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Use of SimpleT5 for the CLEF workshop JokeR: Automatic Pun and Humor Translation

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Abstract
In this paper, we present our work in the JokeR workshop. JokeR is a project aiming to study the strategies of localization of humor and puns and to create a multilingual parallel corpus and evaluation metrics in order to put a step forward to Automatic Pun and Humor Translation. 3 Tasks were proposed and to predict the requested fields for each of them, we trained the T5 model specialist in natural language processing tasks. Then we applied the models on test datasets, generating the runs as requested. By doing this we propose a simple method to study the translatability of puns. Also, we propose another way to implement our method to obtain more varied results. All this is to study the multilingual character of wordplay.

Keywords
Computational Humor, CLEF, JokeR, T5 models, SimpleT5

1. Introduction

In the context of the CLEF workshop: JokeR [1], 3 tasks were proposed: 1) Wordplay instances classification, 2) Single-words-wordplay translation, 3) Wordplay-containing-phrases translation. We propose to use the T5 model [2]. T5 models (T5, mT5 or byT5) are mainly used for natural language processing tasks and makes use of Transformers [3]. To train it, we use the SimpleT5 library [4]. SimpleT5 is design from PyTorch-lightning [5], a high-level python library for PyTorch [6], a machine learning framework. SimpleT5 provides an easier way to use pre-trained models and makes it easy to train our T5 models with a few lines of code. First, we'll explain our method, how to train the model, and how to use it. In a second step, we will present our results, and explain why they are not so good, then we propose a way to obtain better results while maintaining our process.

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2. Method

The objective is for tasks 2 and 3 to translate from English to French or for task 1 to predict classification fields for a given sentence. To do that, the method is the same for each task. First, we train the t5 model to predict what we want, and then we generate the runs with a script that apply the model to the input dataset.

2.1. Training scripts

The training scripts are divided into 2 parts, the first is the dataset reading and its formatting. Then comes the training of the model.

For tasks 2 and 3, the input dataset is three-fields-composed, the identifiers, the words/sentences in English then the same words or sentences in French.

Before doing anything, we start by cleaning the data, that is to say, we go through all the existing fields by checking the correspondence of the types as well as the content. Indeed, a column that must contain character strings must not contain anything other than strings, likewise, no null values must appear in the entire dataset.

So we start by separating the data in the form of data-frames into two parts. A train part and a test part. These two data-frames are then mixed. We end up removing the identifiers field and renaming the "en" and "fr" columns to "source_text" and "target_text" respectively. *(cf. Table 1)*

"source_text"	*"target_text"*
My boyfriend and I started to date after he backed his car into mine. We met by accident.	*Mon petit ami et moi avons commencé à sortir ensemble après qu'il ait reculé sa voiture contre la mienne. Nous nous sommes rencontrés par accident.*

Table 1
Table detailing the precision of each field of Task 1

Now the model training can begin by using the SimpleT5 librarie. We first load T5 model, before running the training method.

Now that the T5 model is trained, it is ready to predict the "target_text" field according to the "source_text" given to it.

Note that we have given the example of Tasks 3 because it is simpler and more condensed to present, but concerning Task 1, it is the same process. The only difference is in the number of fields to predict, so we have 1 training per field to predict. The shape of the data-frames is the same too.

2.2. Generalizing script

Now that we have a trained model, we can launch our runs. Of course, just like during the training, we must clean the input dataset, to make sure to not have erroneous values.

For this, we just need to have a data frame with a column containing values similar to the preceding "source_text" fields. Then we have to load the trained model. Then using the apply method of the Pandas library, we can predict one by one all the desired corresponding values ("target_text").

We finish everything by formatting all the results in the JOKER-requested way.

2.3. Method summarization

We have seen that to predict each desired field in tasks 1, 2, and 3, it was necessary each time to organize and format the input data to train the T5 model. We also saw that once a model was trained, it was then possible to apply it to a given input dataset. Without forgetting to be rigorous about the formatting of the output data which must correspond to the given format.

3. Results

3.1. Task 1

Task 1 is quite special due to its number of fields to predict. Therefore we have chosen to train a model for each of these fields. It was quite possible and even better to couple certain fields during the prediction.

