Data Science in ESL

Using EFL blog writing patterns to predict L1 backgrounds

Acronyms

EFL (English as a foreign language)

ESL (English as a second language)

L1 (First language)

L2 (second language)

Background

- 1. Observations
- 2. Hypothesis
- 3. Goals

Research

- 4. Data Source
- 5. Data Exploration
- 6. Language Samples
- 7. Models
- 8. Areas of Improvement

1. Background

Observations

- ESL students acquire different English skills at different speeds
- ESL acquire English quicker when there are similarities between their L1 and L2
- Students from the same backgrounds use similar English expressions

Hypothesis

Students from other countries who are studying English will have unique writing patterns reflective of their L1.

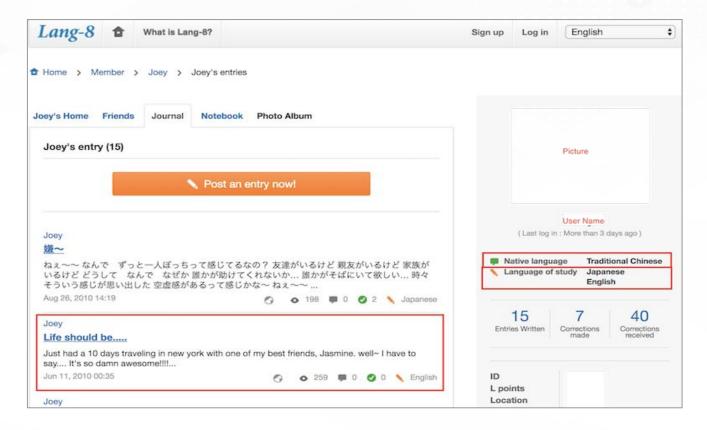
Goals

 Use models to predict the L1 from blog writing style

 Use observations from data exploration to help ESL teachers develop material for students

2. Research

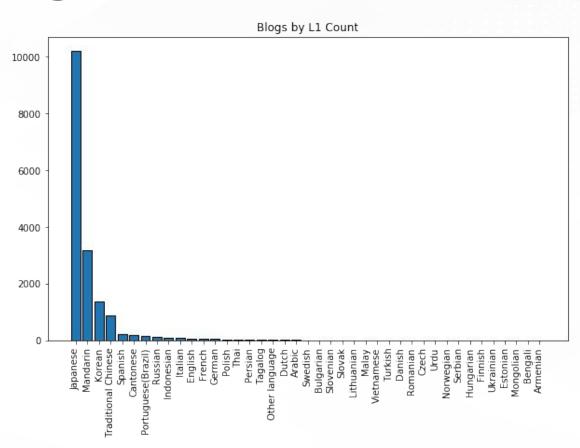
Data Source



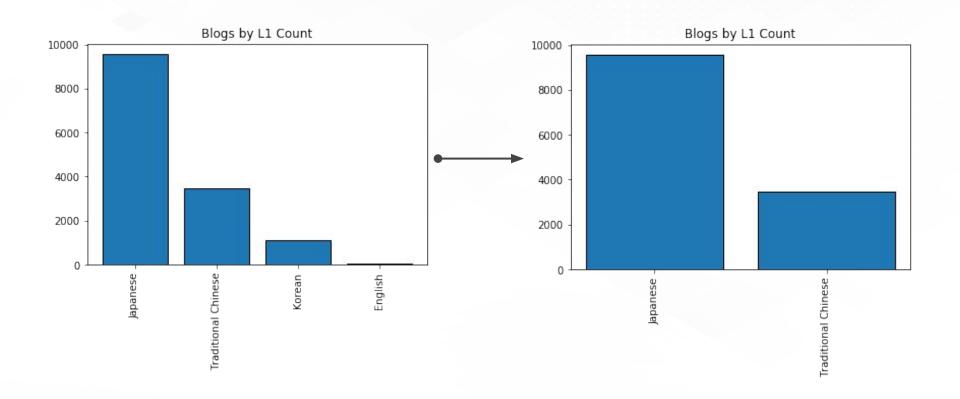
Scraped Data

	id	time	title	content	language
15	3	2018-03-16 00:01:59.746874+00:00	I NEED SOMEBODY'S HELP ASAP!!	I want to apply for an internship but I don't	Japanese
16	4	2018-03-16 00:05:54.394085+00:00	As they get older	The other day, a man who is around 70 mention	Japanese
17	4	2018-03-16 00:05:58.308874+00:00	I went to Nagoya port to welcome my foreign gu	I went to Nagoya port to welcome my foreign g	Japanese
18	5	2018-03-16 00:07:34.015592+00:00	英単語 (no need to correct)	sooner the better rugged bank on loyal fan	Japanese
19	5	2018-03-16 00:07:34.758156+00:00	英単語 (no need to correct)	millage TaxPropertyTax rate levy: an act of I	Japanese

