Translating a Classifier

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1 Overview

1.1 The Data

In order to work on translating a classifier, I need similar data in different languages. The first thing I'm going to use is reddit, starting with March 2017 (and adding others if I need more data), using langdetect (https://pypi.python.org/pypi/langdetect) on comments that have at least 15 unique words. I'm going to try to pull 10k each of Spanish, French, and Italian. Unfortunately this is either slow or sparse, and is taking a while. Hopefully it will finish by tomorrow or something.

Alternatively/additionally, if I can find different-language wikipediae, I can use page category as the classes.

1.1.1 LID data

We can make sure the LID worked reasonably well by checking the subreddits represented

Subreddit	Count	Subreddit	Count	Subreddit	Count
argentina	4,632	france	7,772	italy	7,862
mexico	1,840	Quebec	1,052	oknotizie	525
podemos[1]	1,622	montreal	197	ItalyInformatica	351
chile	592	ParisComments	116	italy_SS	327
vzla	280	French	44	italygames	86
Argaming	87	Lyon	35	perlediritaly	69
Spanish	80	FiascoQc	34	lisolachece	62
uruguay	75	SquaredCircle_FR	32	Romania	61
PuertoRico	50	effondrement	27	ItaliaPersonalFinance	54
Colombia	44	melenchon	23	ItalyMotori	40

1.1.2 Subreddit corpora

Using the data from the LID stuff, we can also just create the corpora by using all the posts from some subreddits. I propose[2]

[1] Spanish political party

[2] We'll fix this later

Spanish
argentina
mexico
chile
vzla
uruguay
Colombia

French
france
Quebec
montreal
Lyon

Italian
italy

2 Classifier

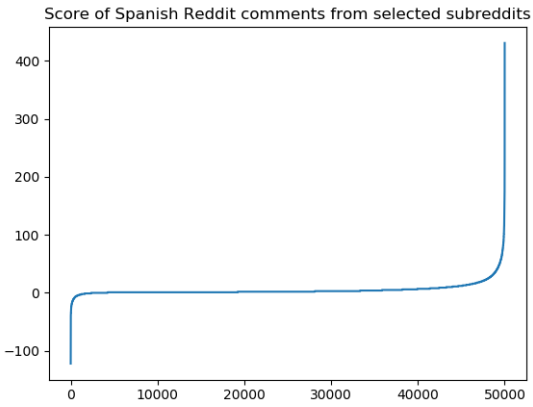
In order to make this work, we need to have some aspect that we're trying to classify against. One thing that has been done in the past is classification based on subreddit; based on the subreddits represented this could be possible: national subreddit (argentina, france, italy), gaming (Argaming, jeuxvideo, italygames), however maybe not much else. For reference, these are the fields I have to work with for each comment:

author	author_flair_css_class	author_flair_text	body	controversiality
created_utc	distinguished	edited	gilded	id
link_id	parent_id	retrieved_on	score	stickied
subreddit	subreddit_id			

Here are what I think:

- Controversiality
  Pro: Should be fairly language independent
  Con: Pretty sparse, only about 3% of the documents are "controversial". Controversial comments might tend to be in English, as well (comments from outsiders)

- Score: (binned)
  Pro: Should be fairly language independent
  Con: Borderlines between bins might be difficult, also more extreme scores are very sparse ($< 0.2\%$ have scores of at least 100)



- Gilded: (binary)
  Pro: Should be fairly language independent
  Con: Extremely sparse (¡ 0.03% have been gilded)

- Subreddit:
  Pro: Definitely influenced by context
  Con: Might be biased either towards games that are available in the given language, or the text will involve a lot of English.

- Flair (submissions):
  Pro: Human-decided topic labels *Con:* Submissions are not as common as comments, and the flairs across different subreddits might not align perfectly. Additionally, the title might not represent the content of the link perfectly.

The last idea just sort of came to me while looking at the subreddits. Using title text of submissions might be a good side project if this turns promising. To be specific, this is the number of comments in the smallest class for each of *gilded*, *controversial*, and *score*. (For *gilded* and *controversial*, this is the number of positive examples).

	Gilded	Contro	Score
Spanish-sub	3	347	123
Spanish	0	52	16
French-sub	1	423	70
French	0	64	10
Italian-sub	1	189	24
Italian	1	59	15

First, it's pretty clear that gilded isn't going to work well at all. Second, the bins for score might need to be refined.