So here are the different elements that we have been able to observe : *(cf. A)*

- **Location** : location field predictions are globally accurate (80
  - Short wordplays : they contain only 2 or 3 words, and the pun is on these few words, the model, therefore, predicts that the location is on these words.
  - Sentences with wordplays : In these cases, the location of the puns is often at the end of the sentences and the model easily locates them.

  But in these two cases, it is impossible to say if the model is really precise or if it is based only on the standard of the input data. In fact, as for short puns or sentences, the location is very much the same, the model could very well base itself on this to predict the locations. Therefore it would not predict the location of the pun but the normal location it is supposed to have.
- **Interpretation** : regarding this field, we can see different behaviors but none is really correct :
  - Sometimes the interpretation prediction is just bad and doesn't make sense. The model takes a word and displays it two times.

- Other times the prediction just took the two worded wordplay. It doesn't give us any explanation about the wordplay.
- Otherwise, the prediction took only one word from the original text. So that doesn't give us an explanation either.
- Then, there are some other behaviors, but there are never precisely explaining the wordplay.

- **Manipulation level** : all rows are predicted as "Sound", which is not always true nor false. And even if the "Sound" level is found and true, the interpretation is not able to find the initial word. (probably because both columns have to be trained together)
- **Horizontal and vertical** : this field seems to be exclusively predicted as "vertical".
- **Manipulation type** : This seems to be the most accurately predicted field, but again it's hard to tell if the model is really accurate or if it's not just based on the rate of training values. Which statistically, would allow him to be precise, by chance in a way.

Speaking of statistics *(cf. Table 2)*, despite high accuracy rates in certain fields, it remains difficult to know if our model is accurate, or if it is not based on a certain standard. This standard repeating itself in our test data, most likely allows our model to be accurate.

	Accuratcy rate	Matches	Mismatches	Shapes	Errors
location	0.804819	334	81	415	0
interpretation	0.0578313	24	391	415	0
hor/ver	0.985542	409	6	415	0
Manip_type	0.584541	242	172	414	0
Manip_level	0.99759	414	1	415	0

Table 2
Table detailing the precision of each field of Task 1

3.2. Task 2

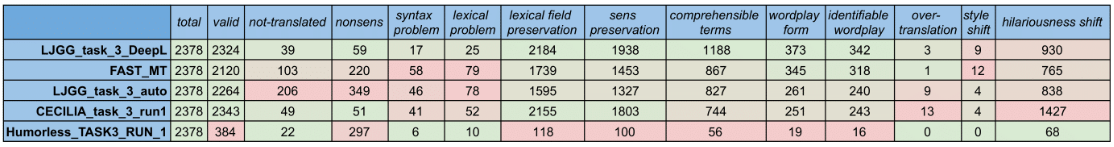
For this task, we want to translate term-based wordplay, e.g. the Pokémon names, from English to French *(cf. B)*. The model has translation difficulties (especially because we had to use the T5 model and not the mT5 model which is more efficient with translations). The results are mostly the same word as the source. Sometimes there are changes with the letters, accents appear and some double letters become single.

3.3. Task 3

For this last task, it was a question of translating sentences containing puns *(cf. C)*. All in all, the translation is not bad if a few small errors are disregarded. The subject of the sentences is often kept, the humorous effect is not always present, or is more complicated to understand after translation. Nevertheless, some sentences work very well in French and have been translated well.

English	*“Some burglars are always looking for windows of opportunity.”*
French	*"Certains cambrioliers cherchent toujours des fenêtres d’opportunité.”*

Table 3
Example of sentence with wordplay that as been translated from English to French retaining meaning



	total	valid	not-translated	nonsens	syntax problem	lexical problem	lexical field preservation	sens preservation	comprehensible terms	wordplay form	identifiable wordplay	over-translation	style shift	hilariousness shift
LJGG_task_3_DeepL	2378	2324	39	59	17	25	2184	1938	1188	373	342	3	9	930
FAST_MT	2378	2120	103	220	58	79	1739	1453	867	345	318	1	12	765
LJGG_task_3_auto	2378	2264	206	349	46	78	1595	1327	827	261	240	9	4	838
CECILIA_task_3_run1	2378	2343	49	51	41	52	2155	1803	744	251	243	13	4	1427
Humorless_TASK3_RUN_1	2378	384	22	297	6	10	118	100	56	19	16	0	0	68

Table 4
Table representing the analyzes made on different runs submitted to JokeR, the color gradient makes it possible to identify which are the best in opposition to each other.

