

Institut de Recherche en Informatique et Systèmes Aléatoires

# Automatic Emotions Analysis for French Email Campaigns optimization

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- PhD student since January 2020
  - Title : "Opinion Analysis for Customer Relationship Optimization"
  - Member of the IRISA laboratory : team EXPRESSION
  - CIFRE fellowship with **UNEEK**
- "Age Recommendation for Texts" LREC 2020
- Graduate from **ENSSAT** engineering school : specialization in Artificial Intelligence
- Master degree in Computer Science from "Université de Rennes 1"



# Uneek Customer Relationship Management

#### How to help CRM users to manage their customer relationship through email?

- Analyze the emotions conveyed by the text of email campaigns
- Evaluate how these emotions affect the performance of newsletters

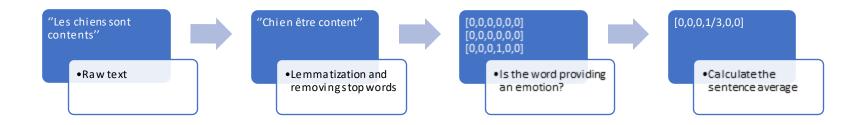




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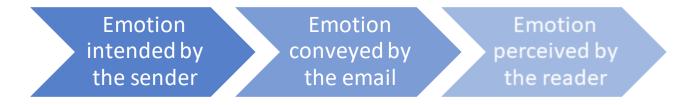
#### Related work – Email analysis

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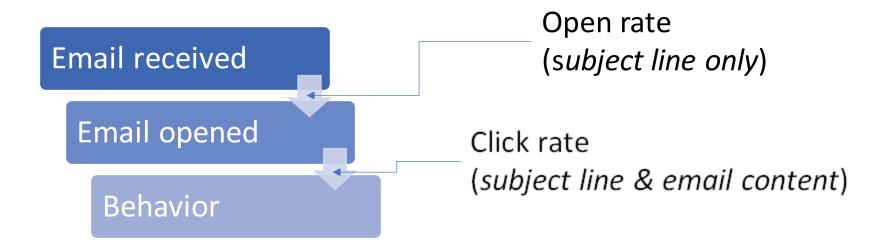
- A baseline approach that considers the 6 fundamental emotions: anger, fear, sadness, joy, disgust and surprise [P.Eckman,1999]
- We added 2 opinion scores: **polarity** and **subjectivity**





- Lack of face-to-face communication and context
- Neutrality or Negativity bias on the perceived emotions [K.Byron,2008; V.Rodriguez et al., 2021]
- Does emotion have an impact on customer behavior?





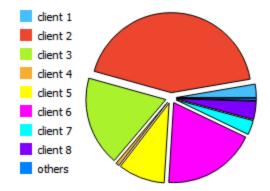
- Other measures of behavior: purchase rate, unsubscribe rate, etc. [R.Miller et al., 2016]
- We focused on open and click rates: most relevant in our dataset



- Analysis of email campaigns using emotion detection
- Explore correlations between newsletter performance and emotion embeddings
- Test how these correlations can help predict newsletter performance based on emotional tone



- More than 950 non-commercial newsletters
- We assume that the emotions conveyed by the email do not depend on the sender
- Each newsletter is characterized by :
  - a subject line
  - a content text
  - an open rate
  - a click rate





# Pearson correlations

Features	Open rate	Click rate
File size (FS)	-0.14***	0.25***
Subject line length (SL)	-0.13***	0.18***
Subject line polarity (SP)	-0.07**	-0.03"
Subject line subjectivity (SS)	-0.01 <sup>ns</sup>	-0.07*
Content Polarity (CP)	-	0.09**
Content Subjectivity (CS)	-	-0.07*
Content Joy (J)	-	-0.10**
Content Fear (F)	-	-0.11***
Content Sadness (S)	-	-0.23***
Content Anger (A)	-	$0.06^{n.s}$
Content Surprise (Su)	-	-0.11***
Content Disgust (D)	-	-0.07*
*n-value < 05 **n-value <	01 ***n-value	< 001 ns not significant

