

GLG Project

A match made in machine learning heaven: linking every client request to the best expert

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Outline



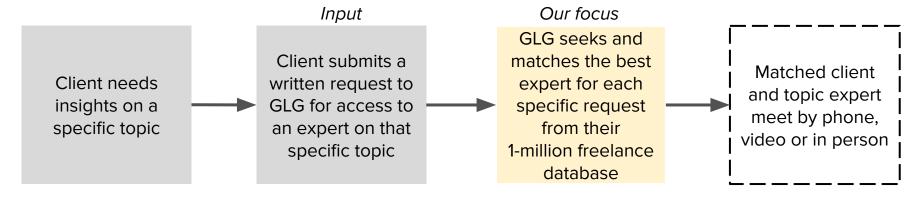
- Problem
- Solution
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- Demo
- MLE Stack
- Future Work
- Q&A and Feedback
- Appendix

Problem





GLG's business largely revolves around *matching clients*, requesting insights on a specific topic, *with an expert* on that topic from their large database so that they can meet by phone, video or in person. Visually:



Since GLG receives **100s of these requests** per day, how can they leverage machine learning to **semi-automate the matching process at scale**?

Solution

Problem | Solution | Data + Model | Demo | MLE Stack | Future Work | Q&A | Appendix



Natural Language Processing (NLP)!

Input

"I need to know what David Guetta is up to these days including what he may do next."

1

NLP models for information retrieval

Output

[David Guetta]_{Person}

Possible Topic 1: DJ, dance music (98%);

Possible Topic 2: French (90%);

Possible Topic 3: Ibiza (60%)

A list of related requests

2*

GLG seeks experts
in their database
based on the topic
categorized by the
model

* Step 2 is outside the scope of this project

Acronyms: DJ (Disc Jockey), GLG (Gerson Lehrman Group)

David

Guetta

Data + Model

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Data

Natural Language Processing Models

Annotated News Corpus
for Named Entity
Recognition | Kaggle:

Has ~48,000 sentences and ~35,000 unique words Model 1, Named-Entity Recognition (NER):

- Trained our NER model
- Leveraged spaCy pre-trained NER model

Model 2, Topic modeling:

- Latent Dirichlet allocation (LDA)

Model 3, Sentence matching:

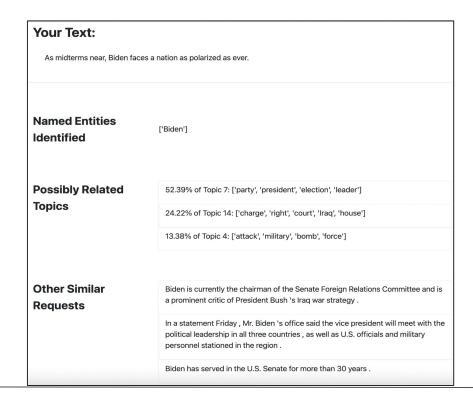
- Used SentenceTransformers for text embedding
- Used k-nearest neighbors (k-NN) model to find nearby texts

Demo

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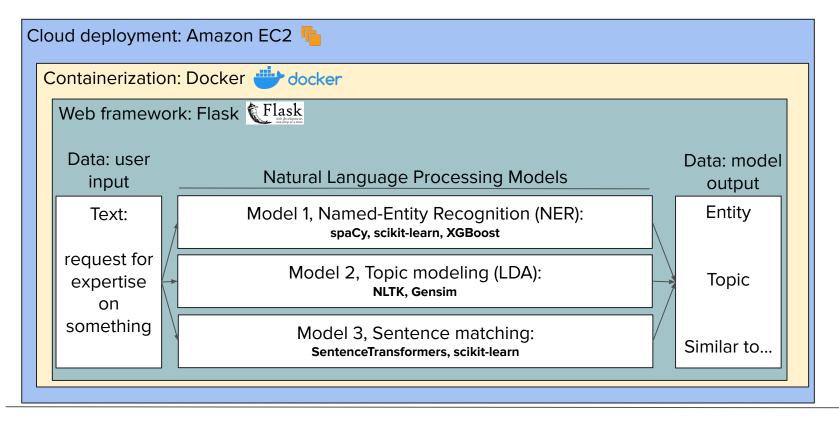
Demo URL



MLE Stack

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- 1. Improve the Topic Modeling:
 - Training an LDA model on a more diverse <u>dataset</u>
 - Using a semi-supervised learning method (SentenceTransformers + Label Propagation)

- 2. Expand the scope of the project:
 - Building the expert(s) recommendation model
 - Adapting our models to cover non-English languages
 (GLG also has offices in Europe, Asia, and the Middle East)



Thank you



Q&A and Feedback

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Named-Entity Recognition (NER) preliminary results

	Test 1: spaCY predic-	Test 2: TPOT for AutoML	Test 3: one-hot encoding		Test 4: TF-IDF encoding		Test 5: one-hot encoding with preprocessed data	
	tions		XGB	Logistic Regression	XGB	Logistic Regression	XGB	Logistic Regression
Accuracy	0.937	Too computa tionally intense for local machine	0.959	0.932	0.935	0.921	0.959	0.932
Recall	0.619		0.906	0.761	0.881	0.612	0.906	0.761
Precision	0.753		0.755	0.659	0.644	0.638	0.758	0.659
F1 Score	0.680		0.824	0.706	0.744	0.625	0.825	0.706





(2) Unsupervised clustering preliminary results

	Model 1: Bag of words + KMeans		Model 2: TF-IDF + KMeans		Model 3: Bag of words + PCA + KMeans		Model 4: Bag of words + PCA + Agglomerative
n_cluster	2	3	2	3	2	3	Aborted: It took
Silhouette Coefficient	0.28	0.17	0.00814	0.000157	0.28	0.17	too long to run; after 50 mins, the model was still
random_ states	1, 5, 10, 42	0, 1					running. The code is tested
				ent decrease er increases			on a small portion of the dataset



Did exploratory data analysis (EDA) on one dataset from Kaggle:

Annotated Corpus for Named Entity Recognition | Kaggle

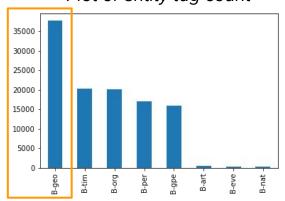
List of entity tags

- geo = Geographical Entity
- org = Organization
- per = Person
- gpe = Geopolitical Entity
- tim = Time indicator
- art = Artifact
- eve = Event
- nat = Natural Phenomenon

Example of entity tag

	Sentence #		Word	POS	Tag
0	Sentence: 1		Thousands	NNS	0
1	NaN		of	IN	0
2	NaN	den	nonstrators	NNS	0
3	NaN		have	VBP	0
4	NaN		marched	VBN	0
5	NaN		through	IN	0
6	NaN		London	NNP	B-geo
7	NaN	'	to	то	0
8	NaN		protest	VB	0
9	NaN		the	DT	0

Plot of entity tag count



Capital vs. non-capital word count

