On the Identification of Emotions and Authors' Gender in Facebook Comments on the Basis of their Writing Style

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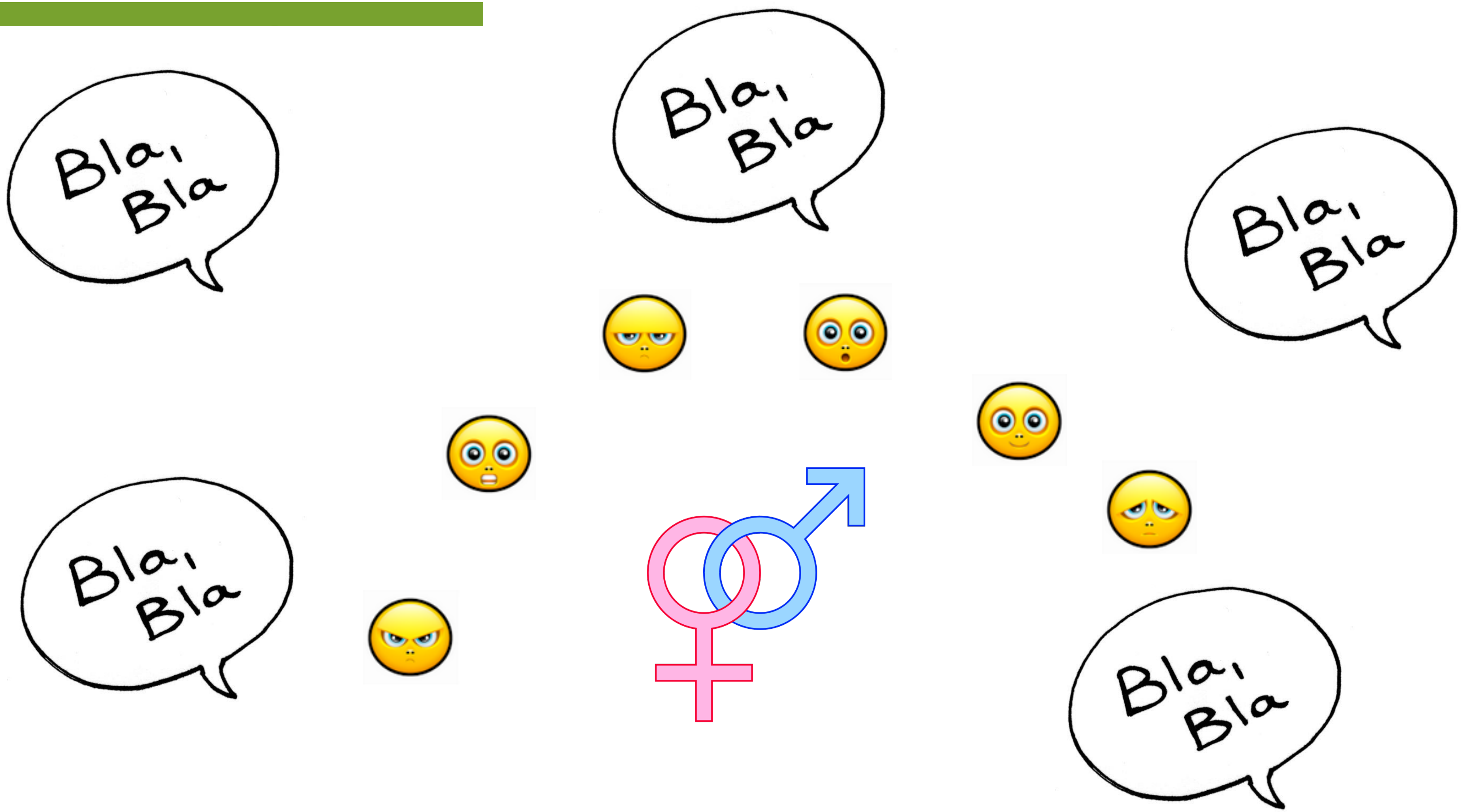
autoritas
nuevas ideas, nuevas soluciones

NLEL Natural Language Engineering Lab

ESSEM 2013

Research Goals



Outline

- Brief review to state-of-the-art
- Style-based language modeling
- Methodology
- Experimental results
- Conclusions and future work