Language samples



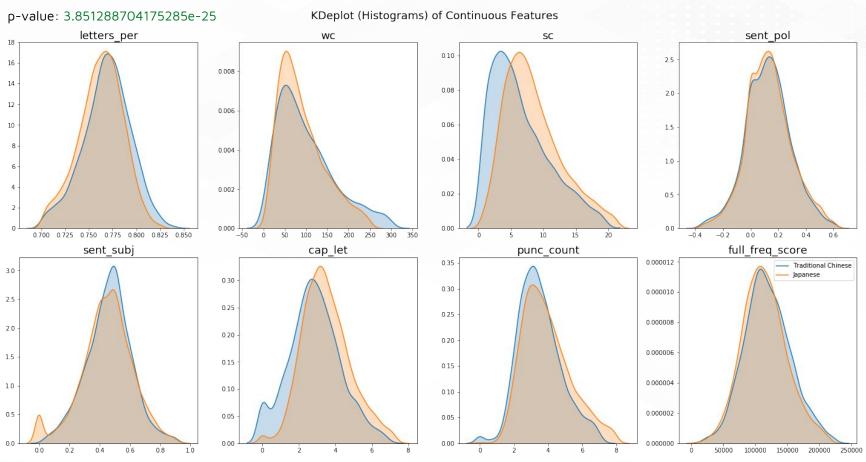
Reduced samples



Continuous Features

Word Count Sentence Count Punctuation % Capital Letter % Frequency Score Subjectivity (textblob) Polarity (textblob)

Japanese vs Chinese

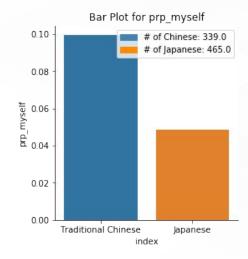


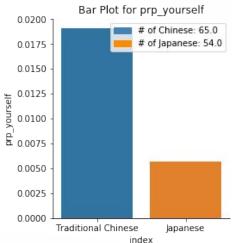
p-value:3.2764552529309356e-38

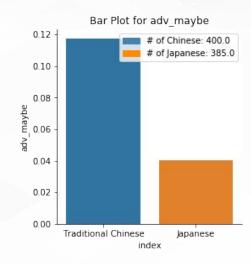
p-value:1.401298464324817e-45

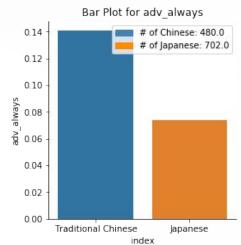
Discrete Features [~15000]

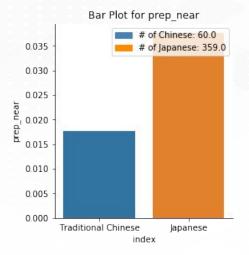
Adverbs [50] Prepositions [83] Pronouns [29] POS (unigram) [36] POS (bigrams) [1003] POS (trigrams) [13266] Letters (unigram) [26] Letters (bigrams) [542]

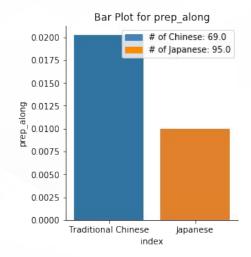












Models

Basic scores for all features with an imbalanced train/test set

model	cpu time	overall score
Logistic Regression	1.74 s	0.730389
K Nearest Neighbors	3.4 s	0.792239
Naive Bayes Bernoulli	168 ms	0.702347
Decision Tree	79.7 ms	0.742943
Random Forest	13.4 s	0.80828

