

# Building a Multimodal LLM-based Search Assistant Chatbot to Enhance Housing Search

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September 2024

**Grupo  
QuintoAndar**



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# Agenda

1. Who We Are

---
2. Why a Search Assistant?

---
3. What it is

---
4. The Chat Component

---
5. The Search Component

---
6. Final Remarks



# Who are we?

We are QuintoAndar Group, the **largest real estate ecosystem in Latin America.**

Driven by a shared purpose of helping people love where they live, we offer a diverse portfolio of brands and solutions that cover all stages of the living journey.

We develop technologies and innovations to transform and enhance the housing experience as a whole.

Grupo  
QuintoAndar



# Where are we?

---

Headquartered in Brazil and with a presence in five other Latin American countries (in addition to a tech hub in Europe), we are a global group that transcends borders.

Grupo  
QuintoAndar



The QuintoAndar Group currently operates in the following countries: **Brazil, Argentina, Ecuador, Panama, Peru, and Mexico.**

Our team is made up of talented professionals who work from various locations around the world.

# Our Numbers

We have formed the largest real estate group in Latin America, and the numbers we've achieved help to illustrate the scale of our brand.

Grupo  
QuintoAndar



Traffic

**45 million monthly visits to our platforms**



Listings

**Over 8 million property listings published**



Assets

**\$30 billion USD in assets under management**



Administration

**Over 270,000 contracts under administration**

# What is the Product

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## Chat

Real estate agent would talk to you until they **understand what you need...**

**So does Copilot!**

## Search

Once a real estate agent understands your need, they will **find** the property **tailored** to your needs, prioritizing things most important for **you...**

**Similar as Copilot!**

# Why did we need LLM-based Search Assistant?

Before

Does apartment have wooden floor?

Need to review all photos manually

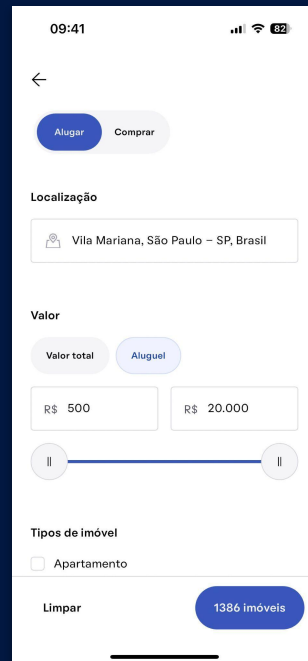
Is apartment close to supermarkets?

Need to go to the map and check

Me and my husband have 2 kids, we need to find nice apartment to fit us all close to the good schools

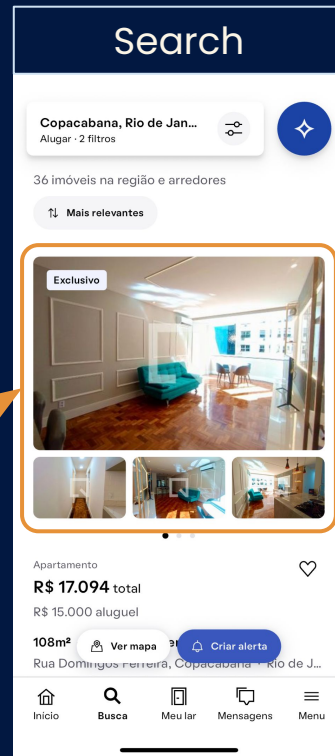
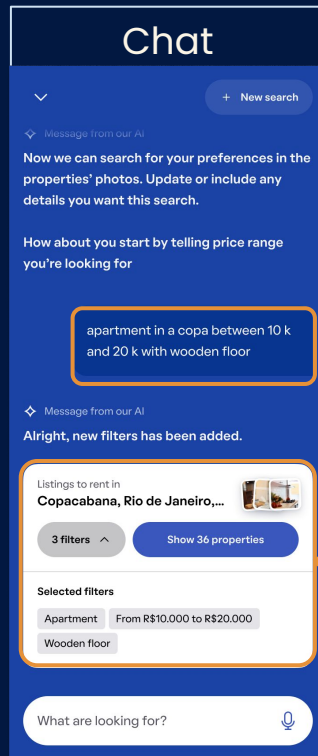
Need to adapt requirements to the filter structure