Outline

- **Brief review to state-of-the-art**
  - Generation of affective resources
  - Affective processing methods

Generation of affective resources

RESOURCE	DATE	LANG	CHARACTERISTICS
GENERAL INQUIRER	1966	ENGLISH	ACTIVE, PASSIVE, STRONG, WEAK, PLEASURE, PAIN, FEELING, AROUSAL, VIRTUE, VICE, OVERSTATED, UNDERSTATED
LASSWELL VALUE DICTIONARY	1969	ENGLISH	WEALTH, POWER, RECTITUDE, RESPECT, ENLIGHTENMENT, SKILL, AFFECTION, WELLBEING
DICTIONARY OF AFFECT IN LANGUAGE (DAL)	1989	ENGLISH	8,812 WORDS WITH ACTIVATION AND ABILITY TO IMAGINE THE EMOTION
AFFECTIVE NORMS FOR ENGLISH WORDS (ANEW)	1999	ENGLISH	ACTIVATION, EVALUATION, CONTROL
CLAIRVOYANCE AFFECT LEXICON	2000	ENGLISH	ANGER, JOY, FEAR + CENTRALITY, STRENGTH
WORDNETAFFECT	2004	ENGLISH	EMOTIONAL CATEGORY, EVALUATION, ACTIVATION
LIWC	2007	ENGLISH	+70 DIMENSIONS SUCH AS DEGREE OF POSITIVE/NEGATIVE EMOTIONS, SELF-REFERENCES, CAUSAL WORDS...
SPANISH ADAPTATION OF ANEW	2007	SPANISH	720 PARTICIPANTS -> TRANSLATED 1,034 WORDS IN TERMS OF POLARITY, ACTIVATION, CONTROL
[MOHAMMAD & TURNEY]	2010	ENGLISH	MECHANICAL TURK 2,000 TERMS RELATED TO EMOTIONS
SPANISH EMOTION LEXICON	2013	SPANISH	2,036 WORDS RELATED TO EKMAN EMOTIONS (JOY, DISGUST, ANGER, FEAR, SADNESS, SURPRISE): NULL, LOW, MEDIUM HIGH + PFA

Affective processing methods

METHOD	FEATURES
UPAR7 (SEMEVAL07)	STANFORD SYNTACTIC PARSER (MAIN TOPIC)+ SENTI WORDNET & WORDNET AFFECT
UA (SEMEVAL07)	THREE SEARCH ENGINES + POINTWISE MUTIAL INFORMATION
SWAT (SEMEVAL07)	SUPERVISED ML + UNIGRAMS + 1,000 TRAIN DOCS + ROGET THESAURUS (SYNONYMS)
WN-AFFECT PRESENCE	PRESENCE OF WORDS FROM WORDNET AFFECT
LSA SINGLE WORD	LSA SIMILITUDE BETWEEN TEXT AND EMOTIONS
LSA EMOTION SYNSET	+WORDNET SYNONYMS
LSA ALL EMOTIONS	+WORDNET AFFECT WORDS
NB TRAINED ON BLOGS	NAIVE BAYES CLASSIFIER TRAINED WITH BLOGS
[Elliot, 1992]	DETECTING KEYWORDS
[Pang et al., 2002]	LEXICAL AFFINITY ACCORDING TO THE PROBABILITY OF CERTAIN WORDS TO BE RELATED TO CERTAIN EMOTIONS
[Liu et al., 2002]	BASED ON THE OMCS2 KNOWLEDGE BASE
[Dhaliwal et al., 2007]	STYLE FEATURES: IMPERATIVE SENTENCES, EXCLAMATION SIGNS, CAPITAL LETTERS, PRESENT AND FUTURE
[García & Alias, 2008]	MODULAR ARCHITECTURE WITH SEMANTIC DISAMBIGUATION PER LANGUAGE + ANEW
[Sugimoto & Yoneyama, 2006]	STYLE FEATURES: SUBSTANTIVES, ADJECTIVES, VERBS. JAPANESE
[Mohammad & Yang, 2011]	SENTIMENT ANALYSIS BY GENDER. THREE KIND OF EMAILS: LOVE LETTERS, HATE EMAILS, SUICIDE NOTES
[Díaz, 2013]	SPANISH. ML APPROACH USING SEL DICTIONARY. SHORT STORIES

