CLASSY

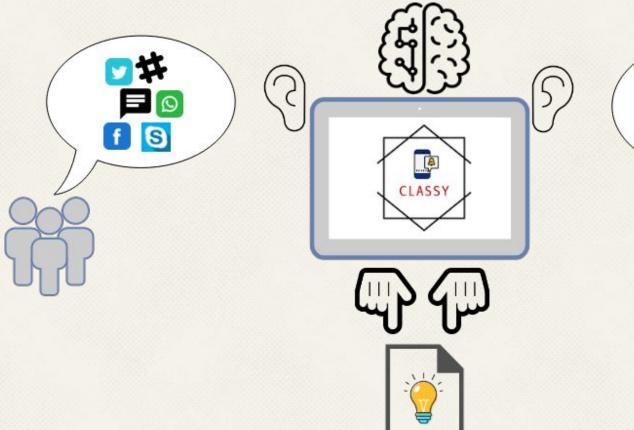
A Conversational Aware Suggestion System

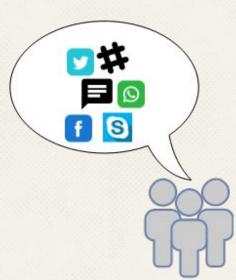




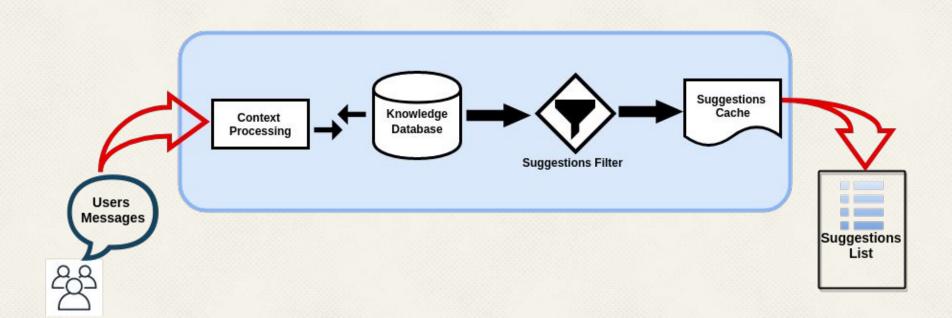
Disclaimer

What for?





Inside CLASSY



Context Processing Module

- Find the keywords
- Management of the current context
- Implicit query formation

```
Q1: Have you seen the last report?
```

Q2: The technical report? Q3: Yes, the third one.

RTQ1: [last, report]

RTQ2: [technical, report]

RTQ3: [third]

IQ: (last report)^1 OR (technical report)^2 OR (third)^3

Knowledge Database

- Pre-process and store information efficiently
- Searchable information (through queries)







Suggestions Filter and Cache ~

Post-process the result list:

- Filters on document attributes
- "Cache" to avoid same suggestions in consecutive (or almost) time-stamped messages

A Search Engine Based System

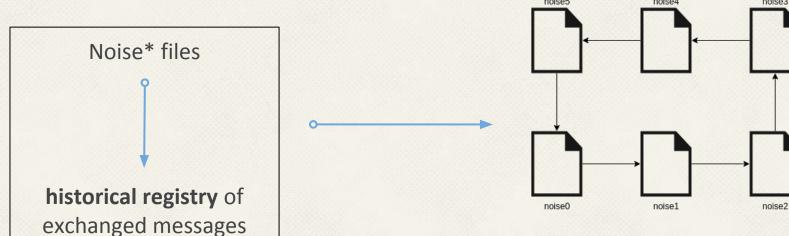
Knowledge database



- Full-text search
- Real-time indexing
- Extendable with custom plugins
- Fault-tolerant
- Scalable

The Noise File System

More conversational topics • More contexts • More noise



queries containing noise* files in the result list are considered noisy

Base Approach (w/ noise file system) Results

Number of noise files	Minimum document score	Total suggestions	Useful suggestions	Accuracy
2	20	102	47	46.08%
3	20	119	67	56.30%
4	20	131	69	52.67%
			0.0010.00000000000000000000000000000000	