Search queries are filter-based only



# Why did we need LLM-based Search Assistant?

Now



# Why did we need LLM-based Search Assistant?

Now

1

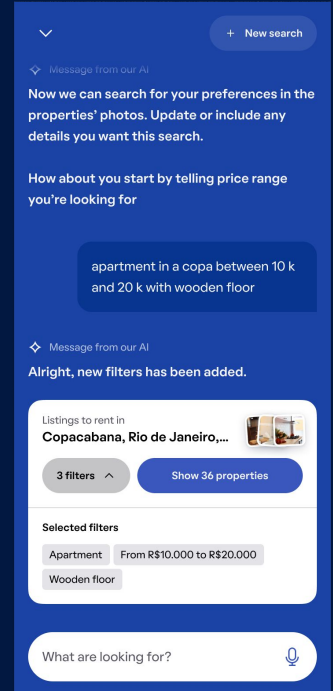
## A Data Collector Chat

A chat that prompts the user to provide preferences until enough data is gathered to perform a search

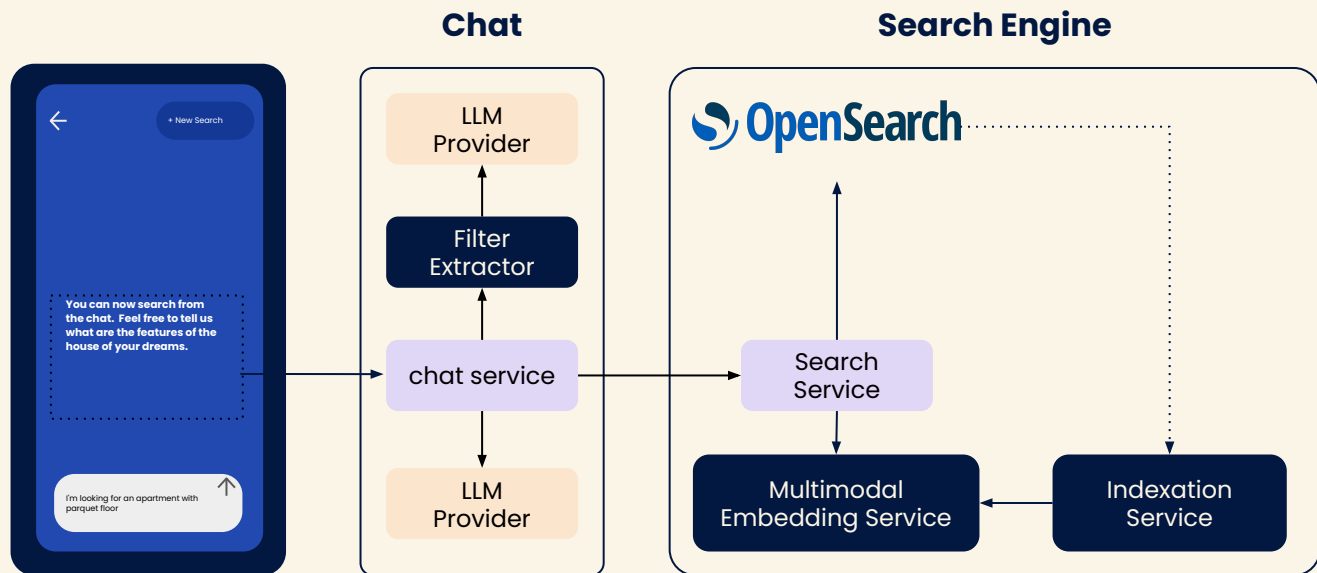
2

## A Search Engine

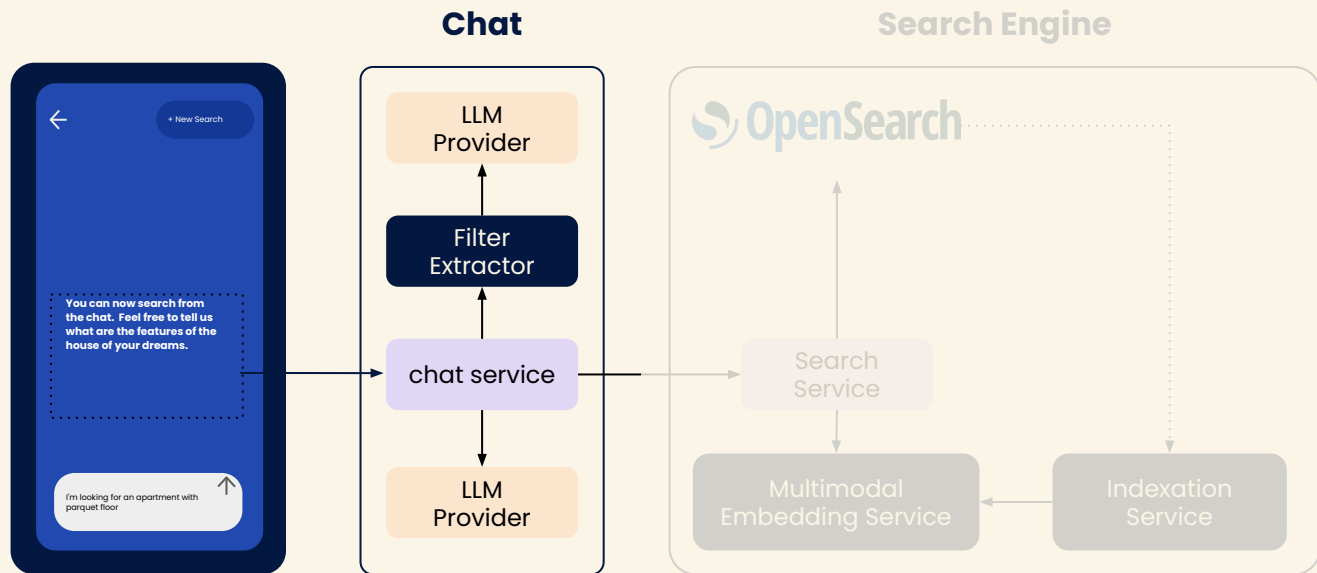
A tool that converts the user's preferences, including visual preferences, into a search.



