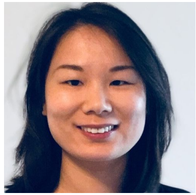
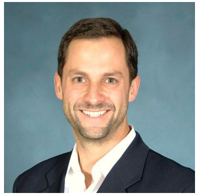
FourthBrain

GLG Project

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

Ying Hu, Cody McCormack, Cris Fortes





Outline

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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:

Client needs insights on a specific topic → *Input:* Client submits a written request to GLG for access to an expert on that specific topic → *Our focus:* GLG seeks and matches the best expert for each specific request from their 1-million freelance database → Matched client and topic expert meet by phone, video or in person

Since they receive **hundreds of these requests** per day, we wanted to explore how machine learning could help ***automate and scale the process***

Solution

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]$_{\textbf{Person}}$

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

David Guetta

* Step 2 is outside the scope of this project

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

Data + Model

Data

[Annotated News Corpus for Named Entity Recognition | Kaggle:]

Has ~48,000 sentences and ~35,000 unique words

Natural Language Processing Models

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

[Demo URL]

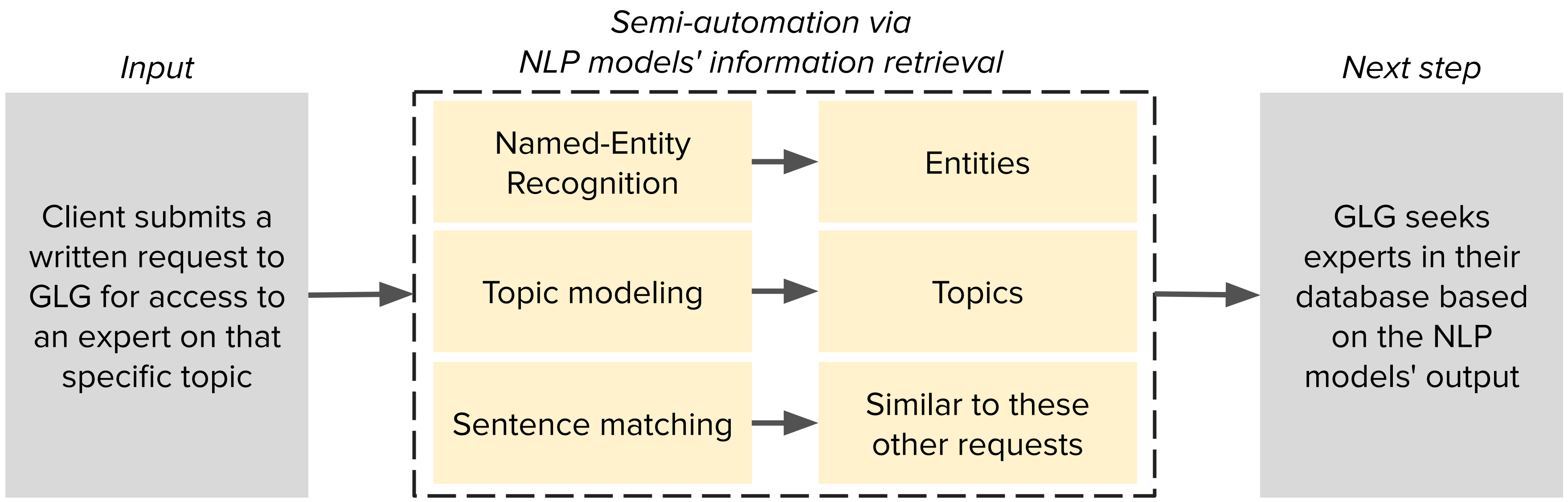
Your Text:

As midterms near, Biden faces a nation as polarized as ever.

Named Entities Identified	['Biden']
Possibly Related Topics	52.39% of Topic 7: ['party', 'president', 'election', 'leader'] 24.22% of Topic 14: ['charge', 'right', 'court', 'Iraq', 'house'] 13.38% of Topic 4: ['attack', 'military', 'bomb', 'force']
Other Similar Requests	Biden is currently the chairman of the Senate Foreign Relations Committee and is a prominent critic of President Bush 's Iraq war strategy . In a statement Friday , Mr. Biden 's office said the vice president will meet with the political leadership in all three countries , as well as U.S. officials and military personnel stationed in the region . Biden has served in the U.S. Senate for more than 30 years .

