

Introduction a la détection émotionnelle dans les textes

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Contenu

I. Survol du domaine

II. Détection émotionnelle dans les textes

III. Campagne d'évaluation SemEval

IV. Détection de la polarité émotionnelle sur twitter

V. Conclusion

VI. Références

I. Survol du domaine

Introduction

- Applications de la détection émotionnelle automatisé
 - Extraire de l'information sur l'état émotionnel de l'utilisateur
 - Adapter système de service a la clientèle
 - Détecter des instances d'intimidation et harcèlement en ligne
 - Récolter l'opinion sur un sujet a grande échelle a des fins politique et/ou marketing

Introduction

- De quel source peut on extraire de l'information émotionnelle?

- Audio

- Service a la clientèle

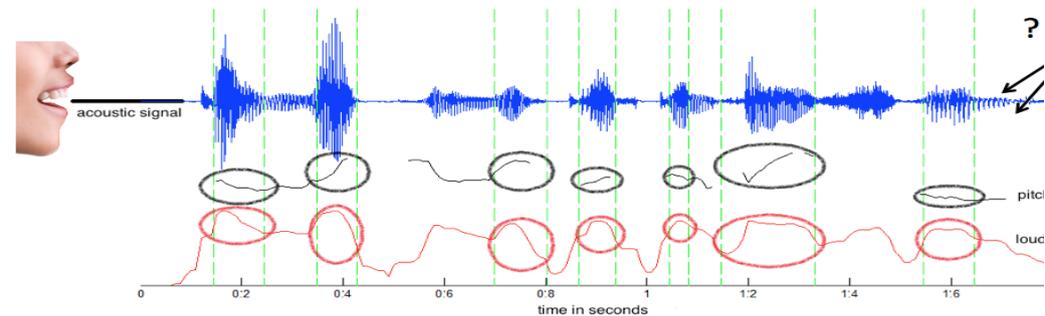
- Vidéo

- Système de surveillance

- Textes

- Service a la clientèle

- Réseaux sociaux



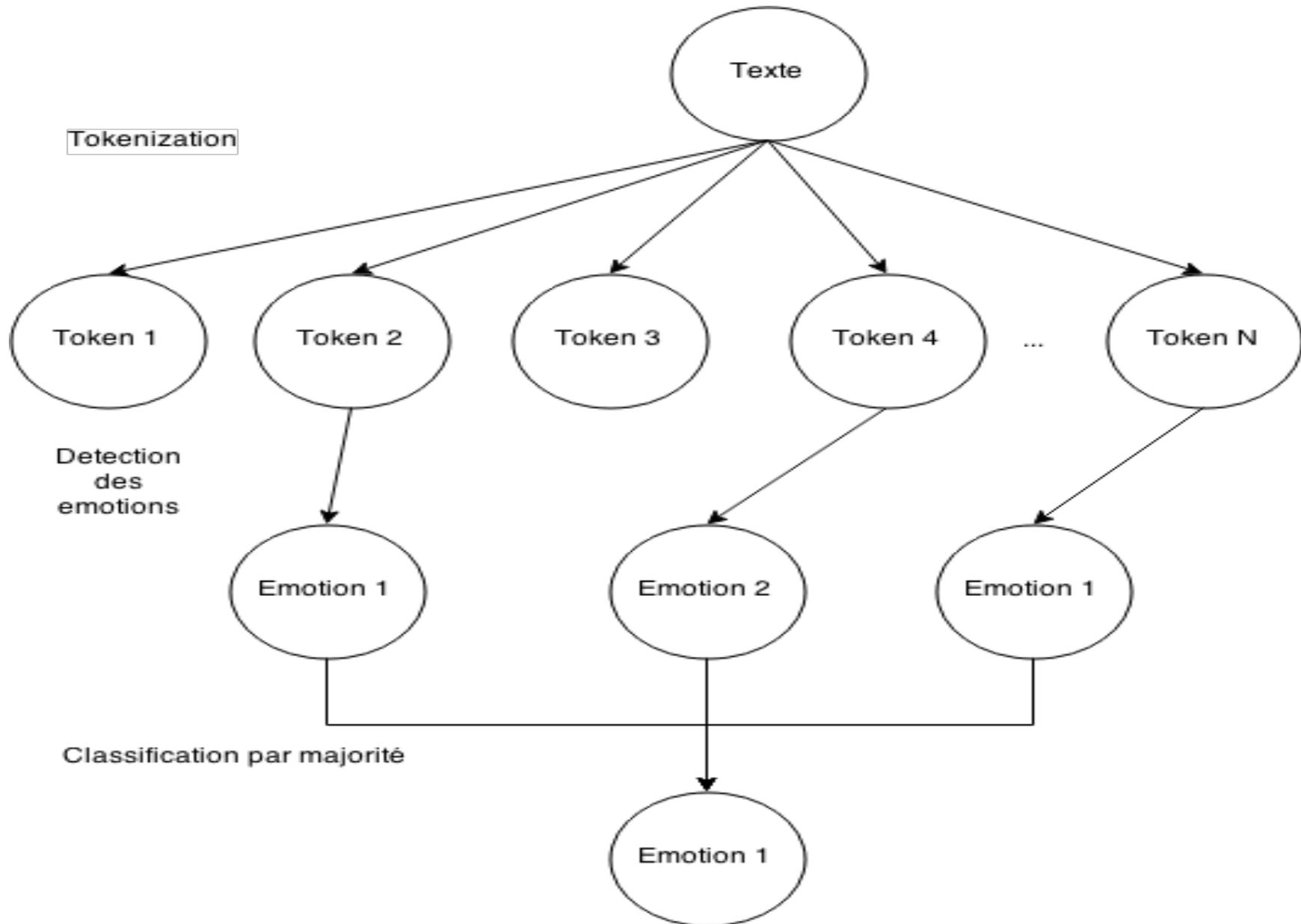
This is **great**
They **lost** ! So **sad** !