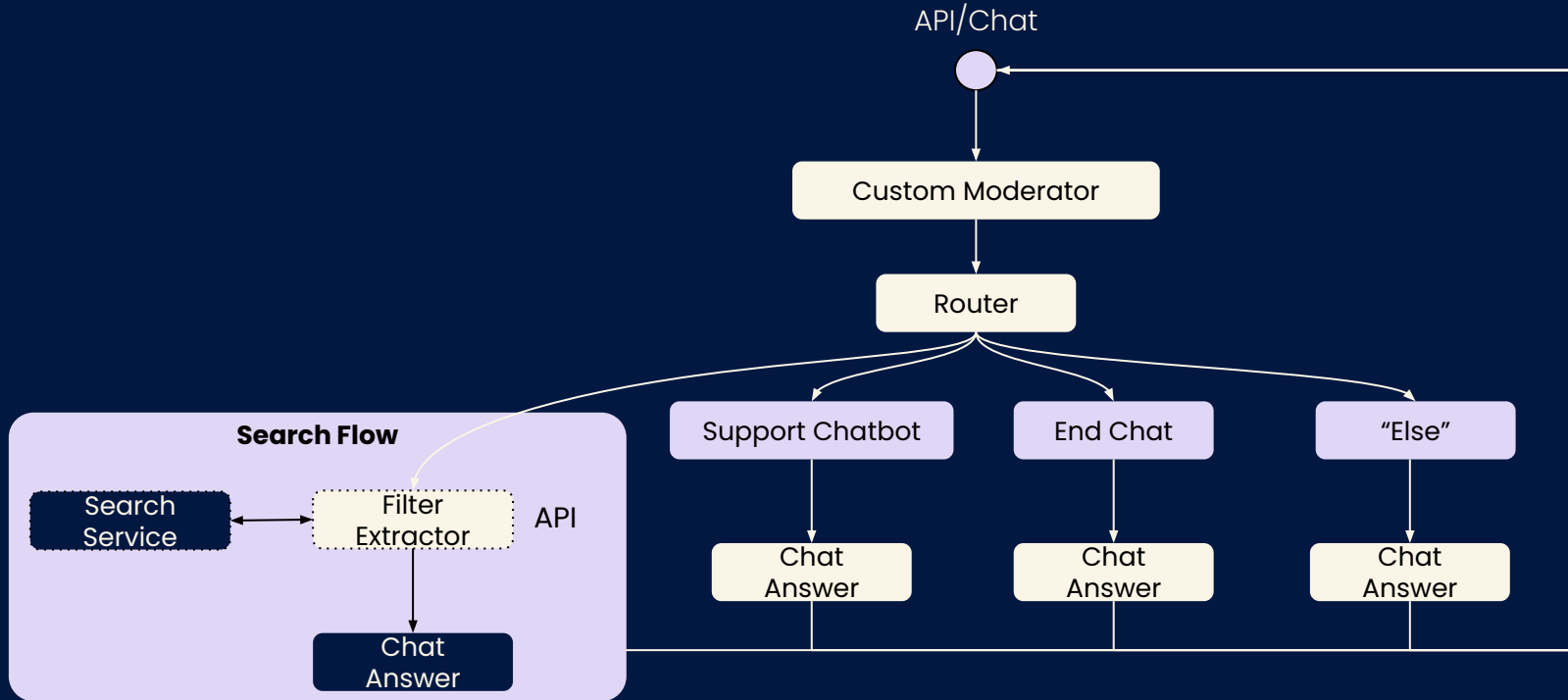
# LLM-based Search Assistant



# LLM-based Search Assistant

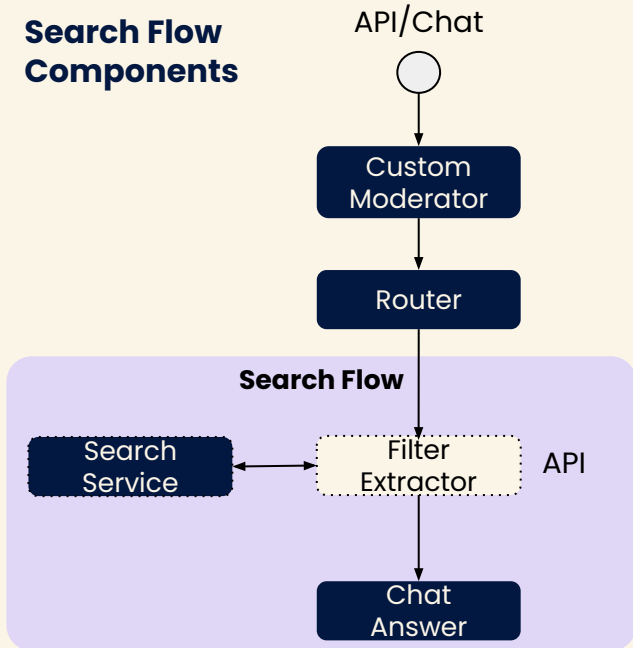


# Chat. Solution



# Chat. Solution

## Search Flow Components



## 1 Filter Extractor

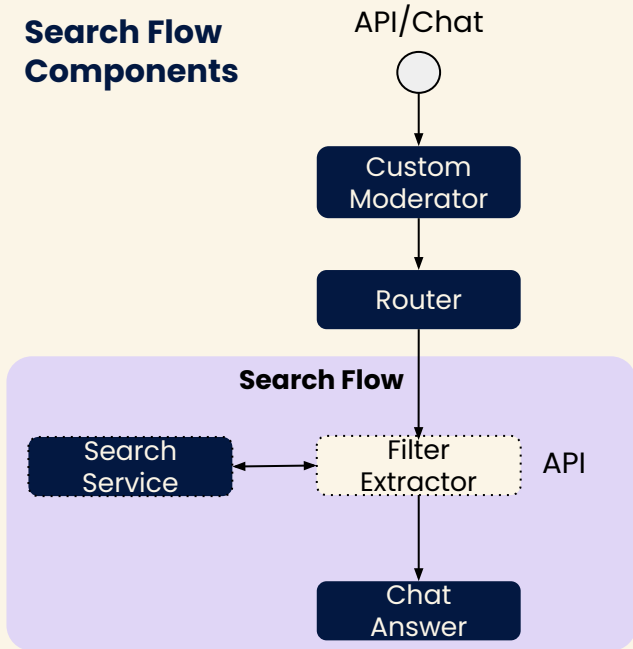
The heart of the system, that generate updated JSONs with user preferences based on user input. Is the interface with the Search Service.

## 2 Chat Answer

Tracks user preferences and extractor actions, communicates updates from the extractor, and guides the user in providing more data. Has some knowledge about locations.