All Features

	No	Tra	nsfo	rma	ation
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Truncated	SVD
Transform	ation

	name	time	total	prec: JA CH	rec: JA CH	f1: JA CH
0	Logistic Regression	0.19	0.631667	[0.89, 0.58]	[0.30, 0.96]	[0.45, 0.72]
1	K Nearest Neighbor	8.06	0.500000	[0.50, 0.50]	[0.02, 0.98]	[0.04, 0.66]
2	Naive Bayes - Bernoulli	0.89	0.635000	[0.71, 0.60]	[0.45, 0.82]	[0.55, 0.69]
3	Decision Tree	0.17	0.636667	[0.87, 0.58]	[0.32, 0.95]	[0.47, 0.72]
4	Random Forest	0.21	0.505000	[1.00, 0.50]	[0.01, 1.00]	[0.02, 0.67]
	name	time	total	prec: JA CH	rec: JA CH	f1: JA CH
0		time 0.01	total 0.540000	prec: JA CH [0.77, 0.52]	rec: JA CH [0.11, 0.97]	f1: JA CH [0.20, 0.68]
0						
	Logistic Regression K Nearest Neighbor	0.01	0.540000	[0.77, 0.52]	[0.11, 0.97]	[0.20, 0.68]
1	Logistic Regression K Nearest Neighbor Naive Bayes - Bernoulli	0.01 0.05	0.540000 0.505000	[0.77, 0.52]	[0.11, 0.97]	[0.20, 0.68]

Selected Features

No Transformation

Truncated SVD Transformation

	name	time	total	prec: JA CH	rec: JA CH	f1: JA CH
0	Logistic Regression	0.05	0.501667	[1.00, 0.50]	[0.00, 1.00]	[0.01, 0.67]
1	K Nearest Neighbor	1.66	0.505000	[0.67, 0.50]	[0.02, 0.99]	[0.04, 0.67]
2	Naive Bayes - Bernoulli	0.15	0.703333	[0.84, 0.65]	[0.51, 0.90]	[0.63, 0.75]
3	Decision Tree	0.04	0.608333	[0.87, 0.56]	[0.25, 0.96]	[0.39, 0.71]
	name	time	total	prec: JA CH	rec: JA CH	f1: JA CH
0	name Logistic Regression	time 0.01	total 0.501667	prec: JA CH [1.00, 0.50]	rec: JA CH [0.00, 1.00]	f1: JA CH [0.01, 0.67]
0						
	Logistic Regression	0.01	0.501667	[1.00, 0.50]	[0.00, 1.00]	[0.01, 0.67]
1	Logistic Regression K Nearest Neighbor	0.01	0.501667 0.505000	[1.00, 0.50] [0.67, 0.50]	[0.00, 1.00]	[0.01, 0.67]
1 2	Logistic Regression K Nearest Neighbor Naive Bayes - Bernoulli	0.01 0.03 0.01	0.501667 0.505000 0.648333	[1.00, 0.50] [0.67, 0.50] [0.79, 0.60]	[0.00, 1.00] [0.02, 0.99] [0.40, 0.89]	[0.01, 0.67] [0.04, 0.67] [0.53, 0.72]

3. Next Steps

Plan to address

- A control variable (English samples)
- Sample distributions
- Deeper look at POS and syntax structure
- Improved feature selection through PCA/SVD and models' ranked features
- More data cleaning blog posts with multiple languages

Language Samples

- Get more Korean samples
- Find more english blog posts to establish control variable
- Work with samples from L1s with more linguistic diversity

More Features?

- Cognates
- Word stemming
- Noun categories
- Syntax structures:
 - imperatives
 - o interrogatives
 - passive vs active sentences

