An email virtual assistant solution for customer services

ABSTRACT

Artificial Intelligence (AI) has opened up new avenues for the improvement of digital services. In the banking industry, back-offices are among the first who could benefit from this opportunity. Indeed, they devote their time to answering emails that require little expertise. This prevents them from attending to higher added-value tasks.

In this work, we design a solution that analyzes an email, identifies the intent of the sender, categorizes the attachment files and finally suggests a response. To do so, we leverage and combine several classes of algorithms. We evaluate our models on a dataset of corporate labeled emails. They prove to be highly competitive.

The solution is co-designed with business banking experts to meet their needs and already deployed in part of the Credit Agricole group. It is currently used by the back-office of the housing loan department's customer service.

EXPERIMENTS

We evaluate our solution on a corpus provided by the department of housing loan at Credit Agricole Ille-et-Vilaine, a regional bank of the Credit Agricole group. This corporate French corpus has been labeled by experts.

We evaluate each model as follows:

1. **Body segmentation:** a dataset of 500 emails. In each email, the sentences are either labeled "signature" or "body", similarly to the Mailgun public dataset [1]
2. **Body classification:** a dataset of 10K emails. Emails have been classified by experts into 18 categories.
3. **Attachment classification:** a dataset of 10K scanned documents. Documents have been classified by experts into 16 categories.

Table 1 displays the evaluation metrics for our models.

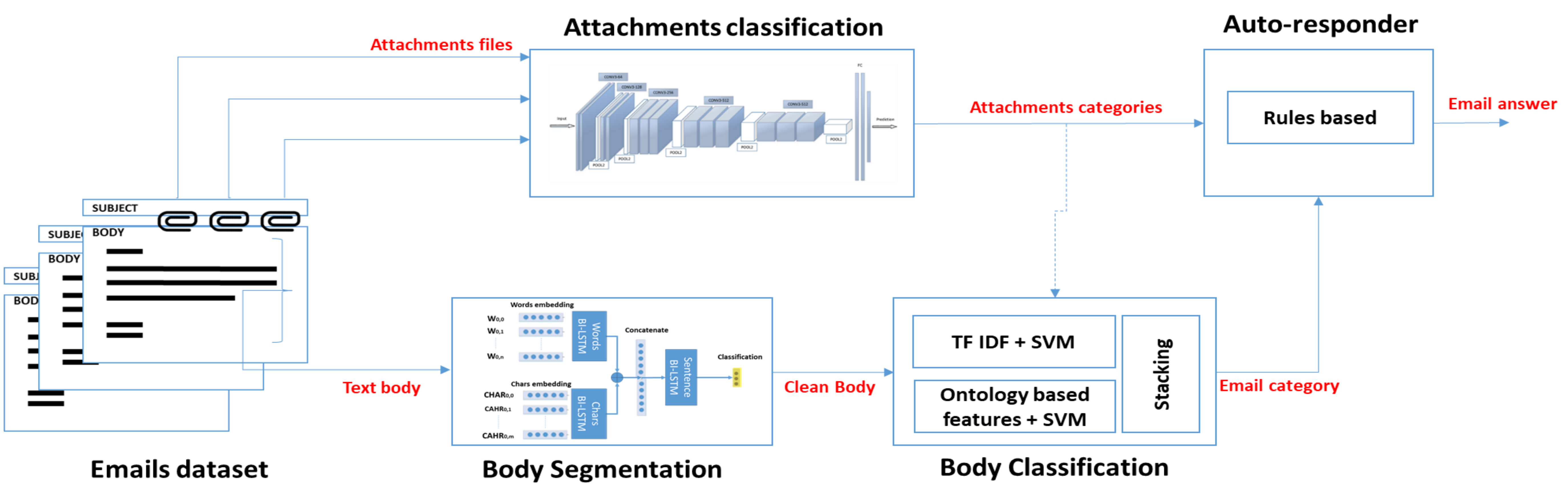

Figure 1: Models architectures for attachment classification, body segmentation, body classification and auto-responder

PROPOSAL

The designed solution is divided into four components (Figure 1):

1. **Body Segmentation**: removes the signature from the email body. The network is a BI-LSTM on sentences, allowing to take into account previous/next sentences during sentence classification. Indeed, signatures are usually preceded by meaningful sentences like: *"Best regards", "Thank you", etc.* Each sentence is encoded into a vector by concatenating (1) a BI-LSTM encoder on words and (2) a BI-LSTM encoder on characters. Hence, the resulting vector encodes both the word-level and the character-level semantics of a sentence.

2. **Body classification**: classifies the clean body. The proposed approach is a stacking of two models:
   a. A Linear SVM classifier on the TFIDF coefficients associated to the documents.
   b. A Linear SVM on features derived from the projection of the corpus on an ontology designed for our use-case. This ontology is an extension of the WordNet ontology, designed to encompass banking concepts.

3. **Attachments classification**: classifies each attached file (a scanned document) based on its visual patterns. The proposed network is the VGG16 convolutional neural network [3], in which we can transfer weights learned on two datasets: a corporate dataset of 300K scanned documents and the Tobacco dataset [2].

4. **Auto-responder:** picks the appropriate answer from a finite set of possible answers. The decision is based on expert hand-made rules combining the following data: body category, attachments categories and sender's email domain.

	Body Segmentation	***Body classification***	***Attachment classification***
Accuracy	**97%**	**89%**	**94%**

Table 1: Test accuracies of the proposed models.

The body segmentation model outperforms by 30 points a simple rule-based approach, that infers the boundaries of the body by detecting split words (*"regards", "thank", etc.*)

The body classification method we use outperforms all the neural network architectures we have tested. This is because 1/ the corpus is relatively small and 2/ the vocabulary is very specific, leaving little room to transfer learning.

The attachment classification model is a standard model for image classification, that has shown good performances on multiple datasets of image documents [3].

CONCLUSION & FUTURE WORK

We proposed in this work a solution for automatic emails analysis, categorization and responding, taking into account both textual and visual data and giving competitive results.

Future works will be devoted to improve the proposed models and develop new ones that are more suitable for new corpora and requirements of other customer services in the Credit Agricole group.

REFERENCES

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2. *The Tobacco public dataset: https://ir.nist.gov/cdip/*
3. *A. W. Harley, A. Ufkes, K. G. Derpanis, "Evaluation of Deep Convolutional Nets for Document Image Classification and Retrieval," in ICDAR, 2015*

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