II. Détection émotionnelle dans les textes

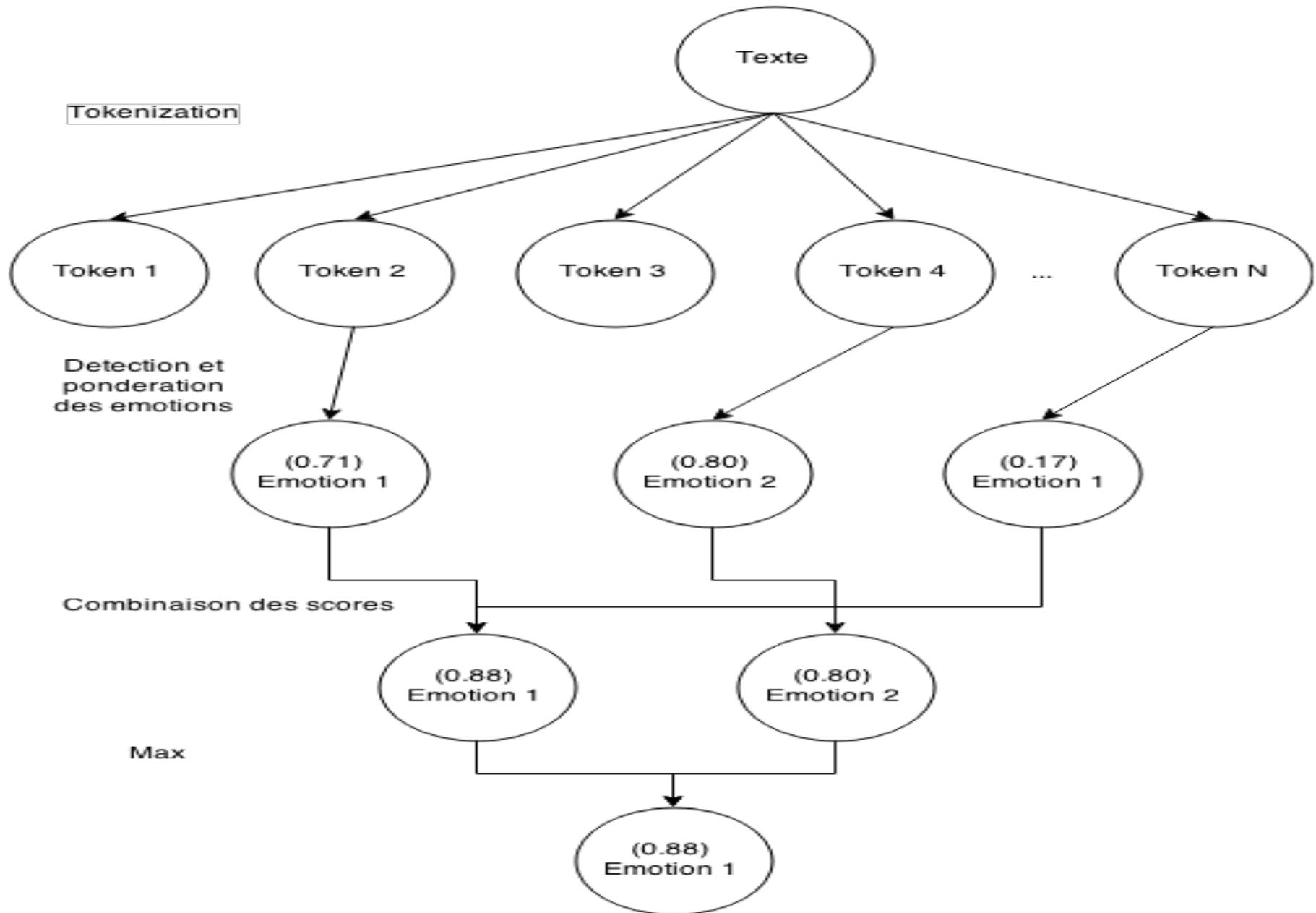
Détection émotionnelle dans les textes

- On peut généralement classer les méthodes de détection des émotions dans les textes en 3 catégories:
- Modèles basés sur des dictionnaires
 - Annotation des tokens en les comparant avec lexique
 - Classification en fonctions de ces annotations
- Modèles basés sur l'apprentissage machine
 - Apprentissage d'un modèle de classification a partir d'exemples d'entraînement
 - Interrogation du modèle pour déterminer a quelle classe appartient une nouvelle instance
- Modèles hybrides
 - Ce sont des modèles qui combine l'information trouver a partir de l'apprentissage machine a celle présente dans les dictionnaires.
 - Basé sur la combinaison des scores des diverse ressources.

Detection dans les textes



Modele ponderé



Traitement de la négation

- Détection des tokens initiant une négation de contexte
- Déterminer la portée du contexte de négation
 - Modèles basés sur les dictionnaires
 - Modifier le score et/ou tag(émotion) de chaque émotion contenue dans cette portée
 - Modèles basés sur l'apprentissage machine
 - Ajout du suffixe `_neg` aux tokens dans cette portée

SemEval

SemEval

- Campagne d'évaluation sémantique qui a débuter en 1998
- Anciennement connu comme sensEval
- A énormément contribuer a l'évolution de la détection émotionnelle

