2021
Machine Learning Engineer
Capstone

GLG FourthBrain

July 8th, 2021
Fourthbrain, Inc.

How GLG Can increase sales by XX% and decrease churn by XX%?

Team: GLG

Tatiana Chebonenko
Milan McGraw
Divyanshu Murli

AGENDA

OVERVIEW

BUSINESS PROBLEM

DEEP DIVE

ASSUMPTIONS

SOLUTION 1

SOLUTION 2

DEMO

WHAT WE ACHIEVED

OVERVIEW

GLG

Gerson Lehrman Group (GLG) is an international consulting firm that enlists freelancers to provide paid advice on a wide array of topics.

HOW GLG WORKS

Clients use GLG:

SOLVE strategic problems
GAIN market feedback
TEST hypotheses

When a client has a request GLG works to find the councilmembers who can best help them solve a problem and learn about a topic.

2X MARKETPLACE

GLG then works with clients to signs consultants who can best help them and learn about that topic. After categorizing and scoping the project, GLG send invitations to consultants with relevant expertise. If the client accepts the consultant, a meeting is convened and payment is given. GLG gets a %.

Business Problem

What if there is no match?

Consultants update their bio which is currently the best tool to match consultants with clients. How does GLG find those uniquely positioned to teach someone?

Business Problem deep-dive

Challenge 1

Topic Modeling

GLG receives millions of requests from clients seeking insights on various topics and need to match profile expertise to a consultant in their database.

Challenge 2

NER

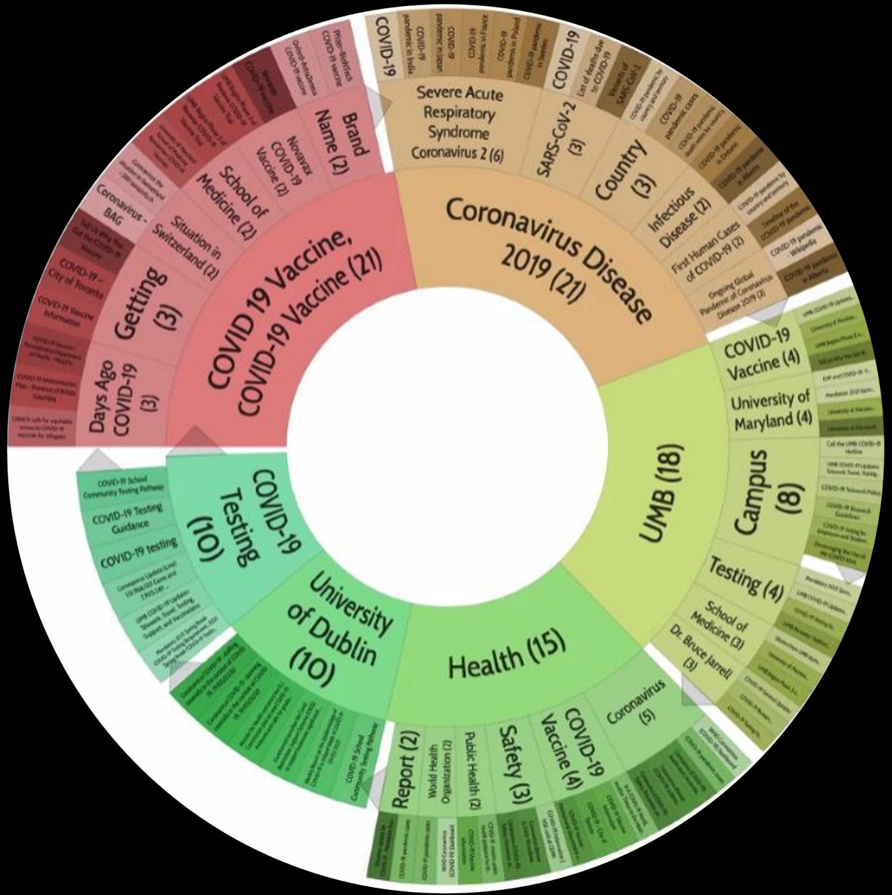
As clients request are being received, GLG needs to quickly understand the subject and body of the client requests and quickly group texts based on their relevance

Challenge 3

Time Sensitive

Client requests generally have a 48-72 hour turnaround and the speed of connecting clients with the right consultants will make the difference.

Brainstormed Solution



Solution Proposal

Solution 1

Hierarchical Topic Modeling

WHY THIS SOLUTION WAS CHOSEN?

BENEFITS

WHY IS THIS BETTER?

