

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

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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

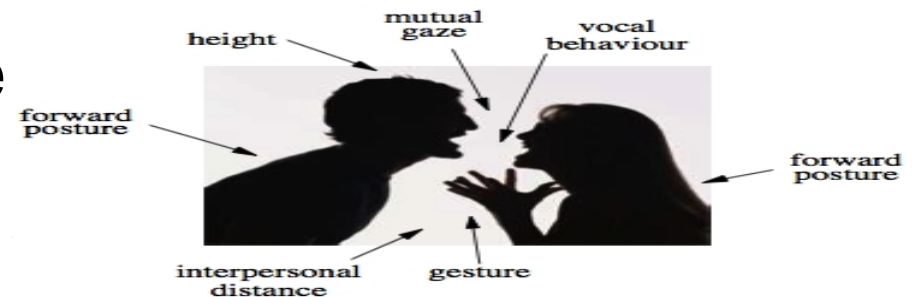
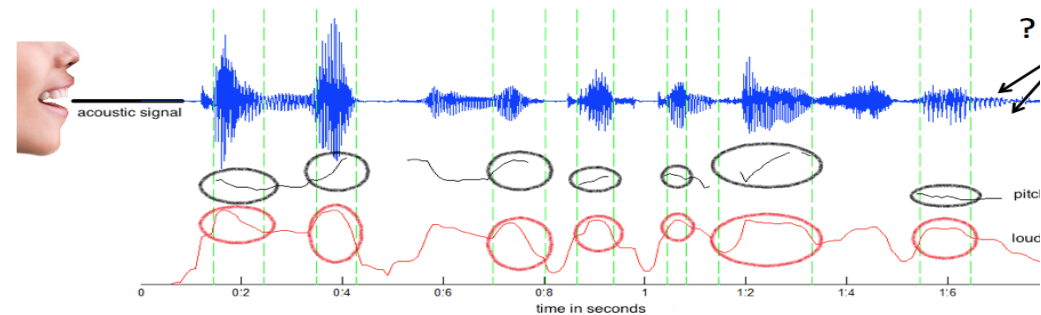
- Vidéo

- Système de surveillance

- Textes

- Service a la clientèle

- Réseaux sociaux



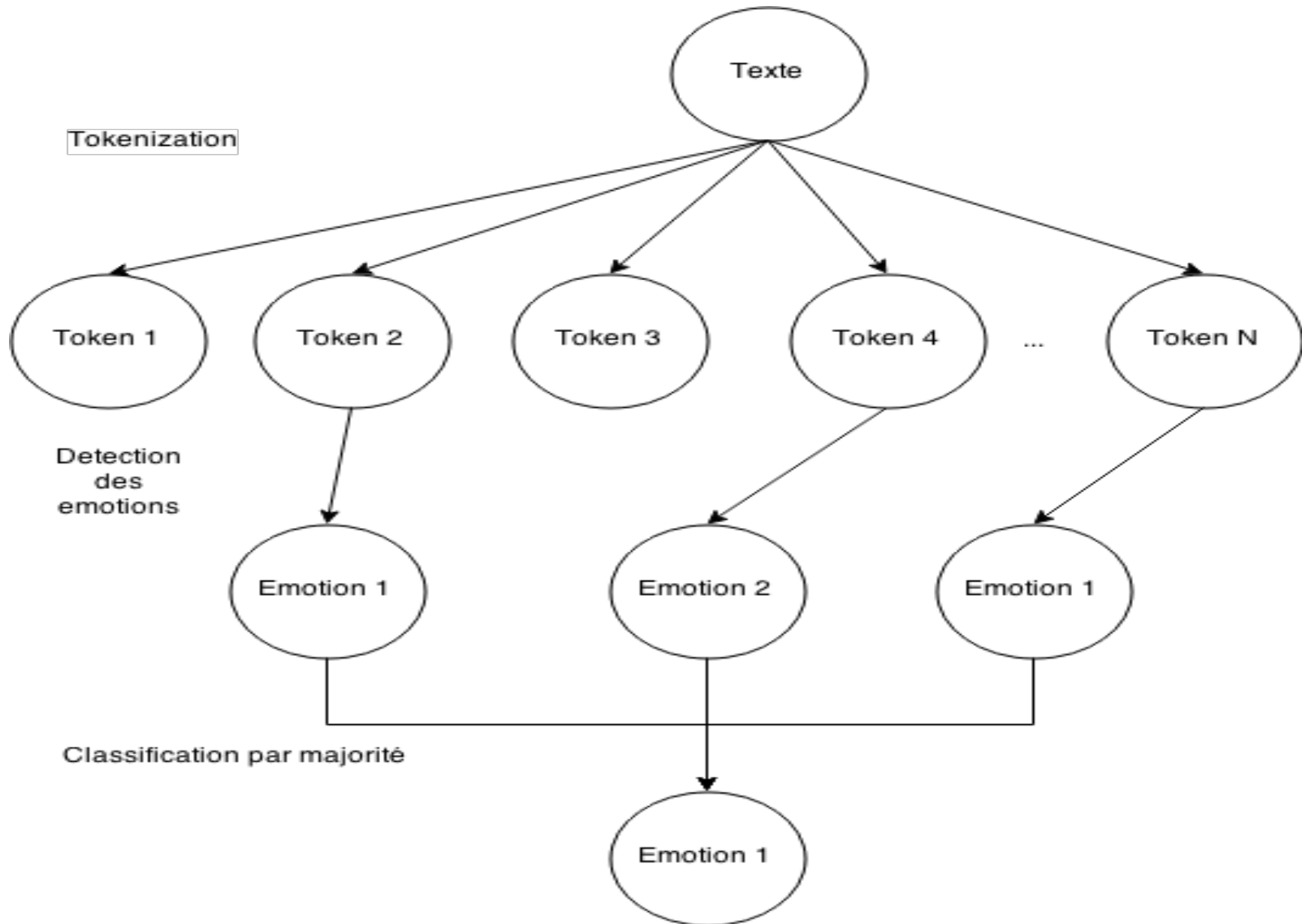
This is **great**
They **lost** ! So **sad** !