SemEval2007-2013

- SemEval2007
 - Task 14: Affective Text
 - Subtask A: Annoter texte avec liste prédéfinis d'émotions candidate
 - Subtask B: Annoter texte selon polarité
- SemEval2010
 - Task 18 : Disambiguating Sentiment Ambiguous Adjectives
- SemEval2013
 - **Task 2: Sentiment Analysis in Twitter**
 - Task A : Contextual Polarity Disambiguation
 - Task B: Message Polarity Classification

SemEval2014

- SemEval2014
 - Task 4: Aspect Based Sentiment Analysis
 - Subtask 1: Aspect term extraction
 - Subtask 2: Aspect term polarity
 - Subtask 3: Aspect category detection
 - Subtask 4: Aspect category polarity
 - **Task 9: Sentiment Analysis in twitter (Rerun)**
 - Subtask A: Contextual Polarity Disambiguation
 - Subtask B: Message Polarity Classification

SemEval2015

- SemEval2015
 - Task 9: CLIPEval Implicit Polarity of Events
 - SUBTASK A: identify the polarity value associated to the event instance.
 - SUBTASK B: identify the event instantiations and associated polarity values.
 - Task 10: Sentiment Analysis in Twitter
 - Subtask A: Contextual Polarity Disambiguation
 - Subtask B: Message Polarity Classification
 - Subtask C: Topic-Based Message Polarity Classification
 - Subtask D: Detecting Trends Towards a Topic
 - Subtask E: Determining strength of association of Twitter terms with positive sentiment (or, degree of prior polarity)