3 Initial Classifiers

I divided my data into 80% train and 20% test and ran a couple classifiers on all of the data. Since *score* is multi-class, the default F1 score doesn't make sense, all of these classifiers will be evaluated on the harmonic mean of the fscores for each class[3]. I'm not sure if this is actually something that's really used, but it will work for our comparison purposes.

naive bayes			
	Gilded	Contro	Score
Spanish-sub	0.0100	0.0001	0.0002
Spanish	1.0000	0.0007	0.0013
French-sub	0.0392	0.0185	0.0002
French	err	0.0006	0.0004
Italian-sub	0.0392	0.0002	0.0004
Italian	0.0392	0.0006	0.0011

logistic regression			
	Gilded	Contro	Score
Spanish-sub	0.0100	0.1551	0.1145
Spanish	err	0.0004	0.1513
French-sub	0.0198	0.1889	0.0644
French	err	0.1523	0.0079
Italian-sub	0.0392	0.1902	0.0038
Italian	err	0.1198	0.0057

[3]Is this a real thing?

4 Bootstrapping

Recalling that controversial comments make up about 3% of the documents, and that classifiers are remarkably bad at picking them out, could we maybe train up a classifier to pick them out by bootstrapping? First, a look at the data:

	# Documents	# Controversial	%
Spanish	163,057	5,243	3.2%
French	207,348	9,449	4.6%
Italian	79,479	3,048	3.8%

We're going to look at Spanish first. Here is the (initial) algorithm:

1. Pick 5,000 documents at random (Random init)
2. Train some classifiers on those documents, splitting the 5,000 into random 80% train and 20% test sets (NOTE: these are not the same for each classifier) We'll use Naive Bayes (NB) and Logistic Regression (LR), run three different times. The table will show the one that works best
3. Pick the classifier with the best f-score, and run it over all the documents
4. Pick the 5,000 documents rated most likely to be controversial by that classifier, excluding any documents previously seen
5. Repeat

				Classifier f-score	
	Doc count	# Yes (repeats)	# Yes (total)	NB	LR
Random init	5000	172 (3.4%)	172	0	**0.087**
Round 1	5000	399 (8.0%)	437 (+265)	0	**0.077**
Round 2	5000	574 (11.5%)	683 (+246)	0	**0.16**
Round 3	5000	710 (14.2%)	928 (+245)	0	**0.097**

Some initial takeaways are that Naive Bayes just can't learn in this environment, but otherwise this process does work. Let's modify the algorithm to see if we can't make Naive Bayes a little happier:

1. Pick 5,000 documents at random (Random init)
2. Train some classifiers on *a subset of the documents, making sure positive documents comprise 33% of the dataset*, splitting *it* into random 80% train and 20% test sets (NOTE: these are not the same for each classifier) We'll use Naive Bayes (NB) and Logistic Regression (LR), run three different times. The table will show the one that works best
3. Pick the classifier with the best f-score, and run it over all the documents
4. Pick the 5,000 documents rated most likely to be controversial by that classifier, excluding any documents previously seen

5. Repeat

	Doc count	# Yes (repeats)	# Yes (total)	Classifier f-score NB	LR
Random init	5000	173 (3.5%)	173	**0.16**	0.30
Round 1	5000	381 (7.6%)	429 (+256)	**0.36**	0.43
Round 2	5000	553 (11.1%)	702 (+273)	**0.31**	0.40
Round 3	5000	724 (14.5%)	1000 (+298)	**0.38**	0.47

Indeed, this did help Naive Bayes get on the scoreboard. Both it and LR improved drastically, although LR still remained ahead. For this batch I decided to bootstrap based on the best NB classifier, to see if it bootstrapped well. Indeed, the general results are very similar. How does this work for French?

Without subsetting					
	Doc count	# Yes (repeats)	# Yes (total)	Classifier f-score NB	LR
Random init	5000	216 (4.3%)	216	0	**0.10**
Round 1	5000	571 (11.4%)	621 (+405)	0.017	**0.12**
Round 2	5000	883 (17.7%)	1034 (+413)	0	**0.17**
Round 3	5000	1124 (22.5%)	1432 (+398)	0.0067	**0.16**

With subsetting					
	Doc count	# Yes (repeats)	# Yes (total)	Classifier f-score NB	LR
Random init	5000	243 (4.9%)	243	**0.42**	0.49
Round 1	5000	533 (10.7%)	637 (+394)	**0.35**	0.44
Round 2	5000	828 (16.6%)	1095 (+458)	**0.36**	0.44
Round 3	5000	1041 (20.8%)	1523 (+428)	**0.38**	0.44

Looks like it works very similarly, with a bonus probably because French has more controversial posts.