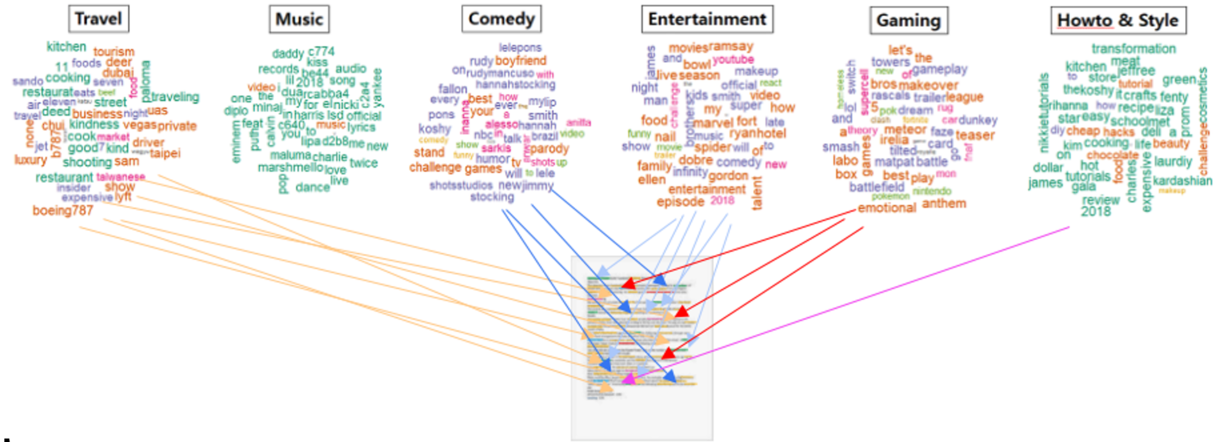
Hierarchical Topic Modeling

Goals	Solution	Benefits
• Find common topics of requests and build topic hierarchy	• Unsupervised learning problem	• Probability of each topic for a new request
• For new requests automatically find most related topic in each level of topic hierarchy	• Each level of hierarchy is a Latent Dirichlet Allocation model	• Model can be updated with new requests without retraining

Hierarchical Topic Modeling

LDA assumptions:

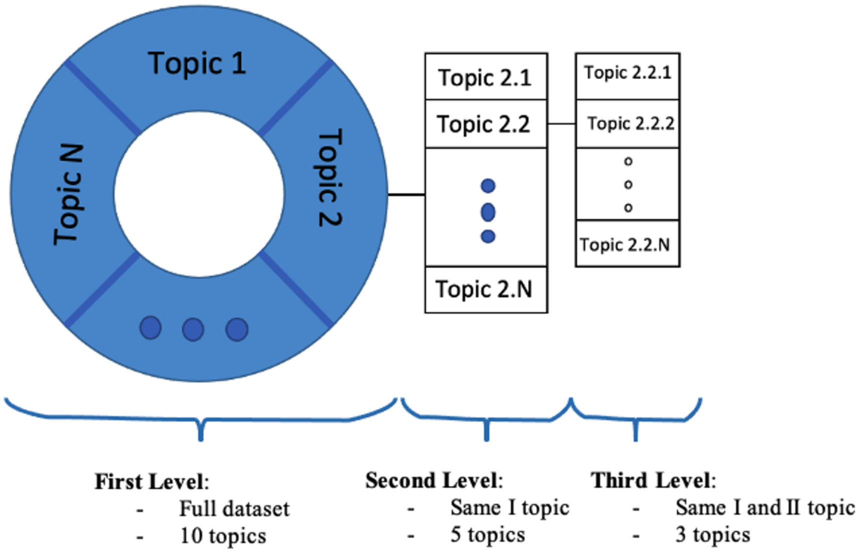
Topics are collections of certain words. Documents are created from topics' words.



Output of LDA model:

Text - Request: **70% "Travel"** + 15%"Entertainment" + 3%"Comedy" +2%"Gaming" + ...

Hierarchical Topic Modeling



- **Texts are transformed** to collections of nouns and verbs
- **LDA models** are trained on the transformed texts
- **Topic name** is defined as the most frequent topic noun among documents that have this topic

Solution 2

NAMED ENTITY RECOGNITION

WHY THIS SOLUTION WAS CHOSEN?

BENEFITS

WHY IS THIS BETTER?

NAMED ENTITY RECOGNITION - NER

When Michael Jordan was at the peak of his powers as an NBA superstar, his Chicago Bulls teams were mowing down the competition, winning six National Basketball Association titles and setting a record for wins in a season that was broken by the Golden State Warriors two seasons ago.