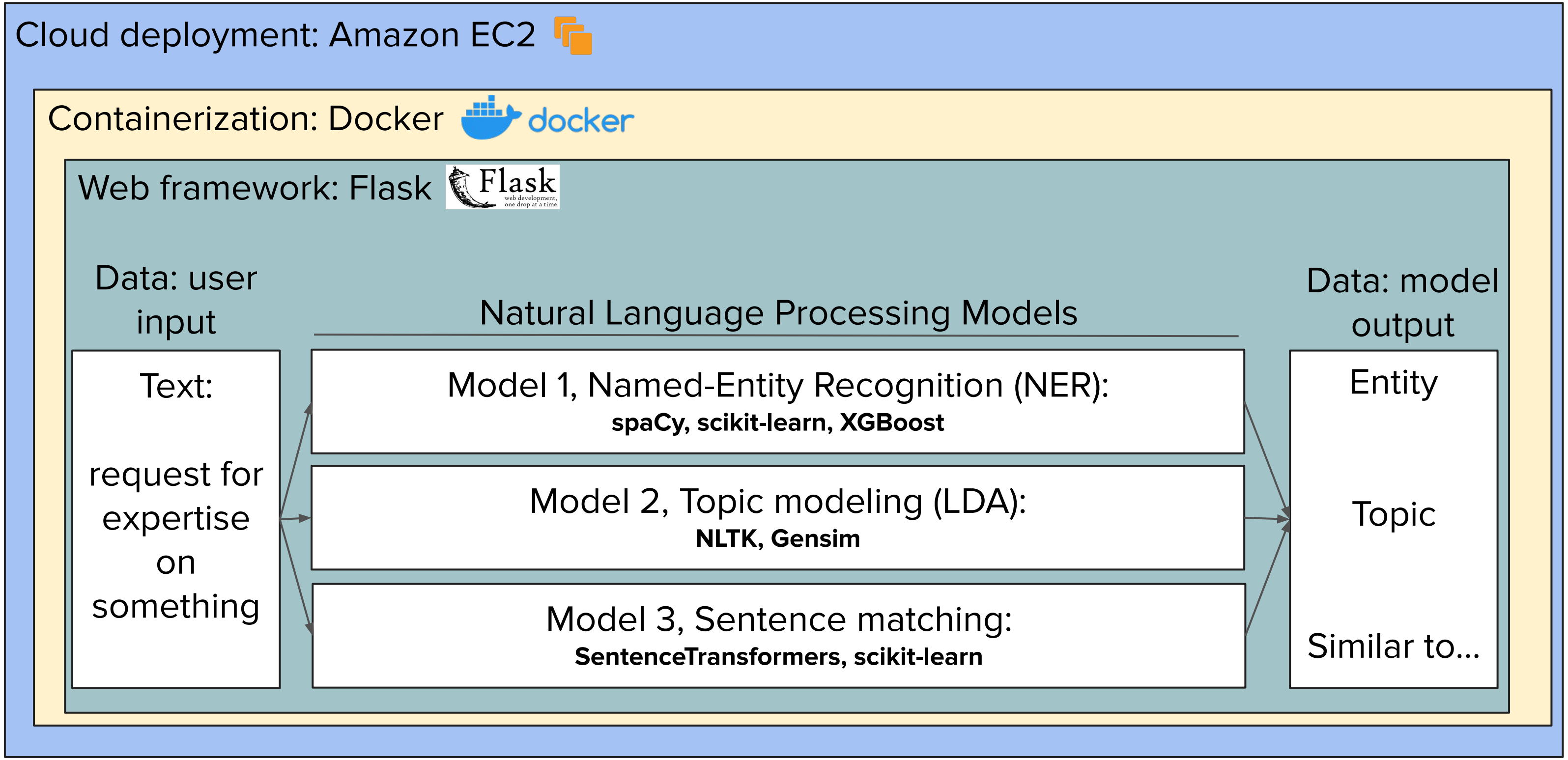
Results

Driving business value by semi-automating the client-expert matching process: expected time savings of 80%*



* 80% time savings expected from applying NLP to a routine process. Source: https://2021.ai/nlp-increase-efficiency/

MLE Stack


Cloud deployment: Amazon EC2
Containerization: Docker
docker
Web framework: Flask
Flask
web development, one drop at a time
Data: user input
Text:
request for expertise on something
Natural Language Processing Models
Model 1, Named-Entity Recognition (NER):
spaCy, scikit-learn, XGBoost
Model 2, Topic modeling (LDA):
NLTK, Gensim
Model 3, Sentence matching:
SentenceTransformers, scikit-learn
Data: model output
Entity
Topic
Similar to…

Future Work

1. Improve the Topic Modeling:
    - Training an LDA model on a **more diverse** dataset
    - 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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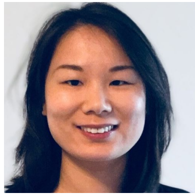
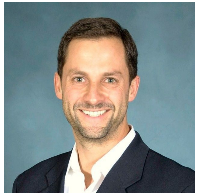




1 Named-Entity Recognition (NER) preliminary results

	Test 1: spaCY predic-tions	Test 2: TPOT for AutoML	Test 3: one-hot encoding		Test 4: TF-IDF encoding		Test 5: one-hot encoding with preprocessed data	
			XGB	**Logistic Regression**	**XGB**	**Logistic Regression**	**XGB**	**Logistic Regression**
Accuracy	0.937	Too computationally 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 too long to run; after 50 mins, the model was still running. The code is tested on a small portion of the dataset
Silhouette Coefficient	0.28	0.17	0.00814	0.000157	0.28	0.17	
random_ states	1, 5, 10, 42	0, 1					
	Silhouette Coefficient decreases as number of cluster increases						

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

[Annotated Corpus for Named Entity Recognition | Kaggle]

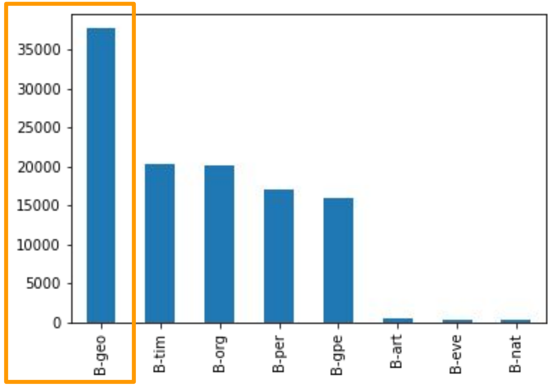
List of entity tags

- 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	O
1	NaN	of	IN	O
2	NaN	demonstrators	NNS	O
3	NaN	have	VBP	O
4	NaN	marched	VBN	O
5	NaN	through	IN	O
6	NaN	London	NNP	B-geo
7	NaN	to	TO	O
8	NaN	protest	VB	O
9	NaN	the	DT	O

Plot of entity tag count



Capital vs. non-capital word count