4.1 Pruning with Logistic Regression

On the pruning experiments, I purposely chose to snowball the Naive Bayes to make sure it actually worked. However, Logistic Regression still had better F-scores, and so it's worth seeing how it does:

Spanish					
				Classifier f-score	
	Doc count	# Yes (repeats)	# Yes (total)	NB	LR
Random init	5000	170	170	0.24	0.49
Round 1	5000	397	460 (+291)	0.29	0.42
Round 2	5000	577	732 (+272)	0.38	0.38
Round 3	5000	745	1029 (+297)	0.25	0.42

French					
				Classifier f-score	
	Doc count	# Yes (repeats)	# Yes (total)	NB	LR
Random init	5000	226	226	0.23	0.34
Round 1	5000	434	572	0.21	0.46
Round 2	5000	772	992	0.24	0.35
Round 3	5000	1026	1413	0.28	0.44

4.2 SVM

Without subsetting				
			Classifier f-score	
	Doc count	# Yes (repeats)	# Yes (total)	SVM
Translated init	5000	151 (3.0%)	151	0.03
Round 1	5000	297 (6.0%)	329	0.06
Round 2	5000	423 (8.5%)	492	0.04
Round 3	5000	593 (11.9%)	705	0.05

With subsetting				
			Classifier f-score	
	Doc count	# Yes (repeats)	# Yes (total)	SVM
Translated init	5000	168 (3.4%)	168	0.39
Round 1	5000	272 (5.4%)	438	0.38
Round 2	5000	264 (5.3%)	702	0.42
Round 3	5000	247 (4.9%)	949	0.40

Oh yeah, SVM doesn't give probabilities, so it doesn't really make sense to ask for the 5,000 most likely documents. What if we instead make it so that we use the three SVM classifiers and rank by voting?

4.3 Many Runs

For the purposes of the next section, we're going to need a classifier that works reasonably well. Let's snowball the hell out of this thing.

	Doc count	# Yes (repeats)	# (total)	NB	LR	SVM
Random init	5000	178 (3.6%)	178	0	0.4	*0.05*
Round 1	5000	331 (6.6%)	365	0	*0.12*	0.07
Round 2	5000	535 (10.7%)	621	0	*0.09*	0.06
Round 3	5000	723 (14.5%)	915	0	*0.12*	0.10
Round 4	5000	845 (16.9%)	1191	0	*0.14*	0.13
Round 5	5000	1051 (21.0%)	1429	0	*0.14*	0.11
Round 6	5000	1258 (25.2%)	1692	0	*0.15*	0.11
Round 7	5000	1462 (29.2%)	1912	0.01	*0.15*	0.12
Round 8	5000	1673 (33.5%)	2127	0.00	*0.18*	0.13
Round 9	5000	1840 (36.8%)	2310	0.01	*0.15*	0.14
Round 10	5000	1977 (39.5%)	2528	0.01	*0.15*	0.13

NB never really did so hot, but what if we take that last LR and now do some pruning

	Doc count	# Yes (repeats)	# (total)	NB	LR	SVM
Round 1	5000	2178	2713	0.33	*0.45*	0.45
Round 2	5000	1534	2956	0.30	*0.45*	0.43
Round 3	5000	1556	3197	0.35	*0.45*	0.44
Round 4	5000	1571	3370	0.34	*0.45*	0.42
Round 5	5000	1540	3542	0.34	*0.46*	0.42

4.4 Different tokenizer

Right now it's word tokenization, but what if we changed it to word 2grams?

	Doc count	# Yes (repeats)	# (total)	NB	LR	SVM
Random init	5000	156	156	0	0.13	0.11
Round 1	5000	364	403	0	0.07	0.04
Round 2	5000	570	683	0.02	0.16	0.18
Round 3	5000	713	841	0.01	0.11	0.12
Round 4	5000	892	1116	0.01	0.11	0.08
Round 5	5000	973	1338	0.01	0.12	0.13

5 Translating a Classifier

The reason we used word tokenization for the classifiers on the bootstrapping, and why we wanted Naive Bayes to work well, is that we're going to try to translate a classifier that works on Spanish to one that works on French. To start, we have a heavily bootstrapped (Round 9) that, in Spanish, has 1,542 of its 5,000 (30.8%) best documents as controversial.

Here's the initial plan:

1. Start with a fairly good classifier (30% accuracy)
2. Grab 500 words that strongly indicate either 'yes' or 'no' to controversiality in this classifier (250 from each side)

3. Translate those words to French

4. Build a new classifier from these words

5. Evaluate the quality

For simplicity, we're just going to use Google Translate to translate the words. Additionally, our first attempt to build the classifier is to use word embeddings trained on the French corpus to infer controversiality based on similarity:

$$p(class|word) \propto \sum_{w \in N_k(word)} p(class|w) sim(word, w)$$

where $N_k(word)$ represents the k-nearest "anchor" words, with k=5. This gives us probabilities for all 8,554 words that occur at least 100 times. So how does this do?