Affective processing methods

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	Fine	Coarse		
	r	Prec.	Rec.	F1
WN-AFFECT PRESENCE	9.54	**38.28**	1.54	4.00
LSA SINGLE WORD	12.36	9.88	66.72	16.37
LSA EMOTION SYNSET	12.50	9.20	77.71	13.38
LSA ALL EMOTION WORDS	9.06	9.77	**90.22**	**17.57**
NB TRAINED ON BLOGS	10.81	12.04	18.01	13.22
SWAT	25.41	19.46	8.61	11.57
UA	14.15	17.94	11.26	9.51
UPAR7	**28.38**	27.60	5.68	8.71

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- Brief review to state-of-the-art
- **Style-based language modeling**

Style-based language modeling

PART-OF-SPEECH (GRAMMATICAL CATEGORIES)	Frequency of use of each grammatical category, number and person of verbs and pronouns, mode of verb, proper nouns (NER) and non-dictionary words (words not found in dictionary);
FREQUENCIES	Ratio between number of unique words and total number of words, words starting with capital letter, words completely in capital letters, length of the words, number of capital letters and number of words with flooded characters (e.g. Heeeelloooo);
PUNCTUATION MARKS	Frequency of use of dots, commas, colon, semicolon, exclamations, question marks and quotes;
EMOTICONS	Ratio between the number of emoticons and the total number of words, number of the different types of emoticons representing emotions: joy, sadness, disgust, angry, surprised, derision and dumb;
SPANISH EMOTION LEXICON (SEL)	We obtained the lemma for each word and then its *Probability Factor of Affective Use* value from the SEL dictionary. If the lemma does not have an entry in the dictionary, we look for its synonyms. We add all the values for each emotion, building one feature per emotion.

IMPORTANT NOTE: NONE OF THE FEATURES IS TOPIC DEPENDENT

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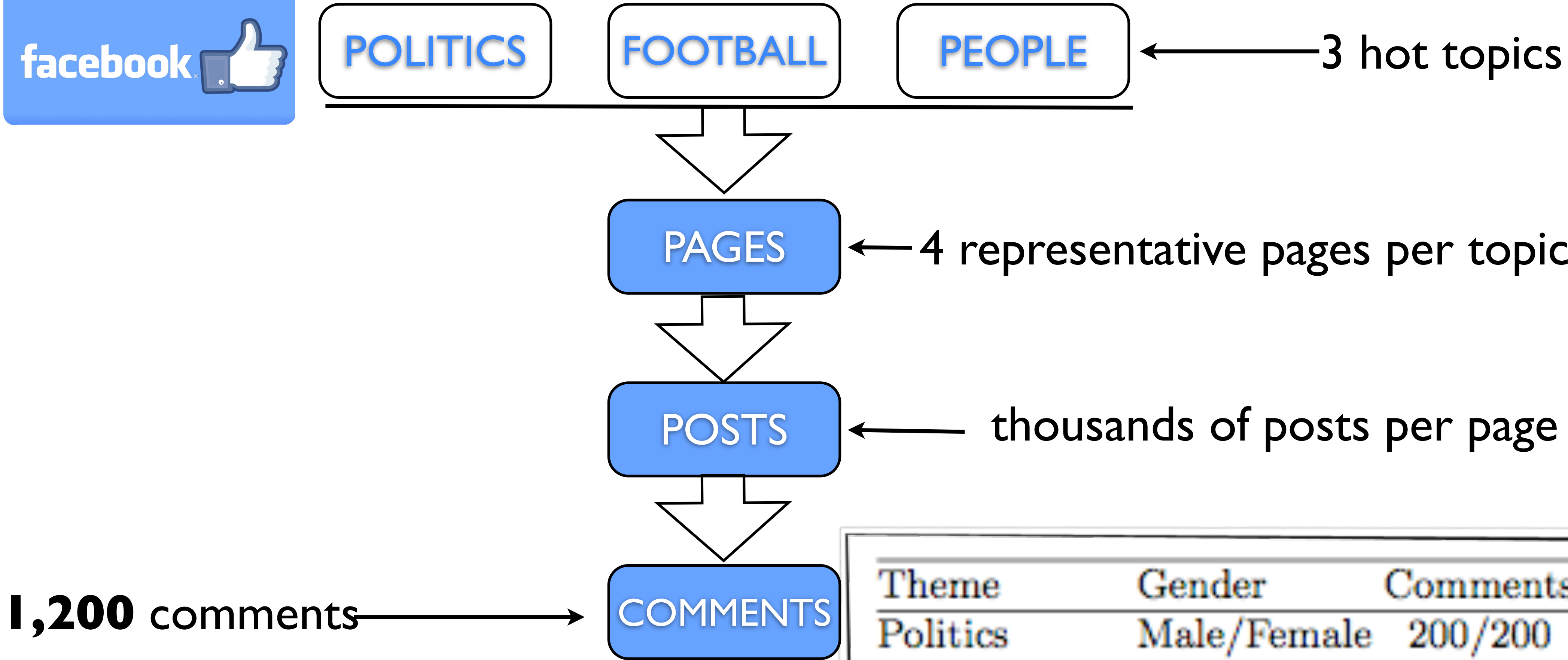
- Brief review to state-of-the-art
- Style-based language modeling
- **Methodology**