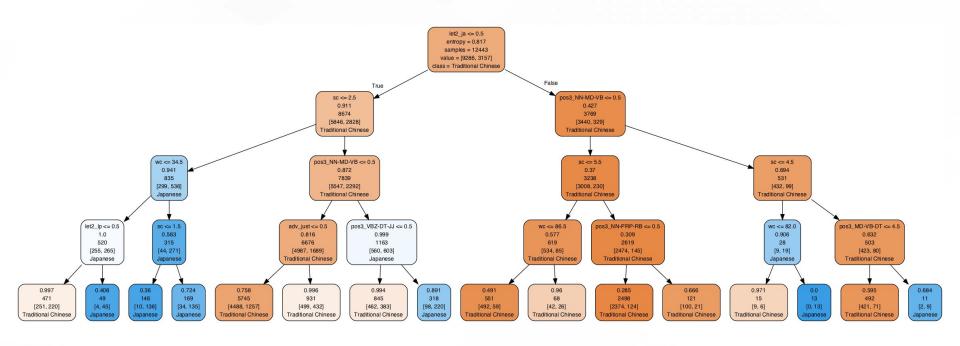
For ESL

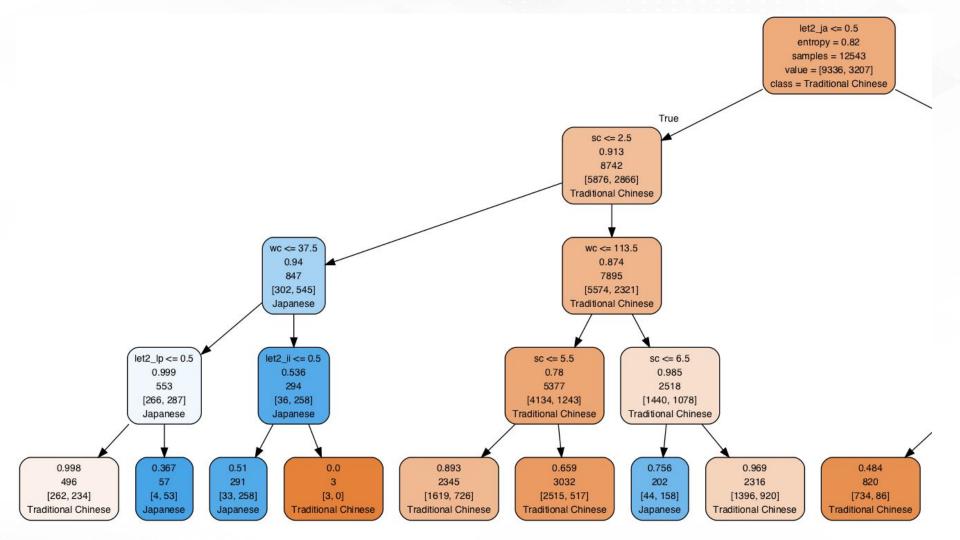
 Add a lesson on the use of reflexive pronouns in English for Japanese students

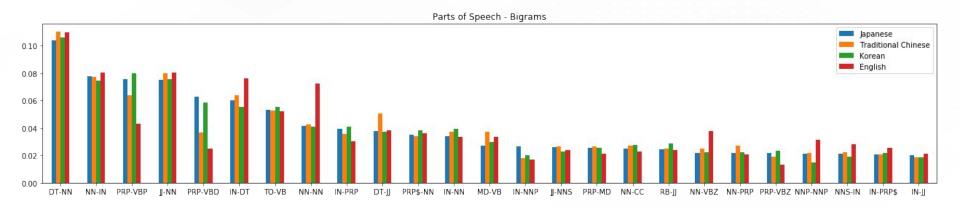
 Add a lesson about hedging for Japanese students

