - Tokenization (preserving punctuation)
  - Target masking
  - Number masking
  - URL masking
  - Lower-casing
  - ASCII-normalization
  - Stopword filtering
  - Stemming
  - TF-IDF weighing





# Lexicon features

- Sentiment lexicons have a numerical score attached to each word
- We calculate:
  - Sum of scores
  - Sum of absolute scores
  - Ratio of positive to negative words
  - + all of the above for every simplified part of speech – noun, verb, adjective, adverb





# Lexicons

- Existing resources
  - SentiWordNet (en) [Esuli and Sebastian, 2006]
  - SenticNet (en) [Cambria et al., 2012]
  - UNTFull, UNTMedium (es) [Perez-Rosas et al. 2012]
- Novel resources: developed using a bootstrapping approach and a corpus of text
  - RenderLex (es, en)
  - RenderLexLinks (en)
    - Also contains the positive and negative link counts – the positive link count is the number of times a word co-occurs with a positive word, or is contrasted with a negative word.





# Features (surface)

- count of fully capitalized words
- character
- count of question-indicating words
- proportion of capital letters
- count of words that start with a capital letter
- proportion of vowels
- count of repeated exclamation marks
- count of negation words
- count of repeated same vowel
- count of contrast words
- count of repeated same punctuation
- count of profanity words

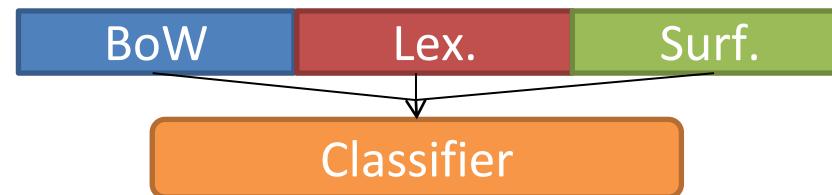




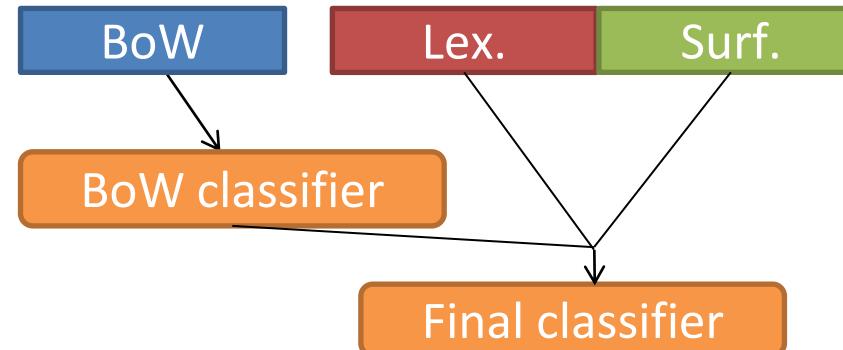
# Modeling hypotheses

- Given the different distribution properties of the BoW space, should we separate the model?