# Chat. Solution

## Search Flow Components



## 1 Filter Extractor

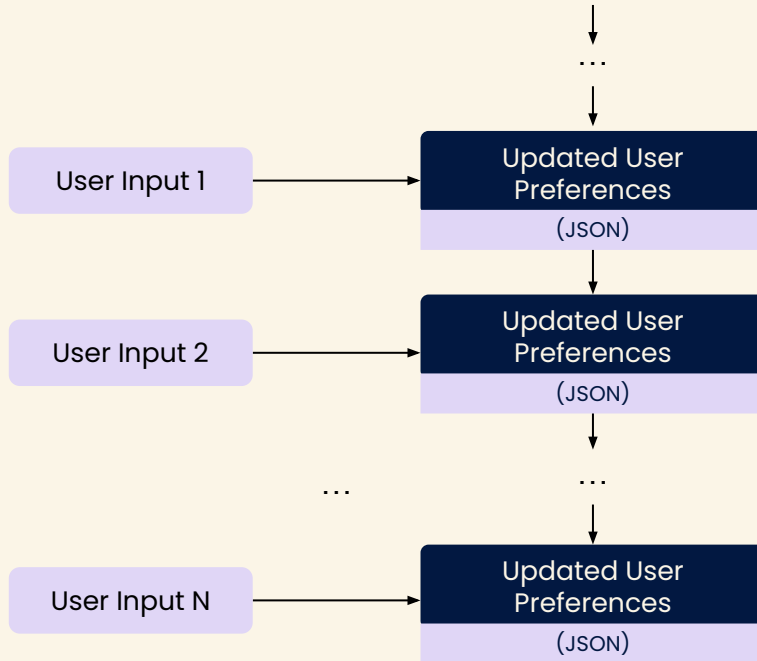
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# Chat. Solution

## Filter Extractor



Add New JSON Fields (Filters)

Updated JSON Fields (Filters)

Remove JSON Fields (Filters)

# Chat. Solution

## Filter Extractor

1

### **71 Different Filters (Classes)**

Property type (House, Apartment, etc)

Business Context (Rent, Sale)

Amenities and Installations

Etc

2

### **Extract Visual Elements**

Characteristics We Can Find in Images

Custom Moderation

Individual Extraction

# Chat. Solution

## Filter Extractor

1

### 71 Different Filters (Classes)

Property type (House, Apartment, etc)

Business Context (Rent, Sale)

Amenities and Installations

Etc

2

### Extract Visual Elements

Characteristics We Can Find in Images

Custom Moderation

Individual Extraction

```
{  
  "property_type": "apartment",  
  "max_price": 3000,  
  "context": "rent",  
  "bedrooms": 3,  
  "location": "Sao Paulo, SP, Brazil",  
  "visual_search": ["modern decor"],  
}
```

# Chat. Solution

## Filter Extractor

### User Current Preferences

```
{  
  "property_type": "apartment",  
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```

### User Textual Input

*"Actually, 2 bedrooms and industrial style."*

# Chat. Solution

## Filter Extractor

### User Current Preferences

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{  
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### User Textual Input

"Actually, 2 bedrooms and industrial style."

Filter Classifier

Filter Extractor

Two Steps  
Dynamic  
Extraction

# Chat. Solution

## Filter Extractor

### User Current Preferences

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Filter Classifier

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Two Steps  
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LLM Call: Detects Preferences Mentioned by the User  
[bedrooms, visual search]

# Chat. Solution

## Filter Extractor

### User Current Preferences

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### User Textual Input

"Actually, 2 bedrooms and industrial style."

Filter Classifier

Filter Extractor

Two Steps  
Dynamic  
Extraction

**LLM Call: Detects Preferences Mentioned by the User**  
[bedrooms, visual search]

**LLM Call: Updates user JSON**  
Given the current user filters and input, updates *only the detected preferences*

# Chat. Solution

## Filter Extractor

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### User Textual Input

"Actually, 2 bedrooms and industrial style."

Filter Classifier

Filter Extractor

Two Steps  
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**LLM Call: Detects Preferences Mentioned by the User**  
[bedrooms, visual search]

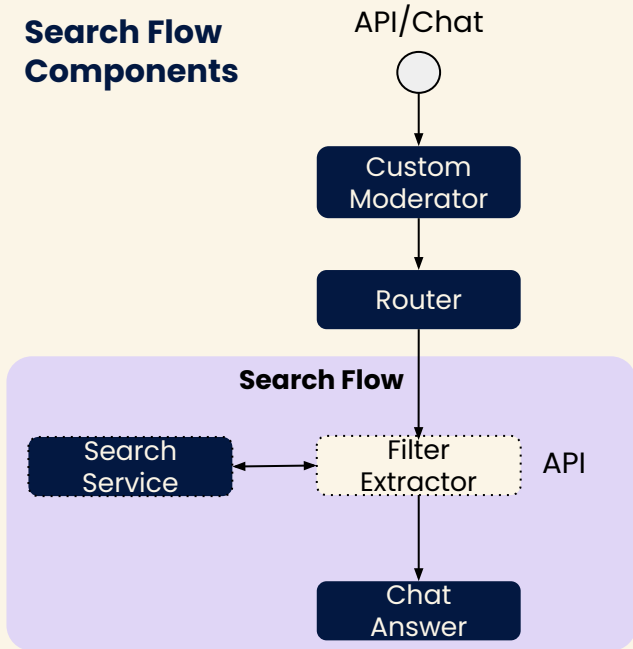
**LLM Call: Updates user JSON**  
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}
```