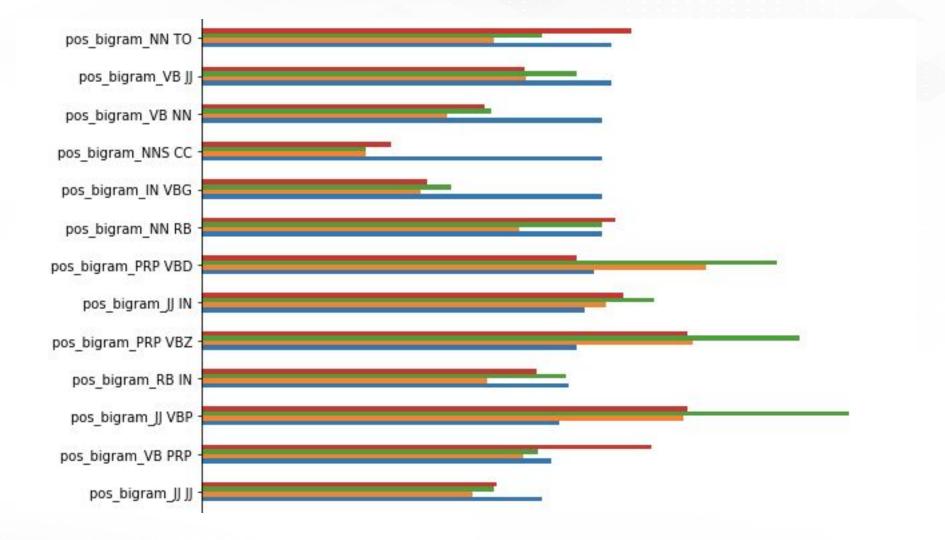
4. Extra Visuals

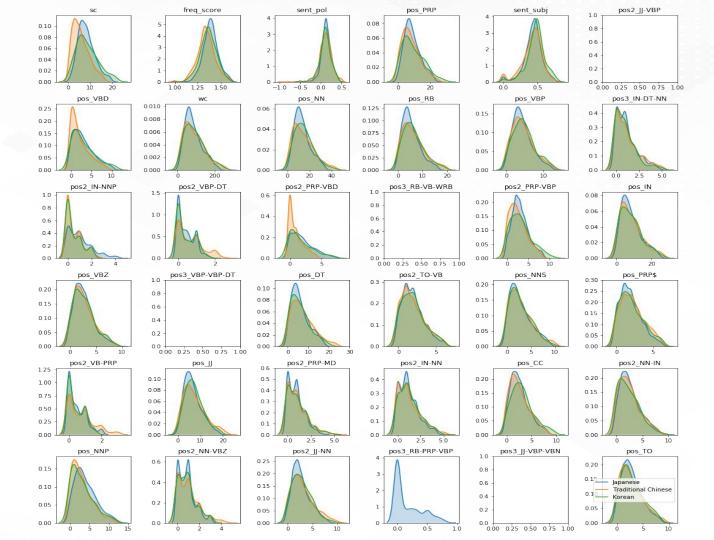
Decision Tree











Chinese vs Japanese

MannWhitney U Test (assumes normality)

sc:stat=536536.5, p=1.7072488700922754e-63 freg score:stat=636197.5, p=4.515381615578102e-44 sent pol:stat=886609.0, p=0.013264065652633338 pos PRP:stat=770243.0, p=5.196098625805676e-08 sent subj:stat=898769.5, p=0.041557713279235915 pos2 JJ-VBP:stat=0.0, p=0.0 pos VBD:stat=655521.0, p=2.716598211138757e-24 wc:stat=843355.5, p=0.26494148060009115 pos NN:stat=837920.5, p=0.1224638429596514 pos RB:stat=816411.0, p=9.39059114470553e-05 pos VBP:stat=868216.0, p=0.31286403071741714 pos3 IN-DT-NN:stat=880339.5, p=0.351431874684187 pos2 IN-NNP:stat=646817.5, p=1.9141116383595614e-31 pos2 VBP-DT:stat=753424.5, p=6.693777692873975e-11 pos2 PRP-VBD:stat=535814.5, p=5.280333996839972e-59 pos3 RB-VB-WRB:stat=0.0, p=0.0 pos2 PRP-VBP:stat=746535.0, p=1.7646331654577458e-12 pos IN:stat=865240.5, p=0.4529202098291991 pos VBZ:stat=897202.5, p=0.4178459416236008 pos3 VBP-VBP-DT:stat=0.0, p=0.0 pos DT:stat=759274.5, p=1.677129429910917e-07 pos2 TO-VB:stat=842474.5, p=0.1148711960934507 pos NNS:stat=798576.5, p=0.2746068949796701 pos PRP\$:stat=780511.5, p=0.00014482613404109238 pos2 VB-PRP:stat=793547.0, p=7.078343140193685e-10 pos JJ:stat=818322.5, p=0.0038570494555401655 pos2 PRP-MD:stat=909842.5, p=0.13433003038081376 pos2 IN-NN:stat=888407.0, p=0.4481120057426727 pos CC:stat=828476.5, p=0.0681338959087248 pos2 NN-IN:stat=818886.0, p=0.06117635396174209 pos NNP:stat=669732.0, p=8.695664716145719e-19 pos2 NN-VBZ:stat=865825.0, p=0.004159327861131947 pos2 JJ-NN:stat=847599.0, p=0.03543135644157996 pos3 RB-PRP-VBP:stat=0.0, p=0.0 pos3 JJ-VBP-VBN:stat=0.0, p=0.0 pos TO:stat=832738.5, p=0.03411138379372657