**Concatenation model:**



**Two-layer words-features (W+F) model:**





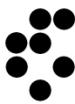
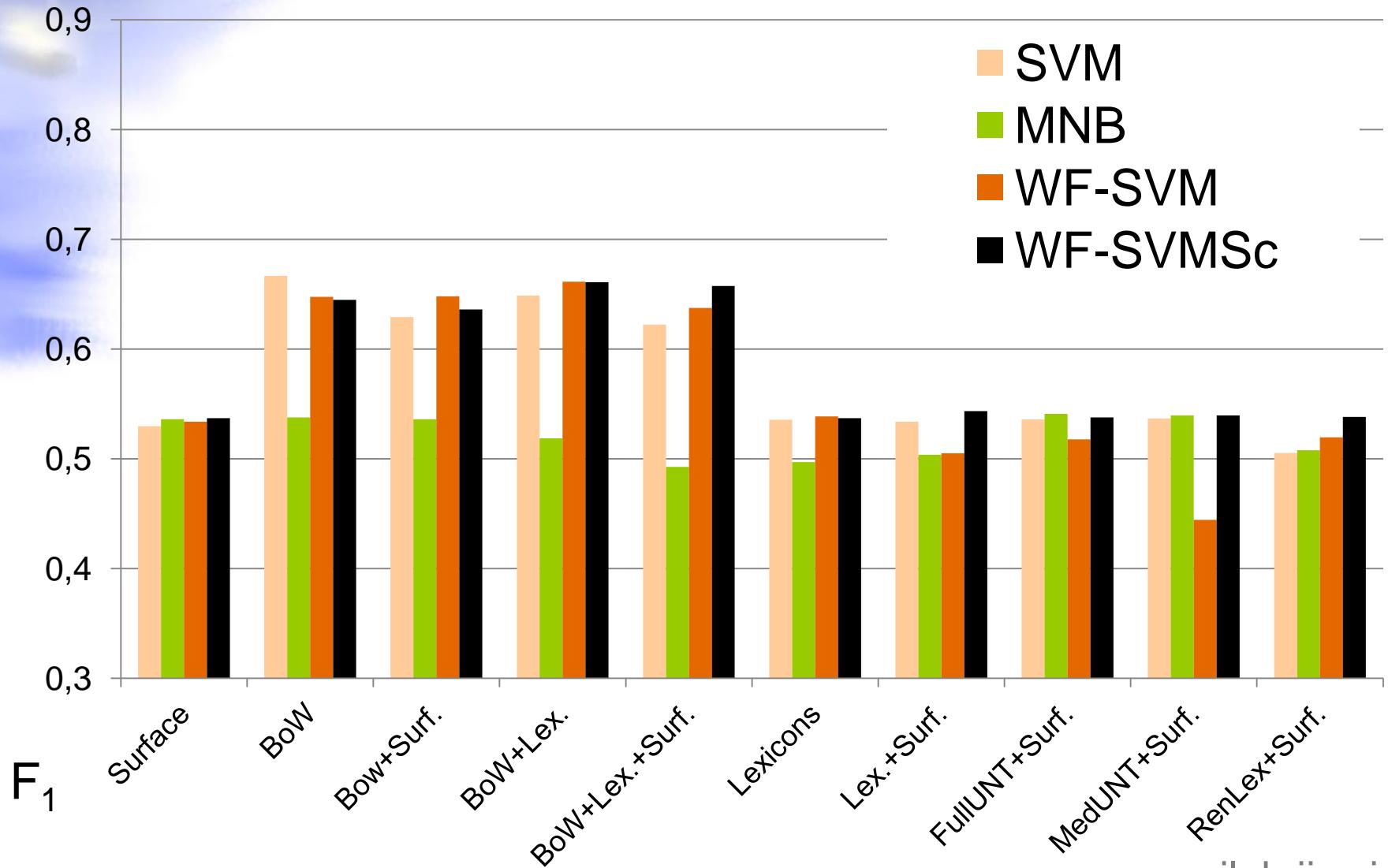
# Experimental setup

- Varying feature representation:
  - Combinations of Surface, Lexicon, BoW
- Model combinations:
  - Two-layer [W+F-\*] vs concatenation
  - FeatureScaling [\*Sc]