→ The Neighborhood Approach

Goal: use semantic similarity as a mean to get similar contexts

How? Using a distribution profile

$$P(u) = [\{w_1, o(u, w_1)\}; ...; \{w_i, o(u, w_i)\}]$$

to build neighborhood vectors

```
D1: This is the third report.
D2: This report describes the built automatic system.
D3: This cost report gives respect to the costs related with the last semester.

RTD1: [third, report]
RTD2: [report, automatic, system]
RTD3: [cost, report, cost, semester]

Report neighborhood(window = 2):
[third: 1, automatic: 1, system: 1, cost: 2, semester: 1]

Report neighborhood(window = 1):
[third: 1, automatic: 1, cost: 2]
```

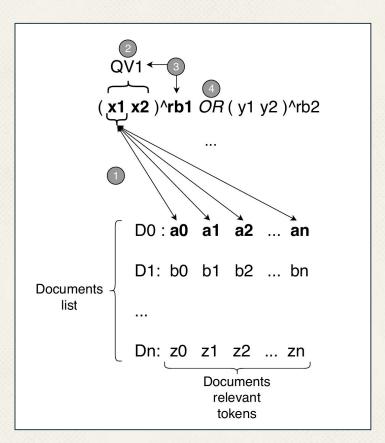
The Neighborhood Score (NS)

$$NS(u, v) = |u| \times |v| \times cosine(u, v)$$

$$cosine(u, v) = \frac{\sum_{i=1}^{n} o(u, w_i) \times o(v, w_i)}{\sqrt{\sum_{i=1}^{n} o(u, w_i)^2} \times \sqrt{\sum_{i=1}^{n} o(v, w_i)^2}}$$

This score is a **good indicator of how related two tokens are** and inherently how can they **refer to the same context**.

NS Computation Steps



- 1. Neighborhood pair computing
- 2. Intermediate sub-query value computation
- 3. Recency boost
- 4. Final score

Neighborhood Approach Results

Minimum document score	Number of noise files	Window size	Total suggestions	Useful suggestions	Accuracy
5	3	1	162	34	20.99%
20	3	1	35	26	74.29%
23	3	1	31	25	80.65%

Although these results seem optimistic, the reason for this sudden accuracy increase is the decrease of contextual suggestions concerning the direct word matches performed by the system.

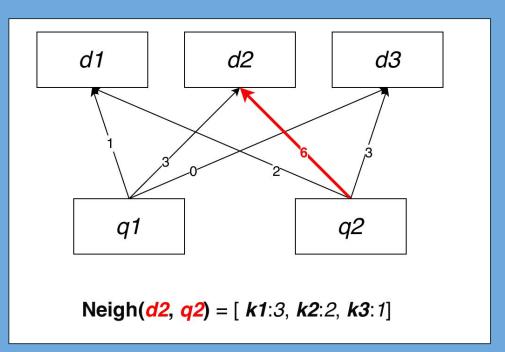
Using Hybrid Score

Hybrid score = Solr score * neighborhood score

Minimum document score	Number of noise files	Window size	Total suggestions	Useful suggestions	Accuracy
40	3	1	142	40	28.17%
140	3	1	46	29	63.04%
220	3	1	35	27	77.14%

The Reinforcement Learning Approach

The (context) States



The singular context state is composed by the top *n* tokens that characterize the strongest neighborhood connection

The (context) States

As each suggestion will have a **defined context regarding the implicit query**, it means that **each implicit query can be described as a set of probabilities** of belonging to each context state:

$$Q = \sum_{i=1}^{n} P(Q|cntx_i)$$

For each implicit query, the **contexts from the top** *n* **results** will be gathered and **used as the state** in order to find the action that maximizes the reward.