4. Discussion

Based on our results, it’s clear that our model needs much better training. Which in our case was complicated to do because of time and material constraints.
Nevertheless, our results allow us to notice several things from the point of view of the training data. especially for task 1, certain classification elements must be more varied, to avoid the models being based on standards that would be detected.

- For example, the classification fields "manipulation_level" and "horizontal/vertical" are not varied enough.

Still concerning Task 1, it would surely be interesting to dissociate short puns and sentences containing puns. always with the aim of improving the models.
Speaking of models, we used T5, but mT5 is the multi-lingual version of T5. Unfortunately we haven’t been able to use it (again for hardware performance reasons). This multi-lingual version would surely have been better for translations.

Now let’s discuss the translation part, we were able to have our results analyzed and we can therefore compare them to other methods and models. Table 4 shows this, the lines represent the runs that were submitted to JokeR, ours being "CECILIA", the columns give us quantitative numerical indications of what was observed. The color code simply shows us who has the best results (green) and who has the worst (red) for each category.

- **Total** : Total row submitted.
- **Valid** : Number of valid submissions.
- **not-translated** : Number of rows that have not been translated.
- **nonsens** : Number of rows that have no sens.
- **syntax_problem** : Number of rows that present syntax errors.
- **lexical_problem** : Number of rows that present lexical errors.
- **lexical_field_preservation** : Number of row that have retained lexical_field
- **sens_preservation** : Number of translation that preserve the sens from english to french.

- **comprehensible_terms** :
- **wordplay_form** : Number of rows that present wordplay form.
- **identifiable_wordplay** : Number of rows that present identifiable wordplay.
- **over-translation** :
- **style_shift** : Number of rows that present shift from the style point of view.
- **hilariousness_shift** : Number of rows that present shift from the hilariousness point of view.

From this table *(cf. Table 2)*, it is much easier to give an opinion on our method and the use of T5. Indeed we have opted for a simple and quick implementation approach that may not be the case for the other proposals. We can then figure out the ratio between efficiency and translation accuracy, not only from the translation point of view as-it-is but also from the puns hilariousness transition aspect.

Now, if we take the time to look at and compare our results to those of the other proposals, we observe several things. First, our method can translate the majority of sentences. Indeed, we present a small number of untranslated fields. However, regarding the presence of syntactic and lexical errors, we are at the opposite, less good. Regardless, this remains at a low ratio, given the total number of translations. Concerning the lexical and meaning preservation fields, we place ourselves this time at the forefront, especially with the second place for both, while remaining close to the first results. The number of understandable terms is not to our advantage, we place ourselves 4th out of 5, but we are still on the same number scale as the first. The number of pun forms is not the highest, but it remains the same magnitude as the best results. The same goes for identifiable puns. Note that we are the ones who show the highest number of over-translations, it is only about ten cases.

Concerning the translation of puns and considering this evaluation, it allows us to show our strong and weak points. Also, we can situate ourselves from others' submissions. What is clear is that our translation is globally good. Indeed our results always follow the norm with no figures standing out, whether for good or less. However, there is one that scores, the more than 1400 hilariousness shifts. We are certainly the only ones having correct translations while having a significantly higher number of translations that have lost their funny character. Our method, therefore, seems to be a good translator, which does not translate the second degree but which translates puns in the first degree *(this can be likened to a form of humor, can't it ?).*

5. Conclusion

In the context of the JOKER workshop, we decided to use existing models and to train them to predict asked fields.

In summary, we don't have any significantly good results. But our method works, and there are only tracks of improvement, mainly around the models and their training. Only for task 1, our version: 1 model per field to predict works but is in our opinion not the only one possible, nor the most efficient. It is nevertheless simple to implement because it follows the same procedure as all the other models that we have been able to use. We indeed think that the coupling of several fields for the training of the models was a concrete track of improvement for the predictions or at least a good way to know what is the best way to do this.