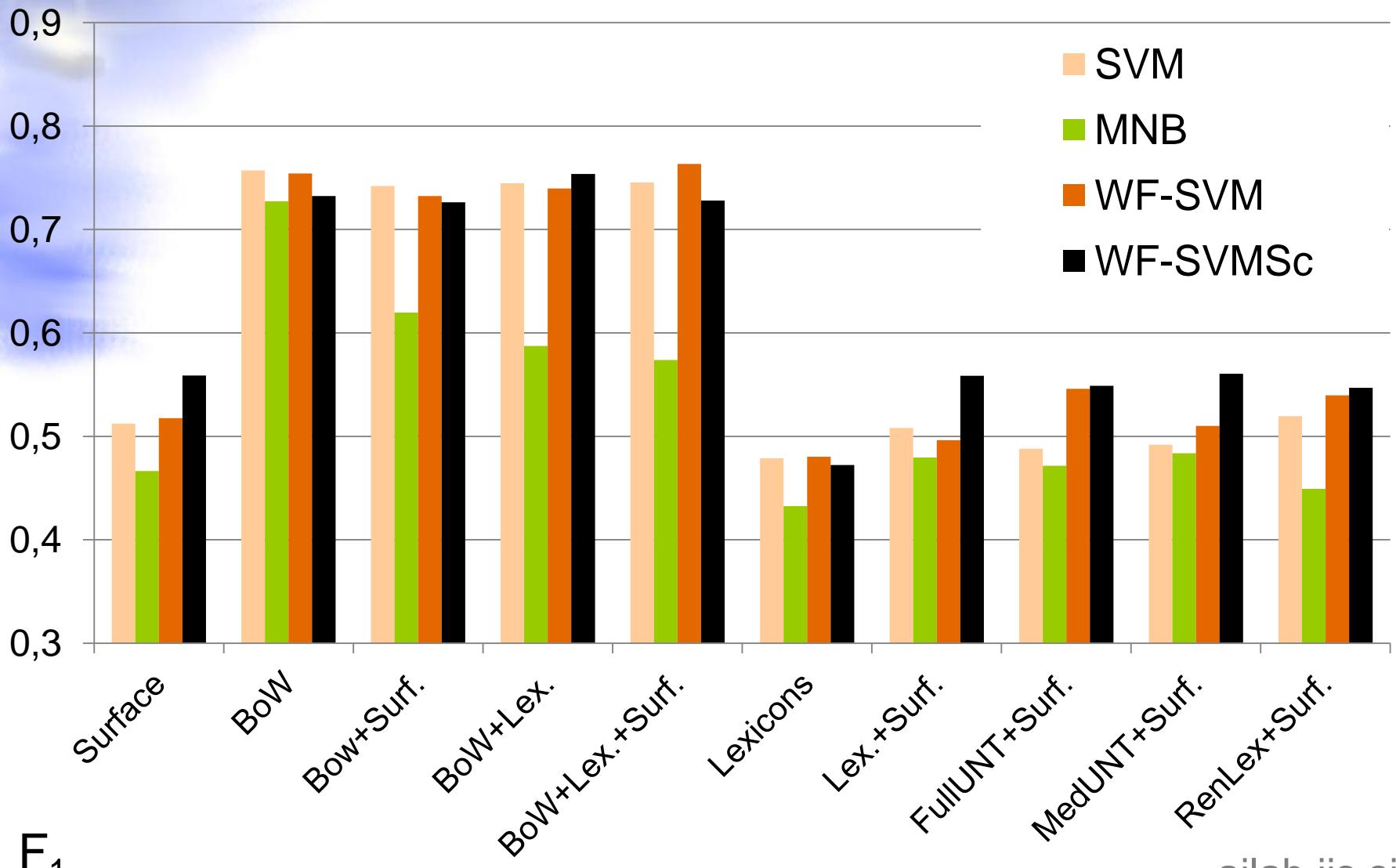


# Results on JRC-ES





# Results on RenderES





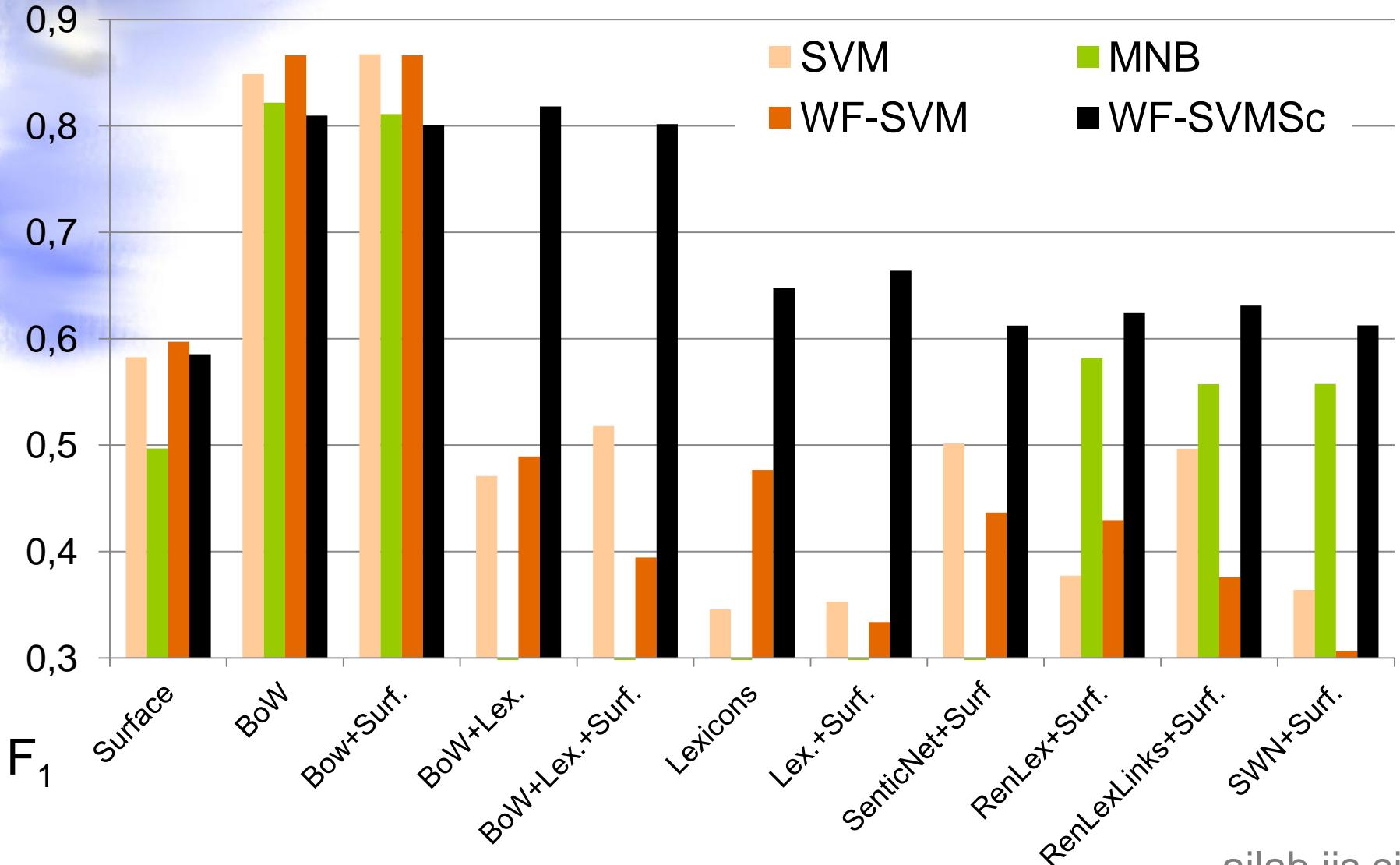
# Results on Spanish data

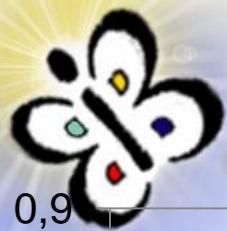
- News domain: no improvement over the SVM BoW baseline.
- Social media: W+F-SVMSc with BoW+L+S significantly outperforms the SVM BoW baseline.