Without subsetting					
				Classifier f-score	
	Doc count	# Yes (repeats)	# Yes (total)	NB	LR
Translated init	5000	213 (4.3%)	213	0	0.05
Round 1	5000	537 (10.7%)	599	0.03	0.09
Round 2	5000	803 (16.1%)	979	0	0.14
Round 3	5000	1069 (21.4%)	1383	0.008	0.17

Random init
Round 1
Round 2
Round 3

Remember, this was French, so this does about as well as a random French model. Let's see if we can improve this at all.

5.1 Spanish to Spanish

To help improve the algorithm, let's take the translations out of it, and instead just build a new model on Spanish from a good original model. Doing the same process as before, we get

				Classifier f-score	
	Doc count	# Yes (repeats)	# Yes (total)	NB	LR
Translated init	5000	150 (3.0%)	150	0	0.09
Round 1	5000	392 (7.8%)	428	0	0.10
Round 2	5000	586 (11.7%)	689	0.01	0.11
Round 3	5000	697 (13.9%)	971	0	0.11

This is about on par with what we usually get. What if we look at the word embeddings?

5.1.1 Word Embeddings

The word embeddings were created using gensim word2vec on the Spanish reddit corpora. Reddit comments are incredibly terrible for NLP tools to work with, namely because

- Multiple authors
- Informal speech
- Multiple languages (mostly English)
- Short comments

So, how well is our word embedding doing? Let's check what words it considers "most similar" for some common words

nosotros	agua	argentina	hombre	tienda
articulos	bariloche	llevábamos	denunicados	burocráticas
pasá	peleados	indicado	chaos	comunismo
rpgs	paleontólogo	odies	uriburu	migratorio
enojar	ajusten	curado	cerebral	militan
apeló	machote	permiten	surprised	luca

In other words, this is trash. We might ask if it's still useful trash though. For how many words does the controversiality of a word agree with its 5 closest neighbors? Well, first off, the words that get marked as controversial more often than not actually tend to be fairly uncommon words. To be sure:

	All words	Controversial words
#	40,483	8,369
Average frequency	11.04	2.56
# with at least 100 occurances	453	3
# with at least 20 occurances	2,160	103

So this is another problem with using word embeddings, is that the controversial words are ones whose meaning won't be captured very well. Anyway, as for neighbor agreement, with a cutoff of 20 occurances:

Neighbors agreeing	Controversial	Non-controversial
0	78	0
1	25	0
2	0	4
3	0	69
4	0	474
5	0	1480

In other words, the controversial words don't pick each other out at all. Do they at least pick out maybe more-controversial words? What if we ask what is the combined controversiality $(y/(y+n))$ of the five nearest neighbors, the five furthest neighbors, and five random words?

%	Controversial	Non-controversial
Neighbors	32.1%	32.9%
Anti-neighbors	32.3%	32.9%
Average	32.8%	32.8%

In other words: yes, these word embeddings are complete trash. I found pre-trained word embeddings here: http://crscardellino.me/SBWCE/, which apparently are actually good word embeddings. What happens if we run the previous tests?

nosotros	agua	argentina	hombre	tienda
tenemos	potable	uruguaya	mujer	tiendas
nos	potabiliza	Argentina	muchacho	supermercado
pensamos	tierra	chilena	joven	zapatería
Nosotros	potabilizada	bonaerense	anciano	abarrotes
estamos	semisurgente	argentinas	gavillero	autoservicio

Alright, that's a good sign. How about controversiality now?

Neighbors agreeing	Controversial	Non-controversial
0	56	0
1	21	0
2	8	14
3	6	62
4	0	373
5	0	1552

%	Controversial	Non-controversial
Neighbors	34.3%	31.3%
Anti-neighbors	31.0%	30.0%
Average	32.8%	32.8%

So yeah, it looks like having better word embeddings does actually help a little. However, it's still not that distinguishing.

5.2 Getting more controversial words

One problem appears to be that we don't have good data on controversial words. To counteract this, let's just train the Naive Bayes on *all* of the data, so that it has controversial counts on every word.