The Actions

Possible actions

Suggest one of the documents that composed the states vector

Optimal action

Suggest the document with **higher probability**

The Probabilities

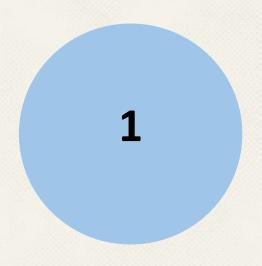
Initially:

All documents are **equiprobable**, with probability $\frac{1}{|contexts|}$

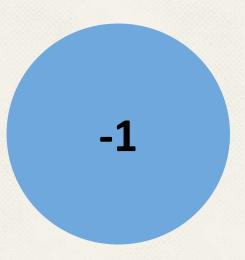
Then:

$$P(state_i, action_j) = P(state_i, action_j) + \begin{cases} reward * alpha & \text{if } suggested \\ \frac{1}{|cntxs|-1} * - reward * alpha & \text{if } not \, suggested \end{cases}$$

The Rewards



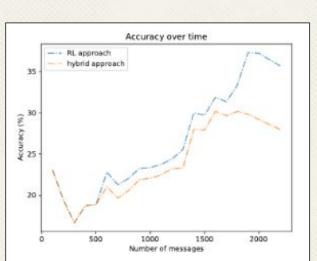
when clicked



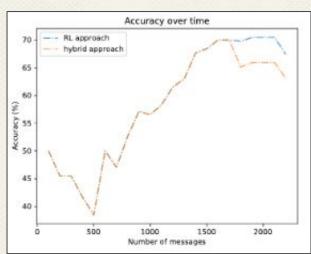
when not clicked during the defined time window

RL Approach Results

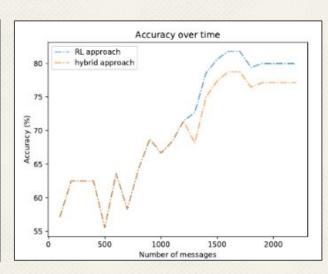
Minimum document score = 40



Minimum document score = 140

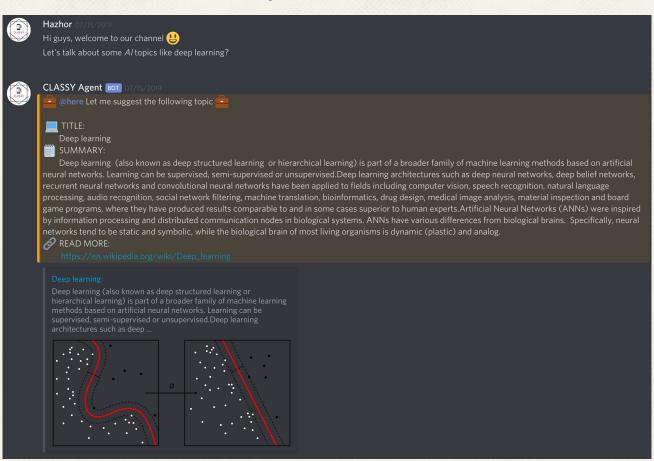


Minimum document score = 220



→ Trust me, it usually works

Discord & Wikipedia A.I Related Articles .



Hangouts & JIRA Issues (simulated in Discord)



Ryan F. BOT 07/15/2019

o JSSIP tem esse problema dos 30s é o timeout a determinar os ICE Candidates



Issues Agent BOT 07/15/2019

@here Let me suggest the following issues

ISSUE_ID:

4195c2f2-0555-49b7-8d71-8c5822b5c85c

SUMMARY:

Melhorias na cache de ice candidates

DESCRIPTION:

Mecanismo de evolução progressiva de timeout de negociação de ice candidates

Future Work

- Test the whole system in a larger dataset (more documents and more meaningful messages)
- Auto-tune system automatically find the best initial thresholds (minimum document score, etc)
- Richer pre-processing step (with more complex and powerful techniques)
- (add yours here)



THANKS!

Any questions?

You can find me at:

https://www.linkedin.com/in/diogofferreira/ https://github.com/diogofferreira