The next step would be an improvement in hardware capabilities to better train our models. Also, the choice of model is not fixed and other models can be used for our objectives such as Jurassic [7] for example.

6. Online Resources

The sources for the three JokeR tasks are available via

- GitHub,

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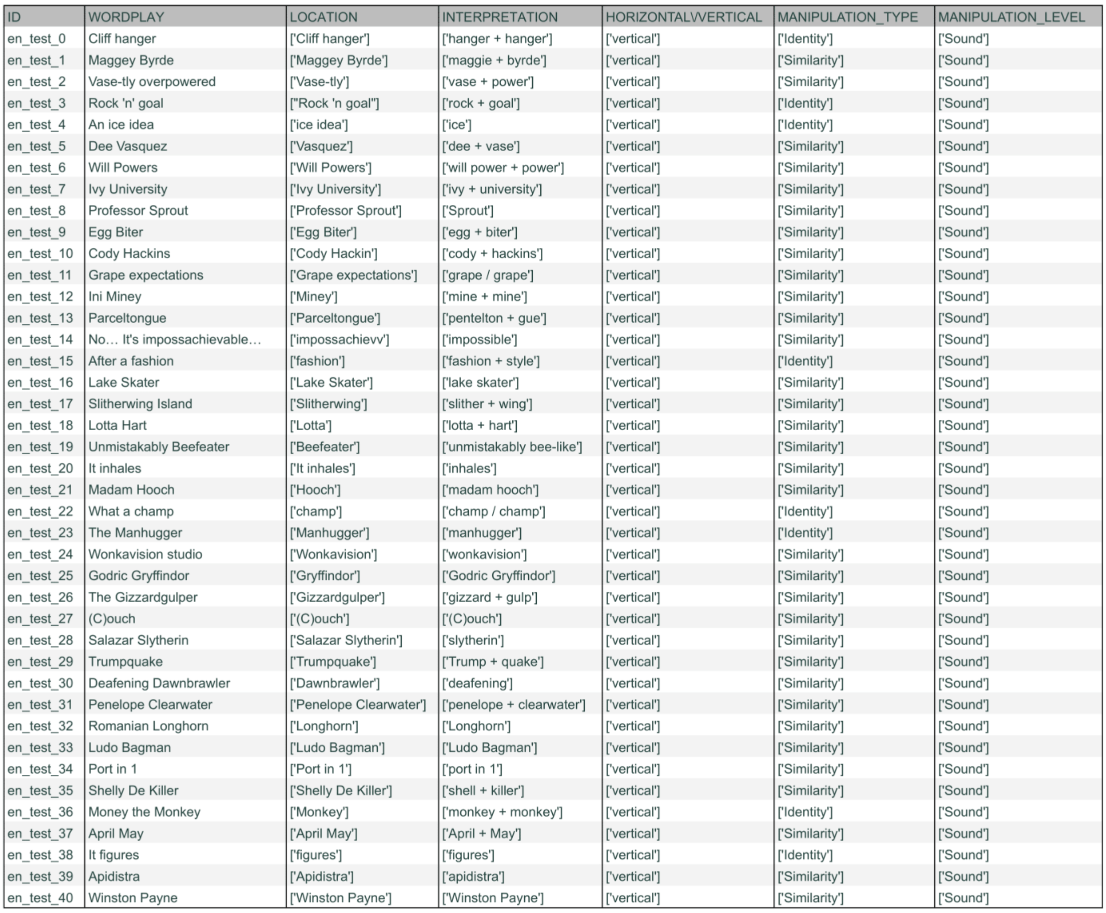
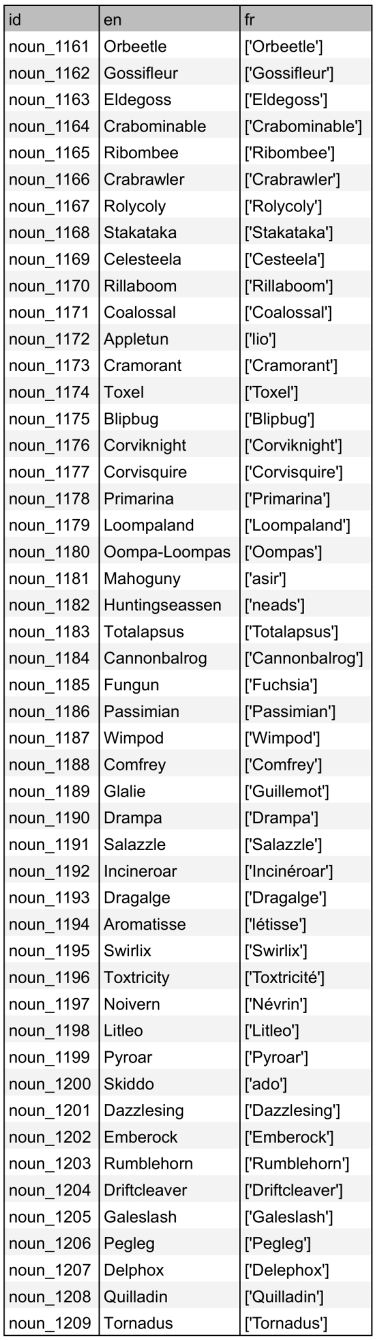
Appendices