#### \*p-value < .05, \*\*p-value < .01, \*\*\*p-value < .001, ns not significant

### Known in email features analysis

# Little to not significant

>Inverse associations



#### • How to determine **the optimal number of clusters**?

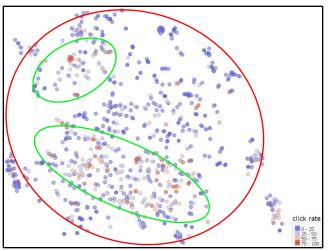
PCA <sup>a</sup>	Explained variance	Number of	silhouette score	
		clusters <sup>b</sup>		
1	24%	2	0.577	
2	40%	2	0.501	
3	53%	4	0.411	
4	63%	2	0.358	
5	72%	2	0.274	
6	79%	2	0.269	
7	86%	3	0.250	
8	91%	2	0.258	— A good compromise
9	96%	4	0.392	
10	100%	4	0.366	

<sup>a</sup> Number of PCA components

<sup>b</sup> The optimal number of clusters is chosen to maximize the silhouette score

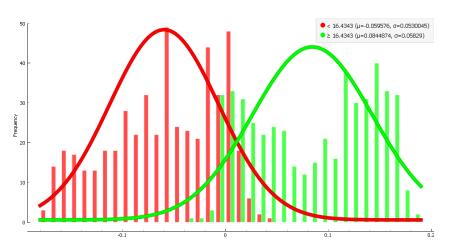


- Are there significant differences in the distribution of emotions between the good (best half) and bad (worst half) newsletters ?
- Bad newsletters seem evenly distributed
- Good newsletters seem to form clusters



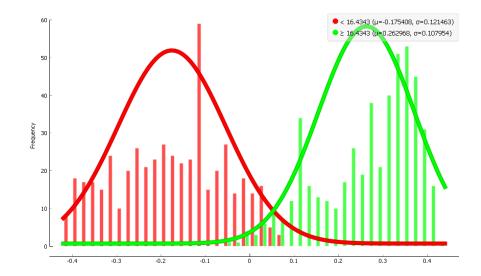
t-SNE projection of our dataset

#### **Our work – Silhouette Scores**



**∮ SIRISA** 

Silhouette score distribution with subject lines



Silhouette score distribution without subject lines

Classifier	F1 Score	Precision	Recall			
With subject line information						
AdaBoost	0.723	0.724	0.724			
Neural Network	0.712	0.712	0.712			
Random Forest	0.711	0.711	0.711			
kNN	0.681	0.688	0.683			
Naive Bayes	0.666	0.666	0.666			
SVM	0.607	0.617	0.612			
Logistic Regression	0.585	0.594	0.590			
Constant	0.500	0.500	0.500			
Without subject line information						
without s	ubject fille fi	normation				
Model	F1 Score	Precision	Recall			
	~		Recall 0.723			
Model	F1 Score	Precision				
Model AdaBoost	F1 Score 0.722	Precision 0.723	0.723			
Model AdaBoost Neural Network	<b>F1 Score</b> 0.722 0.714	Precision 0.723 0.715	<b>0.723</b> 0.715			
Model AdaBoost Neural Network Random Forest	<b>F1 Score</b> 0.722 0.714 0.710	Precision 0.723 0.715 0.710	0.723 0.715 0.710			
Model AdaBoost Neural Network Random Forest kNN Naive Bayes SVM	<b>F1 Score</b> 0.722 0.714 0.710 0.679	Precision   0.723   0.715   0.710   0.683	0.723 0.715 0.710 0.680			
Model AdaBoost Neural Network Random Forest kNN Naive Bayes	<b>F1 Score</b> 0.722 0.714 0.710 0.679 0.666	Precision   0.723   0.715   0.710   0.683   0.666	0.723 0.715 0.710 0.680 0.666			

Feature	F1-score with a	F1-score with
	single feature	all but one
		feature
Subject line polarity	0.498	0.720
Subject line subjectivity	0.503	0.721
Content Polarity	0.614	0.719
Content Subjectivity	0.570	0.725
Content Joy	0.624	0.723
Content Fear	0.604	0.722
Content Sadness	0.633	0.711
Content Anger	0.018	0.713
Content Surprise	0.614	0.721
Content Disgust	0.626	0.721



- Emotions **influence** the performance of French email campaigns
- **Need for further study** to provide a writing recommender tool
- **Improve** our emotion detection analysis
- **Share our dataset** for reproducibility

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# Thank you for your attention