SemEval2015

- SemEval2015 (suite)
 - Task 11: Sentiment Analysis of Figurative Language in Twitter
 - Task 12: Aspect Based Sentiment Analysis

Détection de la polarité des messages sur twitter

Format des données

- Données
 - Entraînement : 9,728 Twitter messages

Authorities are *only too aware* that Kashgar is 4,000 kilometres (2,500 miles) from Beijing but *only* a tenth of the distance from the Pakistani border, and are *desperate* to *ensure instability or militancy* does not leak over the frontiers.

Taiwan-made products *stood a good chance* of becoming *even more competitive thanks to* wider access to overseas markets and lower costs for material imports, he said.

"March *appears* to be a *more reasonable* estimate while earlier admission *cannot be entirely ruled out*," according to Chen, also Taiwan's chief WTO negotiator.

friday evening plans were great, but saturday's plans *didn't go as expected* – i went dancing & it was an *ok* club, but *terribly crowded* :-{

WHY THE *HELL* DO YOU GUYS ALL HAVE MRS. KENNEDY! SHES A FUCKING DOUCHE

AT&T was *okay* but whenever they do something *nice* in the name of customer service it seems like a favor, while T-Mobile makes that a *normal everyday thin*

obama should be *impeached* on *TREASON* charges. Our Nuclear arsenal was TOP Secret. Till HE told our enemies what we had. *#Coward #Traitor*

My graduation speech: "I'd like to *thanks* Google, Wikipedia and my computer! *:D* #iThingteens

Mesure d'évaluation

Utilisation de f-mesure :

- Classe positive :

$$F_{pos} = \frac{2(p_{pos} + r_{pos})}{p_{pos} * r_{pos}}$$

Ppos = précision classe positive
Rpos = rappel classe positive

- Classe négative : calcul similaire a positive
- Calcul Global :

$$F = (F_{pos} + F_{neg}) / 2.$$

SemEval2013 Twitter

TASK 2A: testing on Twitter

Run	Constrained	Unconstrained
task2-NRC-Canada-A-twitter	0.8893	
task2-AVAYA-A-twitter		0.8738
task2-AVAYA-A-twitter	0.8698	
task2-BOUNCE-A-Twitter	0.8679	
task2-LVIC-LIMSI-A-twitter	0.8570	
task2-FBM-A-twitter	0.8550	
task2-GUMLTLT-A-Twitter	0.8519	
task2-UNITOR-A-twitter	0.8460	
task2-USNA-A-twitter	0.8131	
task2-ECNUCS-A-twitter		0.8015
task2-Serendio-A-Twitter	0.8004	
task2-ECNUCS-A-twitter	0.7948	
task2-TJP-A-Twitter	0.7816	
task2-columbia-nlp-A-twitter	0.7494	
task2-teragram-A-twitter		0.7489
task2-sielers-A-twitter	0.7441	
task2-KLUE-A-Twitter	0.7374	
task2-senti.ue-en-A-twitter		0.7138
task-2-OPTWIMA-A-twitter	0.6917	
task2-swatcs-A-twitter	0.6719	
task2-Kea-A-twitter	0.6394	
task2-swatcs-A-twitter		0.6386
task2-senti.ue-en-A-twitter	0.6279	
task2-uottawa-A-TWITTER	0.6020	
task2-IITB-SentimentAnalysts-A-twitter	0.5480	
task2-Senselytic Team-A-twitter	0.5388	
task2-OPTWIMA-A-twitter		0.3691
task2-SU-sentilab-A-tweet		0.3473