Language interest

Data source selection



Theme	Gender	Comments
Politics	Male/Female	200/200
Football	Male/Female	200/200
Public People	Male/Female	200/200

Manual labeling

- **3** independent **annotators**
- **6** basic **emotions** of **Ekman** (*joy, surprise, fear, disgust, anger, sadness*)
- Annotators provided with **Greenberg's** table of primary/ secondary emotions
- Some secondary emotions **shared** by more than one primary emotion

ALEGRÍA	ENFADO	MIEDO	REPULSIÓN	SORPRESA	TRISTEZA
Agradecido	Agresivo	Acomplejado	Aborrecimiento	Extrañeza	Abatido
Alegre	Colérico	Alarmado	Desagrado	Sobresalto	Agobiado
Animado	Crispado	Angustiado	Grima	Susto	Apenado
Calmado	Descontento	Ansioso	Repulsión	Consternación	Confuso
Confiado	Enfadado	Atemorizado	Antipatía	Pasmo	Decepcionado
Contento	Enojado	Aterrado	Aversión	Desconcierto	Deprimido
Dichoso	Excitado	Avergonzado	Repugnancia	Estupor	Desalentado
Encantado	Fastidiado	Confuso	Disgusto	Asombro	Desanimado
Entusiasmado	Furioso	Desesperado	Repudia	Fascinación	Desdichado
Eufórica	Insatisfecho	Desorientado	Repulsa	Admiración	Desmoralizado
Esperanzado	irascible	Horrorizado	Odio	Confusión	Frustrado
Feliz	Malhumorado	Inquieto	Manía	Chasco	Nostálgico
Gozoso	Molesto	inseguro	Rabia	Impresión	Soledad
Satisfecho	Nervioso	Intranquilo	Animadversión	Exclamación	Triste
Tranquilo	Rabioso	Pánico	Nauseabundo	Conmoción	Infeliz
Complacido	Tenso	Preocupado	Indignación	Estupefacción	Desconsolado
Libre	Violento	Temeroso	Enfado		Afligido
Fascinado	Irritado	Tenso	Desprecio		Amargado
Seguro	Indignado	Indeciso	Distanciamiento		Impotente
		Impotencia			

Inter-annotator agreement

- Inter-annotator agreement with **Kappa_DS**
  - Multiple annotators -> 3 in our case: A1, A2 and A3
  - Multinomial variables -> six emotions not mutually exclusive

	A1	A2	A3	REST
A1	-	0.0587	0.2738	0.1662
A2	0.0587	-	0.1042	0.0814
A3	0.2738	0.1042	-	0.1890
TOT		0.1455		

  - Kappa = **14.55%** -> low index of agreement
  - But, high number of variables

Inter-annotator agreement with grouped emotions

- Inter-annotator agreement with **grouped emotions**
  - *joy* with *surprise*
  - *anger* with *disgust*

	A1	A2	A3	REST
A1	-	0.6618	0.5656	0.6137
A2	0.6618	-	0.5773	0.6196
A3	0.5656	0.5773	-	0.5715
TOT		0.6016		

- Kappa = **60.16%** -> higher value of agreement

Labeled dataset

- Concordance of at least two of three annotators (**2/3 rule**)