**Updated  
User  
Preferences**

# Chat. Solution

## Search Flow Components



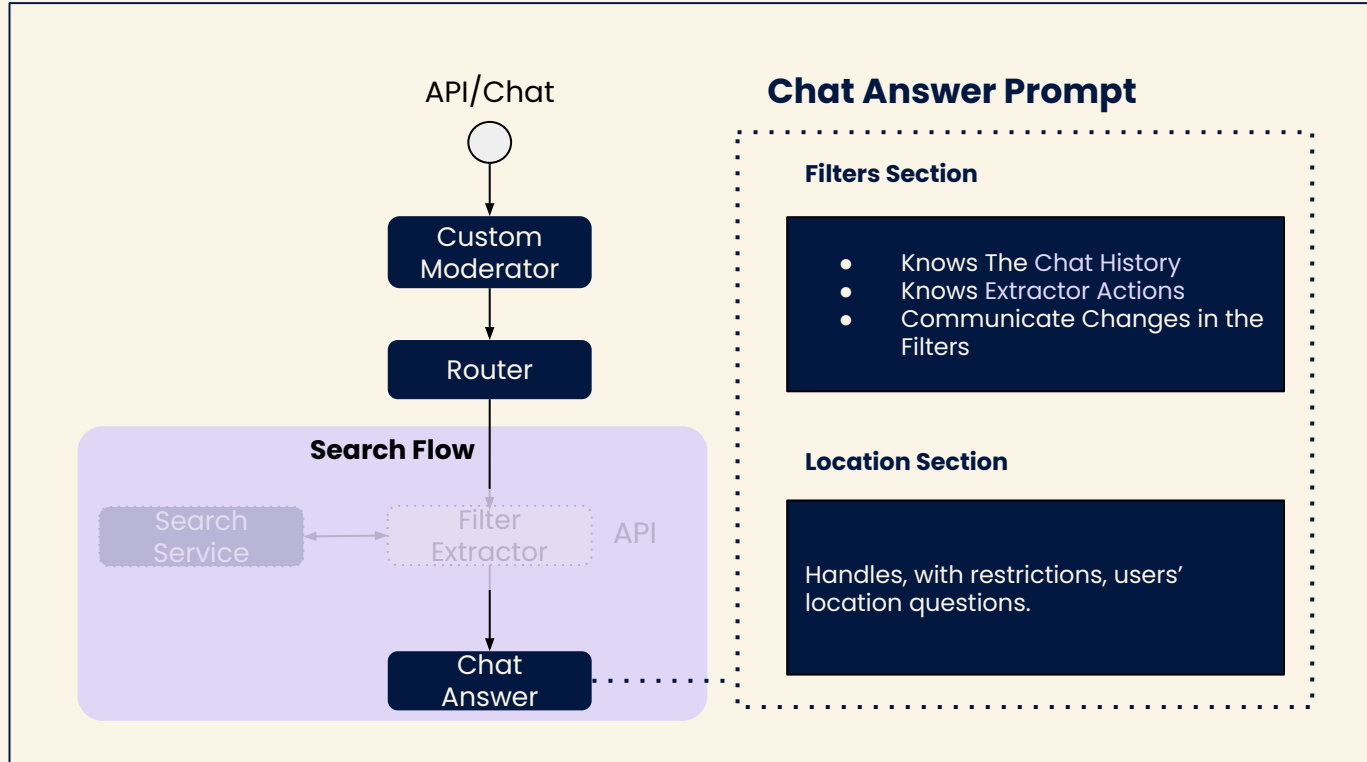
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The heart of the system, that generate updated JSONs with user preferences based on user input. Is the interface with the Search Service.