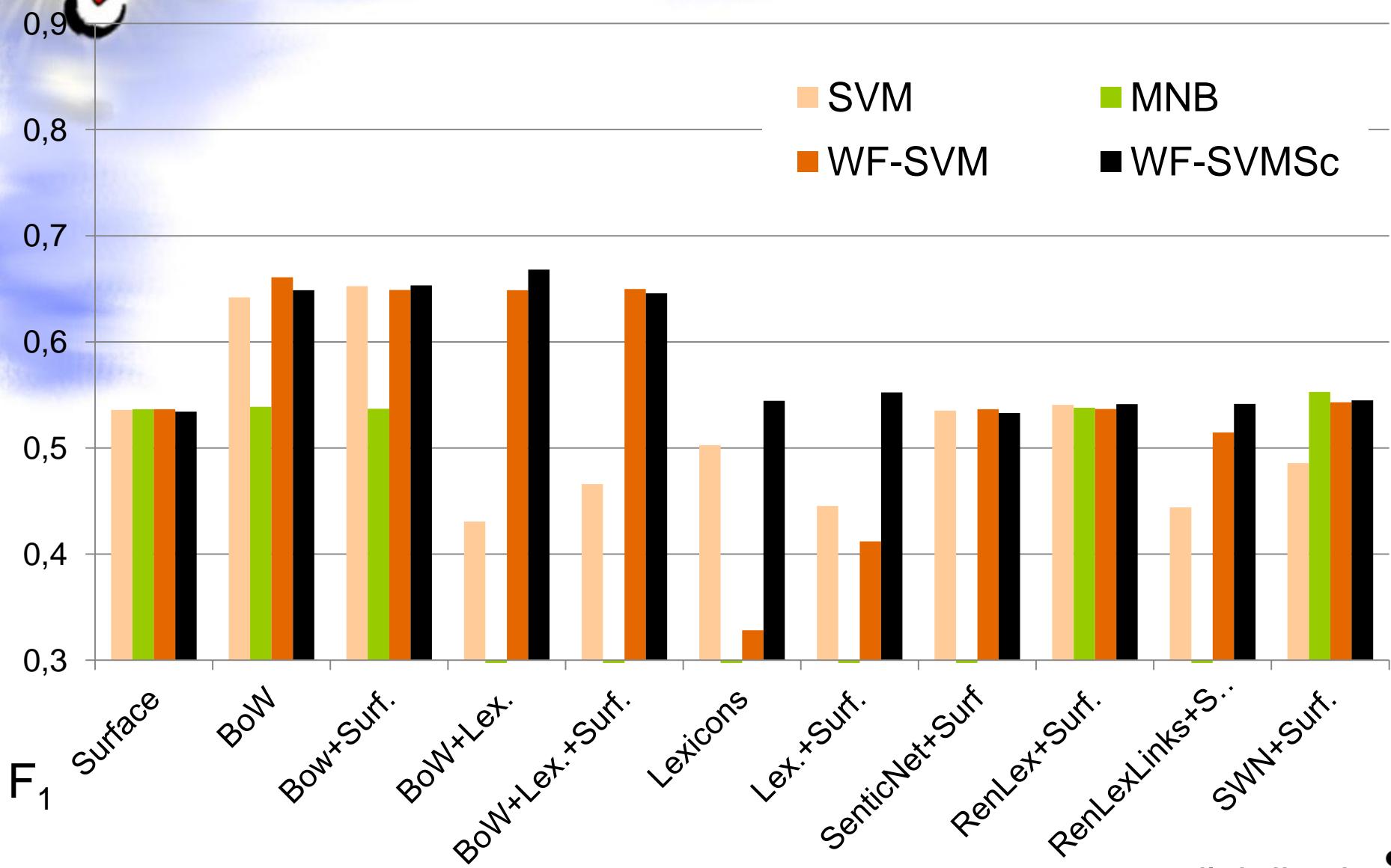


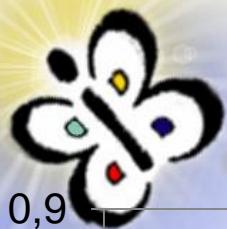
# Results on PangLee



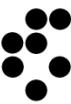
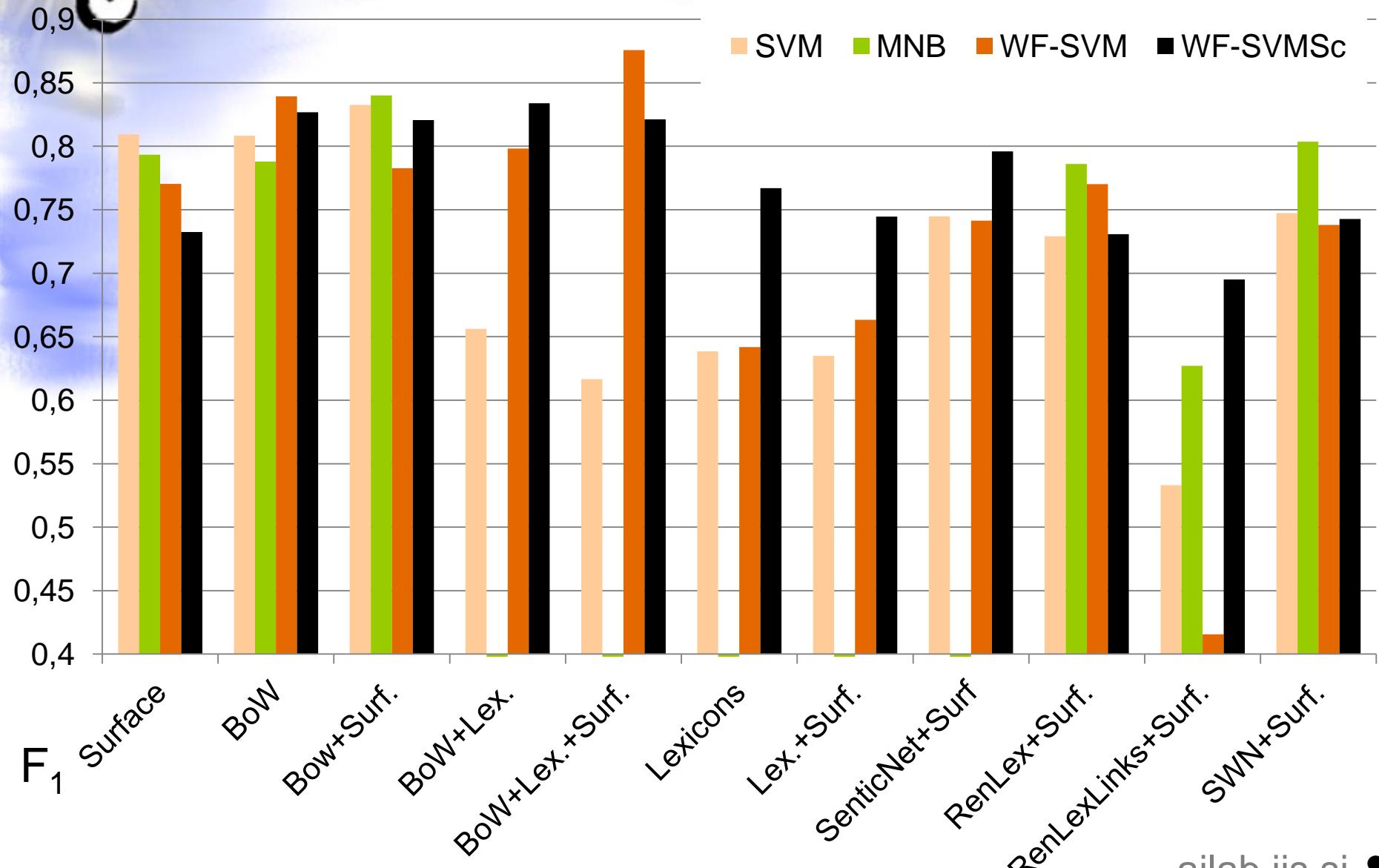


# Results on JRC-EN





# Results on RenderEN





# Results on English datasets

- On reviews, none of the additions beat the baseline.
- On news data, two-layer models help a lot, especially with surface features
- On social media, adding lexicons and surface feature helps a lot, especially in two-layer models (W+F-SVMSc)
- No benefit from using positive/negative link counts





# Model analysis [JRC-ES]

```
full_unt_pos > 0.0
+--yes: [OBJ] [88.0]: 161
+--no: renderlex_noun_sum_neg > 0.0
    +--yes: [SUBJ/NEG] [4.0]: 4
    +--no: numcaps > 0.0386
        +--yes: renderlex_adjective_abs > 0.4069
            |    +--yes: h1w5 > 0.0312
            |    |    +--yes: [SUBJ/POS] [4.0]: 5
            |    |    +--no: [OBJ] [5.0]: 6
            |    +--no: renderlex_all_sum > 3.866
                +--yes: [OBJ] [21.0]: 32
                +--no: h1w5 > 0.0833
                    +--yes: [OBJ] [10.0]: 17
                    +--no: full_unt_neg > 0.0
                        +--yes: [OBJ] [4.0]: 8
                        +--no: repeat_vowel > 0.0244
                            +--yes: [SUBJ/POS] [2.0]: 4
                            +--no: numvowel > 0.3429
                                +--yes: [OBJ] [113.0]: 129
                                +--no: renderlex_all_abs > 2.1249
                                    +--yes: renderlex_all_sum > 2.7152
                                        |    +--yes: [OBJ] [14.0]: 16
                                        |    +--no: [SUBJ/NEG] [9.0]: 14
                                    +--no: [OBJ] [43.0]: 47
+--no: [OBJ] [399.0]: 601
```