SemEval2013 SMS

TASK 2A: testing on SMS

Run	Constrained	Unconstrained
task2-GUMLTLT-A-SMS	0.8837	
task2-NRC-Canada-A-SMS	0.8800	
*task2-AVAYA-A-sms		0.8579
*task2-AVAYA-A-sms	0.8394	
task2-UNITOR-A-sms	0.8249	
task2-TJP-A-sms	0.8123	
task2-LVIC-LIMSI-A-SMS	0.8016	
task2-USNA-A-sms	0.7982	
task2-ECNUCS-A-SMS		0.7734
task2-ECNUCS-A-SMS	0.7669	
task2-senti.ue-en-A-sms		0.7413
task2-sielers-A-sms	0.7348	
task2-FBM-A-sms	0.7295	
task2-teragram-A-sms	0.7283	
task2-teragram-A-sms		0.7283
task2-KLUE-A-SMS	0.7054	
task2-columbia-nlp-A-sms	0.7030	
task2-swatcs-A-sms		0.6768
task2-senti.ue-en-A-sms	0.6609	
task2-swatcs-A-sms	0.6600	
task2-Kea-A-SMS	0.6327	
task2-uottawa-A-SMS	0.5589	
task2-SU-sentilab-A-sms		0.5538
task2-Senselytic Team-A-sms	0.5113	
task2-OPTWIMA-A-sms	0.3732	
task-2-OPTWIMA-A-sms		0.3638

SemEval2013 Twitter Message Task

TASK 2B: testing on Twitter

Run	Constrained	Unconstrained
task2-NRC-Canada-B-twitter	0.6902	
task2-GUMLTLT-B-Twitter	0.6527	
task2-teragram-B-twitter	0.6486	
task2-teragram-B-twitter		0.6486
task2-AVAYA-B-twitter		0.6406
task2-BOUNCE-B-Twitter	0.6353	
task2-KLUE-B-Twitter	0.6306	
task2-AMI_and_ERIC-B-twitter	0.6255	
task2-AMI_and_ERIC-B-twitter		0.6117
task2-FBM-B-twitter	0.6117	
task2-SAIL-B-twitter		0.6103
task2-AVAYA-B-twitter	0.6084	
task2-SAIL-B-twitter	0.6014	
task2-UT-DB-b-twitter	0.5987	
task2-FBK-irst-B-twitter	0.5976	
task2-UNITOR-B-twitter		0.5950
task2-nlp.cs.aueb.gr-B-twitter	0.5891	
task2-ECNUCS-B-twitter		0.5842
task2-UNITOR-B-twitter	0.5827	
task2-LVIC-LIMSI-B-twitter	0.5714	
task2-Umigon-B-Twitter	0.5696	
task2-NILC_USP-B-twitter	0.5631	
task2_DataMining-B-Twitter	0.5552	
task2-ECNUCS-B-twitter	0.5505	
task2-nlp.cs.aueb.gr-B-twitter	0.5473	
task2-ASVUniOfLeipzig-B-Twitter	0.5456	
task2-OPTWIMA-B-twitter		0.5451
task2-bwbaugh-B-twitter		0.5437
task2-SZTE-NLP-B-Twitter	0.5433	
task2-CodeX-B-twitter	0.5389	
task2-Oasis-B-twitter	0.5384	
task2-NTNU-B-twitter	0.5323	
task2-SZTE-NLP-B-Twitter		0.5310
task2-UoM-B-twitter	0.5181	

SemEval2013 SMS Message task

TASK 2B: testing on SMS

Run	Constrained	Unconstrained
task2-NRC-Canada-B-SMS	0.6846	
task2-GUMLTLT-B-SMS	0.6215	
task2-KLUE-B-SMS	0.6203	
task2-AVAYA-B-sms	0.6000	
task2-AVAYA-B-sms		0.5947
task2-teragram-B-sms	0.5910	
task2-teragram-B-sms		0.5910
task2-NTNU-B-sms	0.5797	
task2-CodeX-B-SMS	0.5670	
task2-SZTE-NLP-B-SMS		0.5546
task2-nlp.cs.aueb.gr-B-sms		0.5528
task2-FBK-irst-B-SMS	0.5487	
task2-ECNUCS-B-sms		0.5477
task2-NTNU-B-sms		0.5455
task2-AMI_and_ERIC-B-sms	0.5363	
task2-ECNUCS-B-SMS	0.5321	
task2-AMI_and_ERIC-B-sms		0.5262
task2-UT-DB-b-sms	0.5246	
task2-SAIL-B-SMS		0.5198
task2-SAIL-B-SMS	0.5184	
task2-UNITOR-B-sms	0.5122	
task2-SZTE-NLP-B-SMS	0.5108	
task2-Senselytic Team-B-sms	0.5107	
task2-NILC_USP-B-sms	0.5012	
task2-REACTION-B-sms	0.5011	