Appendix A Outputs example from Task 1



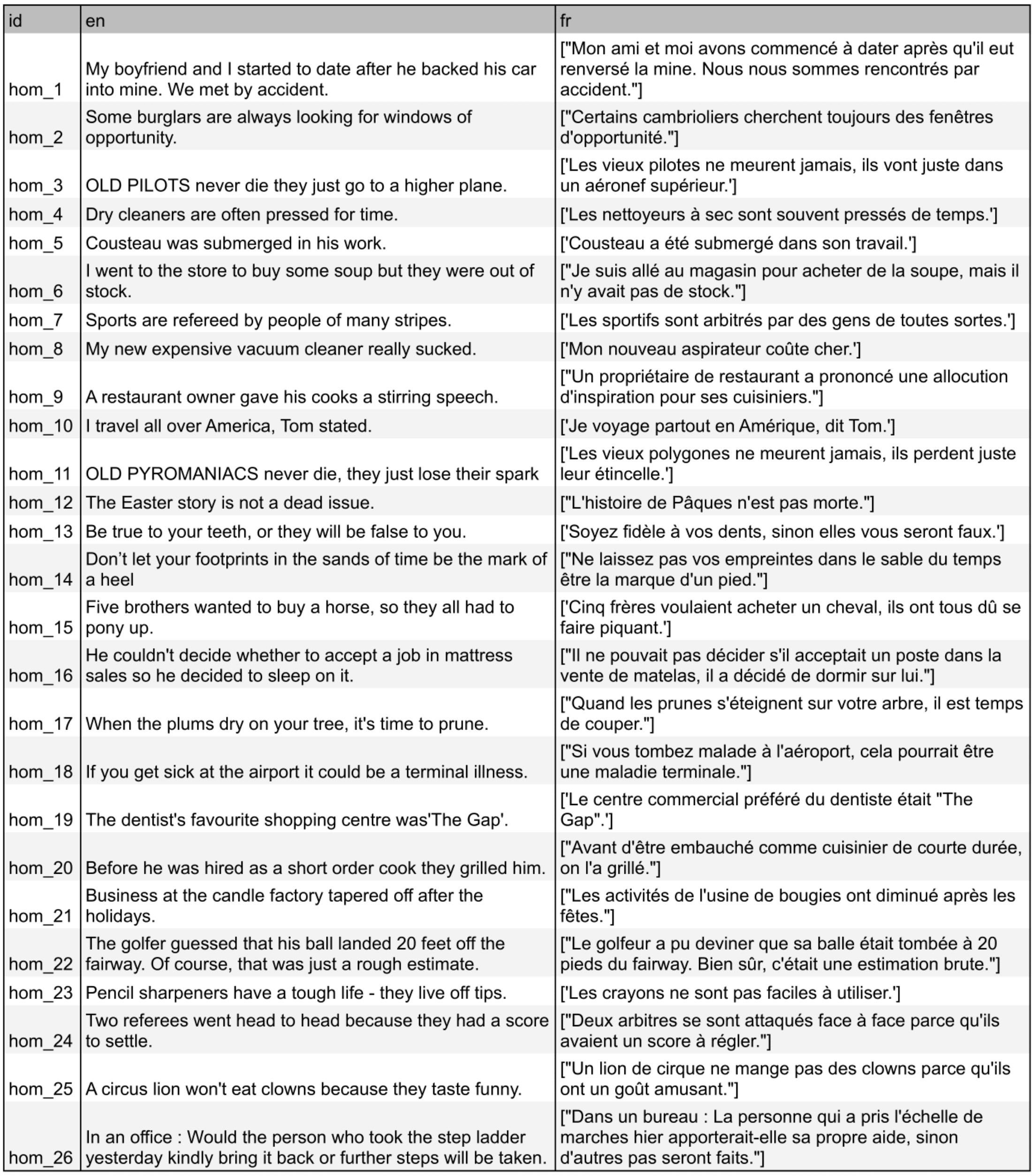
ID	WORDPLAY	LOCATION	INTERPRETATION	HORIZONTAL\/VERTICAL	MANIPULATION_TYPE	MANIPULATION_LEVEL
en_test_0	Cliff hanger	['Cliff hanger']	['hanger + hanger']	['vertical']	['Identity']	['Sound']
en_test_1	Maggey Byrde	['Maggey Byrde']	['maggie + byrde']	['vertical']	['Similarity']	['Sound']
en_test_2	Vase-tly overpowered	['Vase-tly']	['vase + power']	['vertical']	['Similarity']	['Sound']
en_test_3	Rock 'n' goal	["Rock 'n goal"]	['rock + goal']	['vertical']	['Identity']	['Sound']
en_test_4	An ice idea	['ice idea']	['ice']	['vertical']	['Identity']	['Sound']
en_test_5	Dee Vasquez	['Vasquez']	['dee + vase']	['vertical']	['Similarity']	['Sound']
en_test_6	Will Powers	['Will Powers']	['will power + power']	['vertical']	['Similarity']	['Sound']
en_test_7	Ivy University	['Ivy University']	['ivy + university']	['vertical']	['Similarity']	['Sound']
en_test_8	Professor Sprout	['Professor Sprout']	['Sprout']	['vertical']	['Similarity']	['Sound']
en_test_9	Egg Biter	['Egg Biter']	['egg + biter']	['vertical']	['Similarity']	['Sound']
en_test_10	Cody Hackins	['Cody Hackin']	['cody + hackins']	['vertical']	['Similarity']	['Sound']
en_test_11	Grape expectations	['Grape expectations']	['grape / grape']	['vertical']	['Similarity']	['Sound']
en_test_12	Ini Miney	['Miney']	['mine + mine']	['vertical']	['Similarity']	['Sound']
en_test_13	Parceltongue	['Parceltongue']	['pentelton + gue']	['vertical']	['Similarity']	['Sound']
en_test_14	No… It's impossachievable…	['impossachievv']	['impossible']	['vertical']	['Similarity']	['Sound']
en_test_15	After a fashion	['fashion']	['fashion + style']	['vertical']	['Identity']	['Sound']
en_test_16	Lake Skater	['Lake Skater']	['lake skater']	['vertical']	['Similarity']	['Sound']
en_test_17	Slitherwing Island	['Slitherwing']	['slither + wing']	['vertical']	['Similarity']	['Sound']
en_test_18	Lotta Hart	['Lotta']	['lotta + hart']	['vertical']	['Similarity']	['Sound']