- Lexicon features!
- Nouns bear the most sentiment
- Capitalization
- Question phrases





# Model analysis [RenderES]

```
numvowel > 0.3246
+--yes: numcaps > 0.8462
|   +--yes: [SUBJ/POS] [13.0]: 15
|   +--no: renderlex_all_sum_neg > 0.2682
|       +--yes: [SUBJ/POS] [7.0]: 9
|       +--no: numvowel > 0.3566
|           +--yes: [SUBJ/NEG] [177.0]: 257
|           +--no: renderlex_adverb_sum_neg > 0.4899
|               +--yes: [SUBJ/POS] [22.0]: 29
|               +--no: repeat_letter > 0.0588
|                   +--yes: [SUBJ/POS] [20.0]: 32
|                   +--no: [SUBJ/NEG] [112.0]: 178
+--no: renderlex_adverb_abs > 0.52
    +--yes: renderlex_adverb_abs > 0.5964
    |        +--yes: [SUBJ/POS] [10.0]: 19
    |        +--no: [SUBJ/NEG] [8.0]: 8
    +--no: negation > 0.0
        +--yes: repeat_letter > 0.0357
        |            +--yes: [SUBJ/NEG] [11.0]: 13
        |            +--no: [SUBJ/POS] [12.0]: 17
        +--no: full_unt_neg > 0.0
            +--yes: [SUBJ/NEG] [8.0]: 10
            +--no: length > 27.0
                +--yes: renderlex_noun_abs > 4.4911
                |                    +--yes: sad_face > 0.0
                |                    |                        +--yes: [SUBJ/POS] [9.0]: 9
                |                    |                        +--no: [SUBJ/NEG] [2.0]: 2
                |                    +--no: [OBJ] [15.0]: 22
                +--no: [SUBJ/POS] [75.0]: 102
```

- Expression of sentiment through writing form
- Capitalization, vowels, repetition
- Negation
- Adverbs bear most sentiment





# Model analysis [PangLee]

```
renderlex_adjective_sum > 0.1096
++yes: senticnet > 15.509
|   +-yes: renderlex_adverb_abs > 8.1989
|   |   +-yes: swn_posneg_ratio > 5.2202
|   |   |   +-yes: [SUBJ/POS] [146.0]: 207
|   |   |   +-no: numpunc > 0.0313
|   |   |   |   +-yes: renderlex_pos_links > 8025.0
|   |   |   |   |   +-yes: renderlex_adjective_sum > 1.1693
|   |   |   |   |   |   +-yes: [SUBJ/POS] [20.0]: 25
|   |   |   |   |   |   +-no: [SUBJ/NEG] [28.0]: 53
|   |   |   |   |   |   +-no: [SUBJ/NEG] [61.0]: 80
|   |   |   |   |   +-no: [SUBJ/POS] [111.0]: 181
|   |   |   +-no: [SUBJ/POS] [126.0]: 164
|   +-no: numvowel > 0.2808
|       +-yes: renderlex_adjective_abs > 0.3998
|       |       +-yes: [SUBJ/NEG] [90.0]: 164
|       |       +-no: [SUBJ/POS] [15.0]: 17
|       +-no: swn_total_pos > 17.0
|           +-yes: [SUBJ/NEG] [35.0]: 37
|           +-no: renderlex_noun_sum > 7.8051
|               +-yes: [SUBJ/POS] [4.0]: 4
|               +-no: [SUBJ/NEG] [6.0]: 8
+-no: senticnet > 27.085
|   +-yes: [SUBJ/POS] [98.0]: 182
|   +-no: repeat_letter > 0.1193
|       +-yes: senticnet > 13.511
|       |       +-yes: [SUBJ/POS] [13.0]: 14
|       |       +-no: [SUBJ/NEG] [6.0]: 9
|   +-no: ... (continues)
```

