Academia's Influence on Policymakers

Paul Laliberte'

Amit Khandelwal (Columbia Business School)

David Atkin (MIT)

CBS - Summer Research

August 1, 2017

Statement

- **Statement:** To inspect whether there exists a disconnect between economic policy proposed by academic and non-academic institutions.

- **How:** Sentimental analysis of published articles.

Methodology

- **Methodology:**
  1. **Data Collection and Cleaning:**
     - Collecting data through web scraping.
     - Cleaning for punctuation and translating foreign text.
  2. **Machine Learning Methods:**
     - Stochastic Gradient Descent.
     - Support Vector Classifier.
     - Evaluation Metrics.
  3. **Natural Language Processing:**
     - Term Frequency - Inverse Document Frequency (tf-idf).
     - Latent Dirichlet Allocation (LDA) Topic Models.
  4. **Domain Expertise in Economics:**
     - Amit and David.

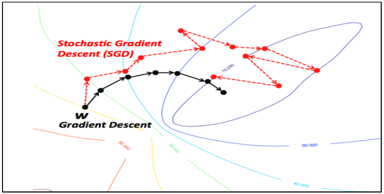
Data Collection and Cleaning

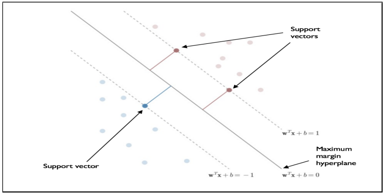
- **Web scraping:**
  - Final dataset consisted of 2.5 million articles from academic journals and institutional working papers.

- **Cleaning and Translation:**
  - Removing punctuation.
  - Translate all articles into a common language (English).

Machine Learning

- Stochastic Gradient Descent (SGD) and Support Vector Classifier (SVC):



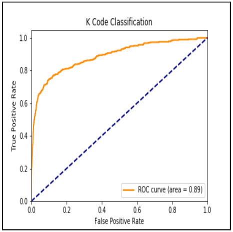


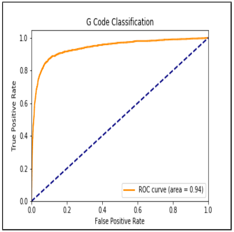
Source: Hong, K. (n.d.): n. pag. Web. 24 July 2017. <https://bogotobogo.com>.

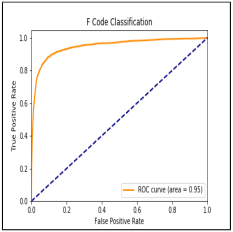
- SGD was used to train the SVC quicker.
- SVC used to predict JEL Codes (D, E, F, G, H, I, J, K, L, and O).
  - Overview: { articles **with** JEL Codes } $\xrightarrow{\text{train SVC}}$ { article to predict } $\xrightarrow{\text{Predict JEL Code}}$ {Code or None}.

Machine Learning (Continued)

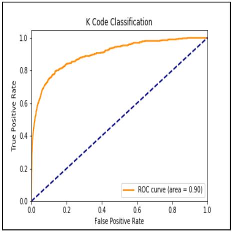
- Evaluation Metric: ROC curve.
  - Working papers:

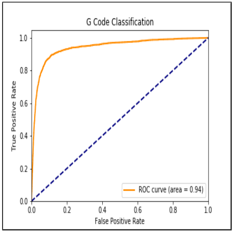


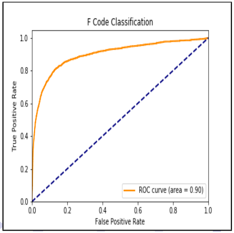




  - Journals:







Natural Language Processing

- **Tf-Idf:**
  - Tf: the number of times a term t appears in a document (article).
  - Idf: $\log\left(\frac{\text{total number of documents in corpus}}{\text{number of documents with term } t}\right)$.
  - Tf-Idf = Tf $\times$ Idf.

- **n-grams:**
  - Example: New York is the best city.
    - Unigrams: {New, York, is, the, best, city}.
    - Bigrams: {New_York, York_is, is_the, the_best, best_city}.
    - Trigrams: {New_York_is, York_is_the, is_the_best, the_best_city}.