II. Détection émotionnelle dans les textes

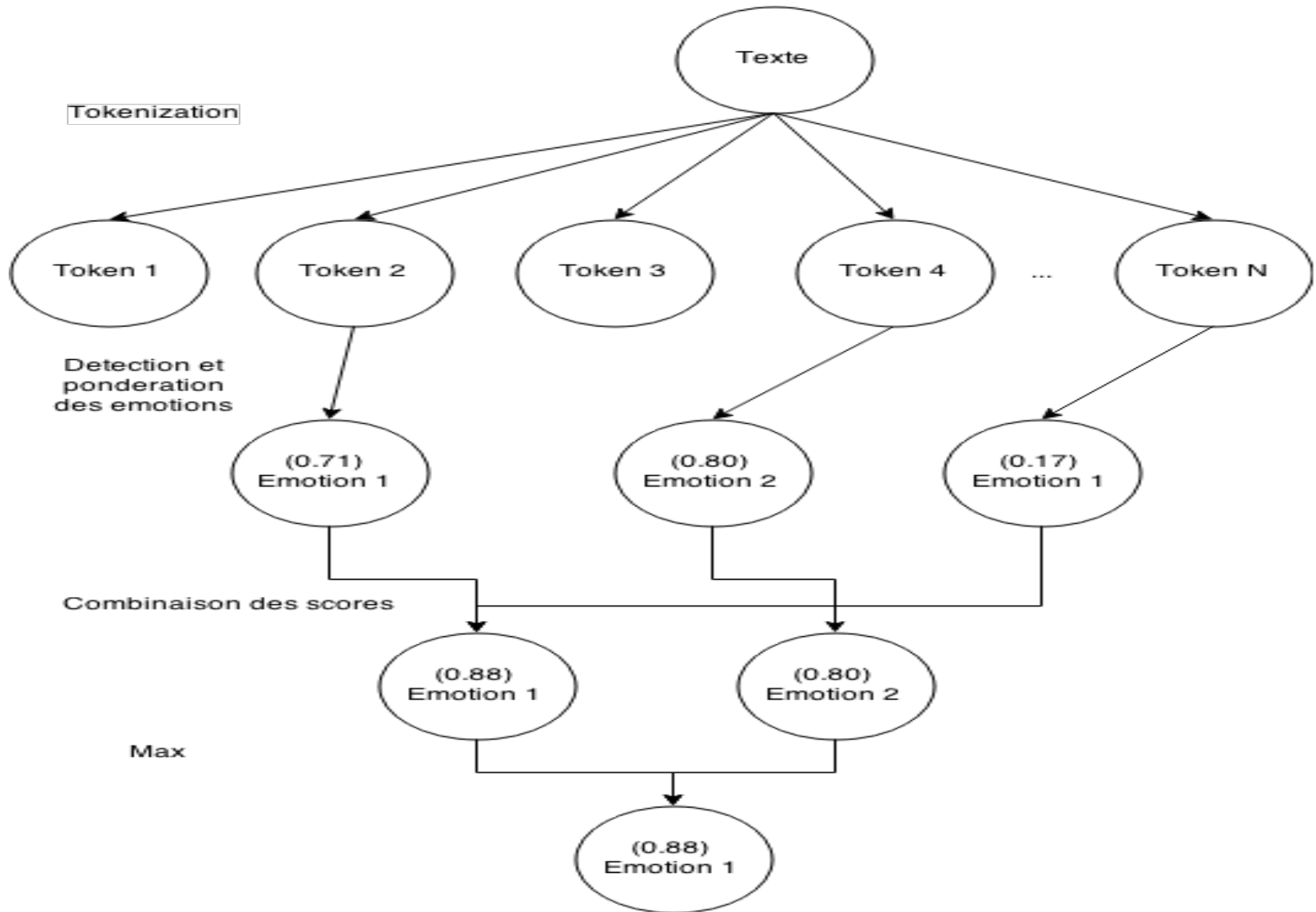
Détection émotionnelle dans les textes

- 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

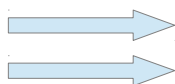
Run	Constrained	Unconstrained
task2-NRC-Canada-B-SMS	0.6846	
task2-GUMLTLT-B-SMS	0.6215	
task2-KLUE-B-SMS	0.6203	
task2-AVAYA-B-sms	0.6000	
task2-AVAYA-B-sms		0.5947
task2-teragram-B-sms	0.5910	
task2-teragram-B-sms		0.5910
task2-NTNU-B-sms	0.5797	
task2-CodeX-B-SMS	0.5670	
task2-SZTE-NLP-B-SMS		0.5546
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
cooooIII-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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