	TOTAL	%
Joy	338	28.17
Anger	151	12.58
Fear	3	0.25
Disgust	129	10.75
Surprise	390	32.50
Sadness	76	6.33
Neutral	262	21.83

- The low number of documents labeled with the *fear* category did not allow us to perform experiments with this emotion

Learning and evaluation

- A **binary classifier** for each emotion
  - Positive samples -> texts with such emotion
  - Negative samples -> the rest
- **10-fold cross** validation
- **2** different evaluation **measures**
  - Pearson's Kappa
  - Precision, recall and F1
- **4** learning **algorithms** (Weka)
  - J48 decision trees
  - Naïve Bayes
  - Bayes Net
  - Support Vector Machines

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  - Gender identification

Emotions identification

- Experimental results
  - **By method**
    - J48 -> highest precision
    - BayesNet -> highest recall and F1
    - Statistical ones (NB & BN) -> best r
    - SVM -> lowest results
  - **By emotion**
    - Joy/Surprise -> highest F1
    - Sadness -> lowest results
- Conclusion
  - Results **competitive** to SoA ones (p.s. SemEval2007 r=[9.06, 28.38]
  - Results quite **balanced** between precision/ recall

Emotion	Algorithm	r	Prec.	Rec.	F1
Joy	J48	27.1	49.7	43.2	46.2
	NB	**27.9**	45.4	56.8	50.5
	BN	25.6	40.9	**73.7**	**52.6**
	SVM	24.9	**56.9**	30.5	39.7
Anger	J48	16.6	**32.3**	19.9	24.6
	NB	**22.6**	25.9	60.3	**36.3**
	BN	22.2	25.6	**60.9**	36.0
	SVM	10.8	25.8	15.2	19.2
Disgust	J48	21.7	**36.1**	23.3	28.3
	NB	15.7	19.7	55.8	29.1
	BN	**24.9**	25.5	**64.3**	**36.5**
	SVM	6.2	11.7	5.4	7.4
Surprise	J48	**25.8**	**50.4**	48.7	49.5
	NB	20.6	42.7	**67.2**	**52.2**
	BN	20.7	43.0	64.6	51.6
	SVM	17.2	49.4	30.5	37.7
Sadness	J48	12.1	**20.0**	14.5	16.8
	NB	6.1	9.8	35.5	15.4
	BN	**16.7**	16.3	**51.3**	**24.7**
	SVM	8.2	17.9	0.92	12.2
Average results					
	J48	20.7	**37.7**	29.9	33.1
	NB	18.6	28.7	55.1	36.7
	BN	**22.0**	30.3	**63.0**	**40.3**
	SVM	13.5	32.3	16.5	23.2

Gender identification

- Experimental results
  - **r=18** -> classifier works over the random chance
  - **Acc=59** -> competitive to PAN-AP 2013 (*"6th position"*)
- Conclusion
  - Features used for identifying emotions allow us to **identify gender**...
  - ... there is a certain **correlation** between the use of the language, the emotions and the author's gender

Gender	Acc	r
Male / Female	59.0	18.0

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Conclusions

Some answers…

- Dataset built
  - Facebook comments
  - Spanish
  - Manually labeled with six basic emotions of Ekman
  - Kappa-DS analysis of concordance
- Method for automatically identifying emotions
  - Stylistic features + affective dictionary
  - Competitive results
- Method also used for identifying author's gender
  - Style features provide information for such task

Future work

...many new questions

- Investigate what are the most **relevant features**, and their relationship to both tasks
- Analyze the effect of identifying **combined emotions**
- We aim at comparing to **PAN-AP13** task...
  - ...we will include **emotions as features** for identifying age and gender because...
  - ...we want to investigate the **relationship** between **demographics** (age, gender) with the **emotional** and **personality** profiles
- We plan to **analyze the discourse** more in depth...
  - ...for example using **collocations** because...
  - ...**order** is very important: “She married and become pregnant vs. she become pregnant and married” Michael Zock and Debela Tesfaye

Thank you very much!!

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Our main objective is to build a common framework which allows us to better understanding how people use the language and how the language helps profiling them

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