- **Stemming:** reducing words to their derived stem root.
  - Example: {learning, learns, learned} $\xRightarrow{\text{reduced to}}$ {*learn*}.

Natural Language Processing (Continued)

- **LDA Topic Model:**
  - Work in reverse: {collection of documents} $\longrightarrow$ {inferred topics}.
  - Use of the Dirichlet distribution.
  - Simplified probability:

$$P(T|t,d) = \frac{\text{total number of tokens } t \text{ in topic } T}{\text{total number of tokens in } T + \beta} \cdot (\text{total words in } d \text{ that belong in } T + \alpha),$$

where β and α are non-zero constants.

  - Example:

"Genetics"	"Evolution"	"Disease"	"Computers"
human	evolution	disease	computer
genome	evolutionary	host	models
dna	species	bacteria	information
genetic	organisms	diseases	data
genes	life	resistance	computers
sequence	origin	bacterial	system
gene	biology	new	network
molecular	groups	strains	systems
sequencing	phylogenetic	control	model
map	living	infectious	parallel
information	diversity	malaria	methods
genetics	group	parasite	networks
mapping	new	parasites	software
project	two	united	new
sequences	common	tuberculosis	simulations

Source: David M. Blei. "Probabilistic Topic Models." Communications of the ACM, v. 55, n.4, April 2012.

Domain Expertise

- Results still need to be interpreted.
  - What is the actual topic?
  - Are the tokens representing a topic even meaningful?
- Example:

genome	evolutionary	host	models
dna	species	bacteria	information
genetic	organisms	diseases	data
genes	life	resistance	computers
sequence	origin	bacterial	system
gene	biology	new	network
molecular	groups	strains	systems
sequencing	phylogenetic	control	model
map	living	infectious	parallel
information	diversity	malaria	methods
genetics	group	parasite	networks
mapping	new	parasites	software
project	two	united	new
sequences	common	tuberculosis	simulations

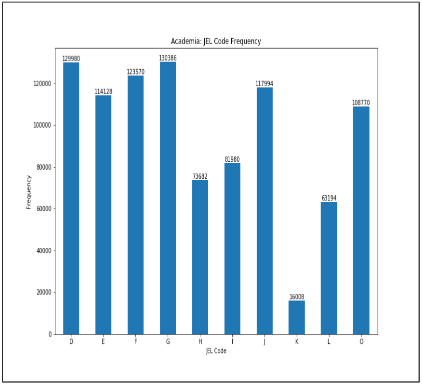
Source: David M. Blei. "Probabilistic Topic Models." Communications of the ACM, v. 55, n.4, April 2012.

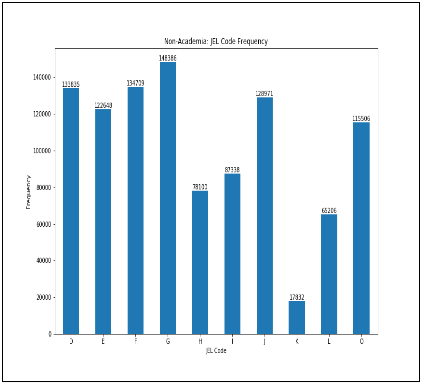
Results

- We separated the 2.5 million articles into two groups:
  1. Written by an individual(s) who spends the majority of their time at an academic institution.
  2. Those who do not fall into category 1 (FED, Brookings Institute, ect.).

- Results consisted of overall frequencies, frequencies and tf-idf of individual JEL Code, and a topic model.

JEL Code Frequency





- Not any distinct differences.