SemEval2014 TaskA

System	LiveJournal2014	SMS2013	Twitter2013	Twitter2014	Twitter2014Sarcasm
NRC-Canada-A-constrained	85.49	88.03	90.14	86.63	77.13
SentiKLUE-A-constrained	85.61	85.16	90.11	84.83	79.32
CMU-Qatar-A-constrained-late	83.89	88.08	89.85	83.45	78.07
CMUQ-Hybrid-A-constrained-late	84.21	87.98	88.94	84.40	76.99
Think_Positive-A-unconstrained	80.90	87.65	88.06	82.05	76.74
ECNU-A-unconstrained	81.69	89.26	87.29	82.93	73.71
ECNU-A-constrained	81.67	89.31	87.28	82.67	73.71
Lt_3-A-constrained	80.44	85.26	86.28	81.02	70.76
LyS-A-constrained	83.95	81.44	85.69	79.92	71.67
Kea-constrained-late	81.16	84.14	84.83	81.22	65.94
senti.ue-A-constrained	81.90	78.72	84.05	80.54	82.75
senti.ue-A-unconstrained-late	79.70	82.93	83.80	77.07	80.02
columbia_nlp-A-constrained	78.19	74.55	81.50	76.54	61.76
TJP-A-constrained	78.27	84.41	81.13	79.30	71.20
UKPDIPF-A-constrained	81.42	79.05	80.45	79.67	65.63
UKPDIPF-A-unconstrained	81.42	79.05	80.45	79.67	65.63
SAP-RI-A-constrained	77.68	80.26	80.32	77.26	70.64
SAIL-A-constrained	70.62	74.46	78.47	76.89	65.56
Citius-A-unconstrained	75.82	69.31	76.59	75.21	68.40
Indian_Institute_of_Technology-Patna-A-constrained	77.99	75.99	76.54	76.43	71.43
Citius-A-constrained	71.64	61.44	74.71	73.03	65.18
SU-sentilab-A-tweet-constrained	69.53	62.58	74.34	68.26	53.31
IITPatna-A-constrained	76.03	77.04	70.91	72.25	66.32
DAEDALUS-A-constrained	61.01	63.92	67.42	60.98	45.27
University-of-Warwick-A-unconstrained-late	67.46	63.01	64.91	67.17	60.59
University-of-Warwick-A-constrained-late	64.89	60.12	62.25	67.28	58.08
DAEDALUS-A-unconstrained	58.65	55.97	61.95	58.11	49.19

SemEval2014 TaskB

System	_liveJournal2014	SMS2013	Twitter2013	Twitter2014	Twitter2014Sarcasm
NRC-Canada-B-constrained	74.84	70.28	70.75	69.85	58.16
SAIL-B-constrained	69.34	56.98	66.80	67.77	57.26
TeamX-B-constrained	69.44	57.36	72.12	70.96	56.50
AUEB-B-constrained	70.75	64.32	63.92	66.38	56.16
CISUC_KIS-B-constrained-late	74.46	65.90	67.56	67.95	55.49
senti.ue-B-constrained	71.39	59.34	67.34	63.81	55.31
UKPDIPF-B-constrained	71.92	60.56	60.65	63.77	54.59
GPLSI-B-constrained	57.32	46.63	57.49	56.06	53.90
UMCC_DLSI_Graph-B-constrained	47.81	36.66	43.24	45.49	53.15
TUGAS-B-constrained	69.79	62.77	65.64	69.00	52.87
BUAP-B-constrained	53.94	44.27	56.85	55.76	51.52
ECNU-B-constrained	69.44	59.75	62.31	63.17	51.43
Synalp-Empathic-B-constrained	71.75	62.54	63.65	67.43	51.06
SWISS-CHOCOLATE-B-constrained	73.25	66.43	64.81	67.54	49.46
SAP-RI-B-constrained	57.86	49.00	50.18	55.47	48.64
SU-FMI-B-constrained-late	68.24	61.67	60.96	63.62	48.34
AMI_ERIC-B-constrained	65.32	60.29	70.09	66.55	48.19
Lt_3-B-constrained	68.56	64.78	65.56	65.47	47.76
RTRGO-B-constrained	72.20	67.51	69.10	69.95	47.09
coooIII-B-constrained	72.90	67.68	70.40	70.14	46.66
Rapanakis-B-constrained	59.71	54.02	58.52	63.01	44.69
KUNLPLab-B-constrained	63.77	55.89	58.12	61.72	44.60
USP_Biocom-B-constrained	67.80	53.57	58.05	59.21	43.56
SentiKLUE-B-constrained	73.99	67.40	69.06	67.02	43.36