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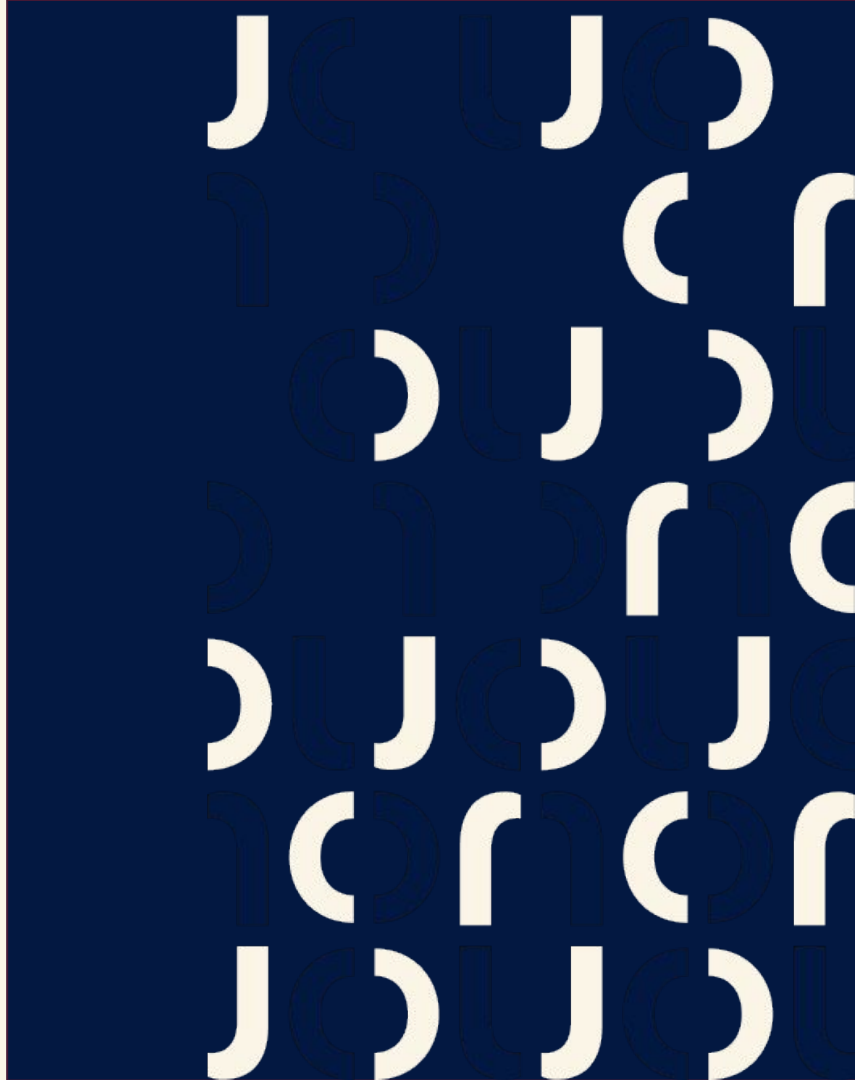
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# Chat. Solution