5.3 Translating Logistic Regression

Logistic regression is just the discriminative version of Naive Bayes, so it should lend itself to this task fairly nicely too. However, that's not the case, as doing this gives

	Doc count	# Yes (repeats)	# (total)	NB	LR	SVM
Translated init	5000	123 (2.5%)	123	0	0.15	0.09
Round 1	5000	276 (6.1%)	304	0	0.13	0.04
Round 2	5000	463 (9.3%)	530	0.02	0.10	0.07
Round 3	5000	600 (12.0%)	812	0	0.14	0.10

If we restrict the words to need to occur at least 100 times in order to be considered for

translation, we get

	Doc count	# Yes (repeats)	# (total)	NB	LR	SVM
Translated init	5000	224 (4.5%)	224	0	0.14	0.10
Round 1	5000	461 (9.2%)	504	0.02	0.10	0.08
Round 2	5000	652 (13.0%)	785	0.01	0.11	0.11
Round 3	5000	819 (16.4%)	1044	0	0.16	0.10

Hey, now that's not too bad. As a reminder, with a random initialization, we start with about 3.2% controversial and end with about 14%, so we've improved over the baseline by about 10%.

5.4 Evaluating the Embeddings

It is a little difficult to tell how well the embeddings capture the controversiality judgements when we don't really know how accurate the judgements for each of the words is. However, we can determine how well the embeddings + the classifier is by looking at a couple datapoints. The main important point is that the three classifiers we are looking at: naive Bayes, logistic regression, and SVM, are all linear classifiers, and so can be interpreted as linear models (logistic regression *is* a linear model). In other words, the classifier assigns each word w a coefficient θ_w so that the classifier judgement on a collection of words $W = (w_i)$ is

$$l(W) = \sum_{w_i \in W} \theta_{w_i}$$

which is converted to a binary classification by comparing it to a threshold value. In this case, the θ_w that are largest in absolute value are the "most important" coefficients, and so we should pay attention to the corresponding words. These "important words" will be called "anchor words".

We can use the embeddings to look at the words that are close to each anchor, and hope that the corresponding coefficients are similar. We would like to be able to infer coefficients for all words, given the coefficients for the anchors. Thus we have four variables:

1. The Embeddings
2. The Classifier
3. The Metric
4. The Inference algorithm

We then can evaluate any such setup by answering the following questions:

1. How well do anchor coefficients correlate with the coefficients of their neighbors?
2. How well do coefficients correlate with the coefficients of the nearest anchors?

3. How well do anchor coefficients represent the coefficients of their neighbors?

4. How diverse are the neighborhoods around the anchor words?

We're first going to look at one setup of the non-classifier variables: the Spanish Gigaword Embeddings, Cosine metric, and weighted average.

5.4.1 Logistic Regression

Words are filtered to only those that occur at least 100 times (6,069 many), anchors are those with scores at least 1 in absolute value (414 many), and neighbors are of size 10.

1. How well do anchor coefficients correlate with the coefficients of their neighbors?

$$\hat{\theta}_a = 0.019\theta_a - 0.059$$

$$r = 0.120 \quad p = 0.014 \quad err = 0.0076$$

2. How well do coefficients correlate with the coefficients of the nearest anchors?

$$\hat{\theta}_w = -0.001\theta_w - 0.081$$

$$r = -0.0041 \quad p = 0.749 \quad err = 0.0035$$

3. How often is the correct sign of label inferred?

	Pos	Neg	Total
Pos	743	1620	2363
Neg	1067	2634	3701
Total	1810	4254	6064

4. How diverse are the neighborhoods around the anchor words?

	Pos	Neg	Total
Pos	1051	1369	2420
Neg	713	1007	1720
Total	1764	2376	4140

5.4.2 SVM

Words are filtered to only those that occur at least 100 times (6,069 many), anchors are the 250 most important on either side (500 many), and neighbors are of size 10.

1. How well do anchor coefficients correlate with the coefficients of their neighbors?

$$\hat{\theta}_a = 0.007\theta_a - 0.037$$

$$r = 0.052 \quad p = 0.250 \quad err = 0.0065$$

2. How well do coefficients correlate with the coefficients of the nearest anchors?

$$\hat{\theta}_w = -0.007\theta_w - 0.034$$

$$r = -0.03 \quad p = 0.018 \quad err = 0.0029$$

3. How often is the correct sign of label inferred?

	Pos	Neg	Total
Pos	533	1804	2337
Neg	954	2773	3729
Total	1487	4577	6064

4. How diverse are the neighborhoods around the anchor words?

	Pos	Neg	Total
Pos	1038	1462	2500
Neg	1044	1456	2500
Total	2082	2918	5000

6 To-Do

Here's what's currently left to do:

- Evaluate Spanish to Spanish "translation"
- Produce images of Spanish word embeddings with colors for controversiality (do same for French)
- Implement Logistic Regression translation
- Implement Topic Model similarity
- Get new word embeddings
- Look at 2-gram word embeddings