Features Engineering

Features

- Features
 - **N-gram de mots**
 - **N-gram de caracteres**
 - **Lexicons features scores (max , sum ,last)**
 - Nombre de mots en majuscules
 - Nombre d'occurrences de chaque POS tag
 - Nombre de séquences contigus de signe de ponctuation
 - Présence de smileys
 - Nombre de mot allongé (ex: Yesssssss)
 - Nombre de contexte de négation
 - Cluster based feature
 - Etc...

Combattre le manque de données

NRC-Canada

- Utilisation de lexique annoté manuellement :
 - NRC emotion lexicon (14000 mots)
 - MPQA lexicon (8000 mots)
 - Bing Liu lexicon (6800 mots)
- Création automatique de nouveau lexique :
 - NRC Hashtag Sentiment Lexicon
 - Détermination de 78 hashtags seed avec forte polarité émotionnelle (Ex : #happy , #sad , ...)
 - Collection de 775000 tweets contenant seed en interrogeant l'api de twitter pendant près de 1 an
 - Extraction de 54129 uni-grammes , 316531 bigrammes et 308808 pair non contigus tous annoté avec polarité associé
 - Sentiment140 Lexicon
 - 1.6 million tweets étiqueté selon smileys
 - 62468 uni-grammes 677698 bigrammes 480010 pair non contigus

AVAYA Labs

- Manual Lexicons
 - MPQA subjectivity lexicon
 - Dictionnaires de négation et d'emoticons
- Automatic lexicon
 - Étiquetage de 475000 tweets sans étiquette a priori a partir d'un modèle initial
 - Création d'un dictionnaire a partir d'extraction de cooccurrence

SentiKLUE

- Amélioration de 17 point pour la tache A comparer a leur système précédent
- Description des changements:
 - Ancien : unigrams , AFINN sentiment lexicon , emoticons and internet slang lexicons
 - 2014: ajout de bigrams , char-n-grams , Bing Liu Lexicon , MPQA Lexicon , SentiWords Lexicon , Sentiment140 , NRC HashTag Sentiment Lexicon

Amélioration du traitement de la négation

NRC-Canada

- Amélioration de la négation par rapport au système précédent:
 - Partitionnement de chaque lexiques en 2 lexiques: 1 pour les contextes positif et 1 pour les contextes négatif
 - Modification de l'opération d'ajout de suffixe au mots en négation de contexte.
 - 2013: Tout les mots en négation de contexte était suffixer par `_neg` peut importe le mot inversant le contexte
 - 2014: Les mots en négation de contexte ont comme suffixe le mot entraînant la négation de contexte
Ex:(`_not`,`_never`,`_shouldn't`,etc)
- Gain d'environ 1 point comparer a l'année précédente

Analyse de features

SentiKlue2014 Observations

task	classifier	CV		development set					test set (gold standard)					
		F _{all}	F _{pos}	F _{neg}	F _{ntr}	F _{all}	F _{p/n}	acc.	F _{pos}	F _{neg}	F _{ntr}	F _{all}	F _{p/n}	acc.
B	MaxEnt	.727	.724	.651	.772	.735	.688	.734	.731	.650	.750	.726	.691	.725
B	SGD	.725	.728	.645	.773	.736	.686	.734	.733	.656	.749	.727	.695	.726
B	LinSVM	.702	.687	.604	.743	.700	.646	.701	.699	.599	.716	.689	.649	.690
B	SVM	.702	.721	.631	.742	.716	.676	.712	.729	.636	.720	.709	.683	.706
A	MaxEnt	.864	.890	.872	.179	.849	.881	.863	.893	.853	.171	.841	.873	.856
A	SGD	.864	.889	.867	.223	.849	.878	.860	.891	.847	.188	.839	.869	.852
A	LinSVM	.860	.892	.876	.064	.847	.884	.865	.895	.856	.064	.838	.875	.857
A	SVM	.855	.890	.873	.024	.842	.881	.862	.892	.853	.014	.832	.872	.854

Table 2: Performance of different machine learning algorithms on the training data (CV), development set and test set (F_{all} = weighted average F-score; F_{p/n} = official score; best results highlighted in bold font).