Extract

KEYWORDS

Place: Chicago

Name: Michael Jordan

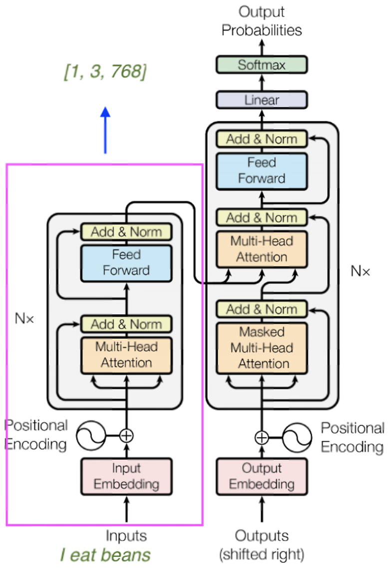
Group: National Basketball Association

Extract

NER - NAMED ENTITY RECOGNITION

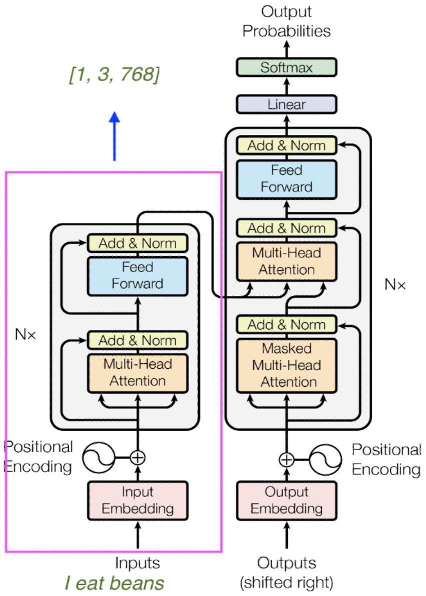
- Pretrained CNN based models exist in spacy, smallest pretrained model has a precision/recall around 0.85, dataset unclear.

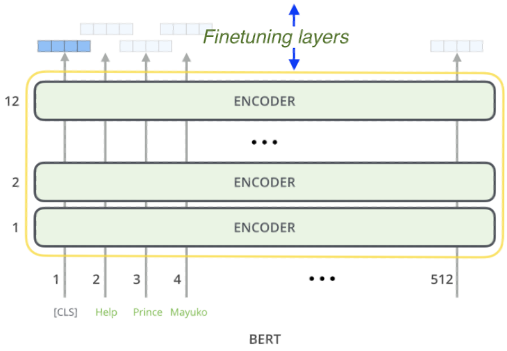
- BERT (Devlin et al, 2018), based on the Transformer (Vaswani et al, 2017). Accuracy of 0.95 on Kaggle entity annotated corpus dataset, after 1 epoch of fine tuning. HF library best for transformer-based architectures

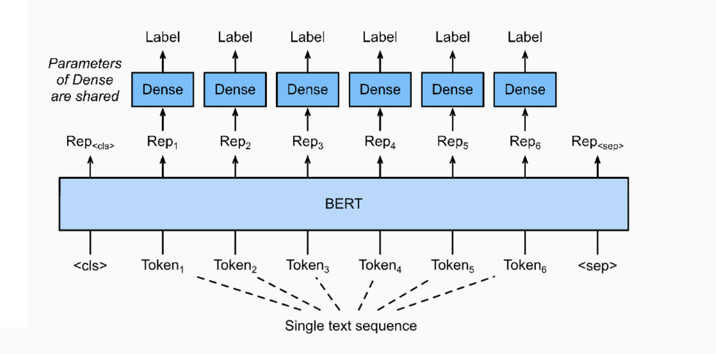


See full transformer deployed model here: Insert Divy's link here

Transformer/BERT







DEMO

GLG Generalists

FourthBrain

Team members:

Tatiana Chebonenko, Milan McGraw, Divyanshu Murli

SUMMARY / NEXT STEPS

TECHNICAL BENEFITS OF THIS PROPOSED APPROACH

MODEL 1 - MODEL CAN BE UPDATED WITH NEW REQUESTS WITHOUT RETRAINING

MODEL 2 - SPACY CNN MODELS EASY TO USE, WITH BERT DRIVES HIGHER ACCURACY AND CUSTOMIZABILITY

ROI / BENEFITS OF THIS PROPOSED APPROACH ~ IMPROVED MATCH RESULTS

REDUCE CHURN - HIGHER CONSULTANT RETENTION

IMPROVE ROI - HIGHER CLIENT RETENTION WITH FASTER TURNAROUND

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Tatiana Chebonenko [Linkedin]
Milan McGraw [Linkedin]
Divyanshu Murli [Linkedin]

Team's Repository [github]

APPENDIX

BERT based model performance

	precision	recall	f1-score	support
art	0.33	0.20	0.25	95
eve	0.35	0.36	0.36	36
geo	0.86	0.90	0.88	5963
gpe	0.95	0.93	0.94	1783
nat	0.90	0.24	0.38	37
org	0.78	0.72	0.75	3667
per	0.81	0.81	0.81	2813
tim	0.86	0.83	0.84	2347
micro avg	0.84	0.83	0.84	16741
macro avg	0.73	0.63	0.65	16741
weighted avg	0.84	0.83	0.83	16741