Frequencies and Tf-Idf

Table 1: F Code Frequencies

Academia:	Count	Non-Academia Batch #1:	Count	Non-Academia Batch #2:	Count:
exchang_rate	5247	exchang_rate	4753	exchang_rate	6820
develop_countri	2579	intern_trade	2222	develop_countri	3478
intern_trade	2450	direct_invest	2048	intern_trade	3385
direct_invest	2018	foreign_direct	1950	direct_invest	2619
foreign_direct	1915	foreign_direct_invest	1941	foreign_direct	2454
unit_state	1607	develop_countri	1842	foreign_direct_invest	2434
free_trade	1603	free_trade	1247	free_trade	2110
trade_agreement	1450	trade_polici	1170	trade_agreement	2102
trade_polici	1346	long_run	1141	trade_polici	1909
real_exchang	1321	unit_state	1136	real_exchang	1696
real_exchang_rate	1314	foreign_exchang	1112	real_exchang_rate	1687
european_union	1184	trade_agreement	1013	european_union	1610
trade_liber	1172	real_exchang	993	trade_liber	1533
long_run	1136	real_exchang_rate	987	world_trade	1442
foreign_exchang	1112	foreign_trade	913	trade_flow	1400
world_trade	1111	european_union	910	foreign_exchang	1392
econom_growth	963	world_trade	900	long_run	1383
trade_flow	918	invest_fdi	882	econom_growth	1227
foreign_trade	892	direct_invest_fdi	877	latin_america	1173

Table 3: F Code Keyword Frequencies

Academia:	Count	Non-Academia Batch #1:	Count	Non-Academia Batch #2:	Count:
exchange_rate	11331	exchange_rate	8977	exchange_rate	14217
international_trade	3338	international_trade	2933	developing_countries	4558
developing_countries	3277	direct_investment	2909	international_trade	4482
exchange_rates	3091	exchange_rates	2789	exchange_rates	3904
direct_investment	2837	foreign_direct_investment	2662	direct_investment	3718
foreign_direct_investment	2559	developing_countries	2209	foreign_direct_investment	3292
free_trade	2502	free_trade	1930	free_trade	3193
real_exchange_rate	2088	foreign_exchange	1638	real_exchange_rate	2693
current_account	1805	foreign_trade	1402	current_account	2654
foreign_exchange	1643	real_exchange_rate	1378	trade_policy	2312
trade_policy	1604	economic_growth	1334	foreign_exchange	2160
european_union	1536	trade_policy	1320	trade_agreements	2151
economic_growth	1500	current_account	1289	european_union	2042
trade_agreements	1466	european_union	1227	economic_growth	1765
foreign_trade	1302	trade_agreements	938	foreign_trade	1545
terms_of_trade	1063	terms_of_trade	915	terms_of_trade	1454
comparative_advantage	907	trade_balance	811	economic_integration	1284
economic_integration	843	purchasing_power	784	comparative_advantage	1101
trade_balance	721	purchasing_power_parity	723	balance_of_payments	847
foreign_investment	680	foreign_investment	674	foreign_investment	835

Table 2: F Code Tf-Idf

Academia:	Tf-Idf	Non-Academia:	Tf-Idf
trade_wto	0.9303	india_trade	1.0
corpor_govern	0.9081	even_high	1.0
trade_credit	0.8971	eu_access	1.0
human_right	0.8840	semin_contribut	1.0
energi_intens	0.8792	air_servic	0.9633
state_aid	0.8750	human_right	0.9177
currenc_reserv	0.8650	trade_mark	0.9045
humanitarian_emerg	0.8642	gold_exchang	0.9030
knowledg_exchang	0.8507	corpor_govern	0.9018
fair_trade	0.8390	mega_ftas	0.8953
humanitarian_aid	0.8352	foreign_languag	0.8921
price_foreign	0.8228	health_insur	0.8916
foreign_offici	0.8126	trade_secret	0.8879
loss_avers	0.8104	antidump_duti	0.8777
big_mac	0.8087	neo_liber	0.8744
steel_import	0.8062	trade_credit	0.8718
civil_war	0.8049	exit_cost	0.8716
australia_china	0.8045	softwood_lumber	0.8706
payment_balanc	0.8035	energi_subsidi	0.8641
domin_posit	0.8020	state_aid	0.8629

Economic Topic Model

- http://nbviewer.jupyter.org/github/PaulLaliberte/jupyter_notebooks/blob/master/columbia/academia/topic_model.ipynb

Next Steps

- **word2vec**
  - Take a sentence and create a vector of word embeddings.
  - Example: $\{$england has kings and queens$\} \Rightarrow \{0.2, 0.0, 0.4, 0.0, 0.4\}$.
- word2vec embeddings can be used for:
  - Similarity of sentences.
  - Finding odd-word-out.
  - Advanced classification: model.most_similar('man', 'queen') = "king."
  - Underlying probability of sentences within a topic.