en_test_19	Unmistakably Beefeater	['Beefeater']	['unmistakably bee-like']	['vertical']	['Similarity']	['Sound']
en_test_20	It inhales	['It inhales']	['inhales']	['vertical']	['Similarity']	['Sound']
en_test_21	Madam Hooch	['Hooch']	['madam hooch']	['vertical']	['Similarity']	['Sound']
en_test_22	What a champ	['champ']	['champ / champ']	['vertical']	['Identity']	['Sound']
en_test_23	The Manhugger	['Manhugger']	['manhugger']	['vertical']	['Identity']	['Sound']
en_test_24	Wonkavision studio	['Wonkavision']	['wonkavision']	['vertical']	['Similarity']	['Sound']
en_test_25	Godric Gryffindor	['Gryffindor']	['Godric Gryffindor']	['vertical']	['Similarity']	['Sound']
en_test_26	The Gizzardgulper	['Gizzardgulper']	['gizzard + gulp']	['vertical']	['Similarity']	['Sound']
en_test_27	(C)ouch	['(C)ouch']	['(C)ouch']	['vertical']	['Similarity']	['Sound']
en_test_28	Salazar Slytherin	['Salazar Slytherin']	['slytherin']	['vertical']	['Similarity']	['Sound']
en_test_29	Trumpquake	['Trumpquake']	['Trump + quake']	['vertical']	['Similarity']	['Sound']
en_test_30	Deafening Dawnbrawler	['Dawnbrawler']	['deafening']	['vertical']	['Similarity']	['Sound']
en_test_31	Penelope Clearwater	['Penelope Clearwater']	['penelope + clearwater']	['vertical']	['Similarity']	['Sound']
en_test_32	Romanian Longhorn	['Longhorn']	['Longhorn']	['vertical']	['Similarity']	['Sound']
en_test_33	Ludo Bagman	['Ludo Bagman']	['Ludo Bagman']	['vertical']	['Similarity']	['Sound']
en_test_34	Port in 1	['Port in 1']	['port in 1']	['vertical']	['Similarity']	['Sound']
en_test_35	Shelly De Killer	['Shelly De Killer']	['shell + killer']	['vertical']	['Similarity']	['Sound']
en_test_36	Money the Monkey	['Monkey']	['monkey + monkey']	['vertical']	['Identity']	['Sound']
en_test_37	April May	['April May']	['April + May']	['vertical']	['Similarity']	['Sound']
en_test_38	It figures	['figures']	['figures']	['vertical']	['Identity']	['Sound']
en_test_39	Apidistra	['Apidistra']	['apidistra']	['vertical']	['Similarity']	['Sound']
en_test_40	Winston Payne	['Winston Payne']	['Winston Payne']	['vertical']	['Similarity']	['Sound']