- Lexicon features dominate
- Minor role of vowel and letter repetition





# Model analysis [JRC-EN]

```
numcaps > 0.0345
++-yes: senticnet_neg > 1.113
|   +-yes: [SUBJ/NEG] [4.0]: 4
|   +-no: renderlex_adjective_sum_neg > 0.2178
|       +-yes: [SUBJ/POS] [5.0]: 10
|       +-no: senticnet_neg > 0.084
|           +-yes: swn_total_neg > 3.0
|               +-yes: [SUBJ/POS] [2.0]: 2
|               +-no: numcaps > 0.037
|                   +-yes: [OBJ] [120.0]: 135
|                   +-no: [SUBJ/NEG] [3.0]: 7
|           +-no: renderlex_all_abs > 1.5025
|               +-yes: senticnet_abs > 0.816
|                   +-yes: renderlex_adverb_sum > 0.8143
|                       +-yes: [SUBJ/POS] [1.0]: 2
|                       +-no: swn_total_neg > 4.0
|                           +-yes: renderlex_adjective_sum > 0.0
|                               +-yes: [SUBJ/NEG] [3.0]: 4
|                               +-no: [OBJ] [5.0]: 5
|                           +-no: [OBJ] [70.0]: 74
|                   +-no: [SUBJ/NEG] [3.0]: 3
|               +-no: [OBJ] [200.0]: 289
+-no: [OBJ] [302.0]: 512
```

- Similar to JRC-ES – important lexicon features, followed by surface features
- More focus on adjectives and adverbs as opposed to nouns





# Model analysis [RenderEN]

```
senticnet_neg > 0.007
+--yes: numvowel > 0.2963
|   +--yes: negation > 0.0
|   |   +--yes: [SUBJ/POS] [2.0]: 2
|   |   +--no: renderlex_all_abs > 0.1811
|   |   +--yes: [SUBJ/NEG] [5.0]: 5
|   |   +--no: [SUBJ/POS] [1.0]: 2
|   +--no: [SUBJ/NEG] [30.0]: 30
+--no: swn_total_neg > 1.5
+--yes: numcaps > 0.0439
|   +--yes: [SUBJ/POS] [1.0]: 2
|   +--no: [SUBJ/NEG] [11.0]: 11
+--no: repeat_letter > 0.125
+--yes: numpunc > 0.0299
|   +--yes: [SUBJ/POS] [13.0]: 13
|   +--no: numcaps > 0.0368
|   +--yes: [SUBJ/POS] [3.0]: 3
|   +--no: [SUBJ/NEG] [2.0]: 2
+--no: renderlex_all_sum > 0.1013
+--yes: numvowel > 0.2727
|   +--yes: renderlex_all_sum > 0.419
|   |   +--yes: renderlex_pos_links > 442.0
|   |   +--yes: numpunc > 0.044
|   |   +--yes: [SUBJ/POS] [5.0]: 5
|   |   +--no: [SUBJ/NEG] [2.0]: 2
|   +--no: renderlex_adjective_sum > 0.0949
|   +--yes: [SUBJ/POS] [1.0]: 2
|   +--no: [SUBJ/NEG] [10.0]: 10
.. (continues)
```

- As opposed to Spanish social media, lexicons play a bigger role than surface features, but still a mix of both.
  - Quality of lexicons?
  - Writing style less indicative of sentiment?





# Conclusions

- Across domains and languages, a two-layer model works better.
- Hierarchical representation did not give better results in any domain
- Feature scaling recommended





# Conclusions

- We perform below state of the art on the reviews data, but improve performance on the news data compared to the dataset authors' approach
- Model analysis shows different feature importance in different domains
- Comparing languages, some possible cultural differences in expression are apparent in social media.





# Questions?