Task B	SMS	Twitter	DEV	LJ14	SMS13	Twit13	Twit14	Sarcasm	GOLD
- bag of words	-.0837	-.0322	-.0502	-.0344	-.0807	-.0316	-.0335	+0.0511	-.0430
- sentiment lexica	-.0445	-.0354	-.0389	-.0690	-.0422	-.0372	-.0092	+0.0750	-.0363
- training weights	-.0033	-.0413	-.0266	-.0275	-.0077	-.0482	-.0204	-.0342	-.0294
- emoticons	-.0071	-.0107	-.0087	-.0006	-.0067	-.0105	+0.0004	+0.0492	-.0048
- bow bigrams	-.0074	-.0005	-.0035	+0.0010	-.0105	-.0012	-.0096	+0.0956	-.0028
- feature scaling	-.0027	-.0010	-.0014	-.0021	-.0030	-.0026	-.0004	-.0034	-.0020
- character n-grams	+0.0029	-.0068	-.0033	+0.0012	+0.0040	-.0044	-.0056	+0.0056	-.0015
- negation	-.0098	+0.0019	-.0014	-.0016	-.0049	+0.0002	-.0012	+0.0351	-.0002
- bow $f \geq 2$	+0.0017	+0.0026	+0.0022	+0.0004	+0.0021	-.0003	+0.0021	+0.0171	+0.0013
sentiment lexica:									
- standard lexica	-.0206	-.0135	-.0152	-.0245	-.0234	-.0124	+0.0035	+0.0586	-.0124
- Twitter lexica	-.0026	+0.0000	-.0019	-.0118	-.0073	-.0007	-.0094	+0.0034	-.0066
- SentiWords	-.0008	-.0010	-.0009	-.0034	-.0015	-.0005	-.0075	+0.0165	-.0017
- hashtag lexica	-.0011	+0.0021	+0.0005	-.0045	-.0039	+0.0035	+0.0011	-.0302	-.0005
- DSM extension	+0.0047	-.0032	-.0002	-.0070	+0.0039	+0.0022	-.0025	+0.0392	+0.0002
- manual extension	-.0008	-.0018	-.0011	-.0015	-.0019	+0.0000	+0.0041	+0.0361	+0.0009
only standard lexica	-.0124	-.0119	-.0120	-.0088	-.0101	-.0108	-.0095	+0.0439	-.0094
only DSM extension	-.0303	-.0260	-.0262	-.0427	-.0287	-.0251	+0.0021	+0.0183	-.0230

Table 3: Results of feature ablation experiments for subtask B. Values show change in F_{p/n}-score if feature is excluded. Rows are sorted by impact of features on the full SemEval-2014 test data (GOLD).

Traitement du sarcasme

Senti.ue

- Particularité intéressantes:
 - Séparation des tweets en plusieurs segments et extraction de features sur chaque parties:
 - LeftText, RightText , sentenceText , chosenText
 - Forte utilisation de la position des éléments comme features
 - Ex: Présence d'un mot contenant une polarité émotionnelle avant ou après signe de ponctuations
 - Utilisation de wordnet pour extraction de synonymes

Constats Généraux

- Corpus d'entraînement biaisé en faveur des exemples positifs.
- Corpus et dictionnaires externe fort utiles
- Beaucoup de système utilise un moyen ou un autre pour réduire le grand nombre de features créer.
- Problème avec la distribution des tweets
- Difficulté a bien traité les messages contenant du sarcasme

Conclusion

Conclusion

- Le domaine de la détection émotionnelle est en pleine expansion
- Il existe de nombreuses applications de cette dernière
- Le traitement du sarcasme reste un problème non résolu
- Les campagnes semEval sont à suivre pour suivre les développements dans le domaine

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