Appendix B Outputs example from Task 2



id	en	fr
noun_1161	Orbeetle	['Orbeetle']
noun_1162	Gossifleur	['Gossifleur']
noun_1163	Eldegoss	['Eldegoss']
noun_1164	Crabominable	['Crabominable']
noun_1165	Ribombee	['Ribombee']
noun_1166	Crabrawler	['Crabrawler']
noun_1167	Rolycoly	['Rolycoly']
noun_1168	Stakataka	['Stakataka']
noun_1169	Celesteela	['Cesteela']
noun_1170	Rillaboom	['Rillaboom']
noun_1171	Coalossal	['Coalossal']
noun_1172	Appletun	['lio']
noun_1173	Cramorant	['Cramorant']
noun_1174	Toxel	['Toxel']
noun_1175	Blipbug	['Blipbug']
noun_1176	Corviknight	['Corviknight']
noun_1177	Corvisquire	['Corvisquire']
noun_1178	Primarina	['Primarina']
noun_1179	Loompaland	['Loompaland']
noun_1180	Oompa-Loompas	['Oompas']
noun_1181	Mahoguny	['asir']
noun_1182	Huntingseassen	['neads']
noun_1183	Totalapsus	['Totalapsus']
noun_1184	Cannonbalrog	['Cannonbalrog']
noun_1185	Fungun	['Fuchsia']
noun_1186	Passimian	['Passimian']
noun_1187	Wimpod	['Wimpod']
noun_1188	Comfrey	['Comfrey']
noun_1189	Glalie	['Guillemot']
noun_1190	Drampa	['Drampa']
noun_1191	Salazzle	['Salazzle']
noun_1192	Incineroar	['Incinéroar']
noun_1193	Dragalge	['Dragalge']
noun_1194	Aromatisse	['létisse']
noun_1195	Swirlix	['Swirlix']
noun_1196	Toxtricity	['Toxtricité']
noun_1197	Noivern	['Névrin']
noun_1198	Litleo	['Litleo']
noun_1199	Pyroar	['Pyroar']
noun_1200	Skiddo	['ado']
noun_1201	Dazzlesing	['Dazzlesing']
noun_1202	Emberock	['Emberock']
noun_1203	Rumblehorn	['Rumblehorn']
noun_1204	Driftcleaver	['Driftcleaver']
noun_1205	Galeslash	['Galeslash']
noun_1206	Pegleg	['Pegleg']
noun_1207	Delphox	['Delephox']
noun_1208	Quilladin	['Quilladin']
noun_1209	Tornadus	['Tornadus']

Appendix C Outputs example from Task 3



id	en	fr
hom_1	My boyfriend and I started to date after he backed his car into mine. We met by accident.	["Mon ami et moi avons commencé à dater après qu'il eut renversé la mine. Nous nous sommes rencontrés par accident."]
hom_2	Some burglars are always looking for windows of opportunity.	["Certains cambrioliers cherchent toujours des fenêtres d'opportunité."]
hom_3	OLD PILOTS never die they just go to a higher plane.	['Les vieux pilotes ne meurent jamais, ils vont juste dans un aéronef supérieur.']
hom_4	Dry cleaners are often pressed for time.	['Les nettoyeurs à sec sont souvent pressés de temps.']
hom_5	Cousteau was submerged in his work.	['Cousteau a été submergé dans son travail.']
hom_6	I went to the store to buy some soup but they were out of stock.	["Je suis allé au magasin pour acheter de la soupe, mais il n'y avait pas de stock."]
hom_7	Sports are refereed by people of many stripes.	['Les sportifs sont arbitrés par des gens de toutes sortes.']
hom_8	My new expensive vacuum cleaner really sucked.	['Mon nouveau aspirateur coûte cher.']
hom_9	A restaurant owner gave his cooks a stirring speech.	["Un propriétaire de restaurant a prononcé une allocution d'inspiration pour ses cuisiniers."]
hom_10	I travel all over America, Tom stated.	['Je voyage partout en Amérique, dit Tom.']
hom_11	OLD PYROMANIACS never die, they just lose their spark	['Les vieux polygones ne meurent jamais, ils perdent juste leur étincelle.']
hom_12	The Easter story is not a dead issue.	["L'histoire de Pâques n'est pas morte."]
hom_13	Be true to your teeth, or they will be false to you.	['Soyez fidèle à vos dents, sinon elles vous seront faux.']
hom_14	Don’t let your footprints in the sands of time be the mark of a heel	["Ne laissez pas vos empreintes dans le sable du temps être la marque d'un pied."]
hom_15	Five brothers wanted to buy a horse, so they all had to pony up.	['Cinq frères voulaient acheter un cheval, ils ont tous dû se faire piquant.']
hom_16	He couldn't decide whether to accept a job in mattress sales so he decided to sleep on it.	["Il ne pouvait pas décider s'il acceptait un poste dans la vente de matelas, il a décidé de dormir sur lui."]
hom_17	When the plums dry on your tree, it's time to prune.	["Quand les prunes s'éteignent sur votre arbre, il est temps de couper."]
hom_18	If you get sick at the airport it could be a terminal illness.	["Si vous tombez malade à l'aéroport, cela pourrait être une maladie terminale."]
hom_19	The dentist's favourite shopping centre was'The Gap'.	['Le centre commercial préféré du dentiste était "The Gap".']
hom_20	Before he was hired as a short order cook they grilled him.	["Avant d'être embauché comme cuisinier de courte durée, on l'a grillé."]
hom_21	Business at the candle factory tapered off after the holidays.	["Les activités de l'usine de bougies ont diminué après les fêtes."]
hom_22	The golfer guessed that his ball landed 20 feet off the fairway. Of course, that was just a rough estimate.	["Le golfeur a pu deviner que sa balle était tombée à 20 pieds du fairway. Bien sûr, c'était une estimation brute."]
hom_23	Pencil sharpeners have a tough life - they live off tips.	['Les crayons ne sont pas faciles à utiliser.']
hom_24	Two referees went head to head because they had a score to settle.	["Deux arbitres se sont attaqués face à face parce qu'ils avaient un score à régler."]
hom_25	A circus lion won't eat clowns because they taste funny.	["Un lion de cirque ne mange pas des clowns parce qu'ils ont un goût amusant."]
hom_26	In an office : Would the person who took the step ladder yesterday kindly bring it back or further steps will be taken.	["Dans un bureau : La personne qui a pris l'échelle de marches hier apporterait-elle sa propre aide, sinon d'autres pas seront faits."]