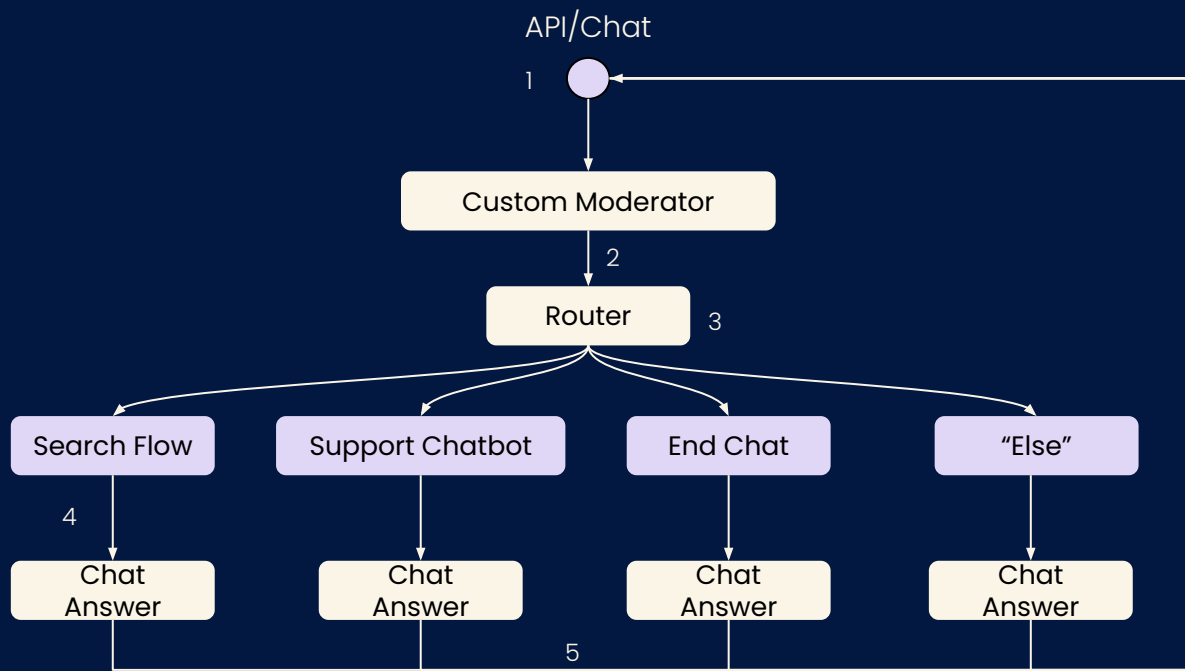


**But...is it  
good at all?**

---



# Chat. Evaluation



1. The user Input
  2. If the input was moderated or not
  3. The Router Predictions
  4. Extracted Filters
  5. Chat Answers
- + LLM Adopted Prompts

# Chat. Evaluation

Chat Component	Validation Type	Eval Dataset	Evaluator
Router	Offline/CICD	Golden Dataset	Classical M.L Metrics
	Online	Production Dataset	LLM As A Judge
Filter Extractor	Offline/CICD	Golden Dataset	Classical M.L Metrics
	Online	Production Dataset	LLM As A Judge
Visual Components	Offline/CICD	Golden Dataset	LLM As A judge
	Online	Production Dataset	
Chat Answers	Offline/CICD	Golden Dataset	LLM As A Judge
	Online	Production Dataset	

# Chat. Evaluation

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## Classical ML Evaluation

- ✓ Objective/Deterministic Tasks, such as Classification (Filter Extractor, Router)
- ✓ Used Offline Only (CI/CD)
- ✓ More Granular/Detailed metrics (Filter-level)

## LLM As a Judge Evaluation

- ✓ Subjective/Open-Ended Tasks, such as Conversation (Chat Answers)
- ✓ Used Online and Offline (CI/CD)
- ✓ General Metrics

# Chat. Evaluation

## Classical ML Evaluation

### Example of Filter Extractor Metrics

Filter Group	Filter Category	F1	Precision	Recall
property_type	condominium	0.909	0.968	0.857
property_type	apartment	0.970	0.963	0.978
business_context	rent	0.991	0.988	0.994
business_context	sale	0.981	0.981	0.981

## LLM As a Judge Evaluation

**User Input:** Santa Cecília 2 bedrooms

Score	1 (Correct)
Score Reason	The LLM correctly updated the location filter to 'Santa Cecilia, São Paulo - SP, Brasil'  Already Existing filter for 2 bedrooms (min_bedrooms: 2), so no change was needed there.

# Chat. Evaluation

## LLM As A Judge

### How We Do It

1

#### **Simplify The Task**

Simplify the original task to make evaluation accurate

2

#### **Chain of Thoughts**

A list of clear instructions

3

#### **Clear Grading Criteria**

Clear grading guide to produce final score

3

#### **Score Reason**

Ask the LLM to Produce a reason for the scoring

# Chat. Evaluation

## LLM As A Judge

### How We Do It

1	<b>Simplify The Task</b> Simplify the original task to make evaluation accurate
2	<b>Chain of Thoughts</b> A list of clear instructions
3	<b>Clear Grading Criteria</b> Clear grading guide to produce final score
3	<b>Score Reason</b> Ask the LLM to Produce a reason for the scoring

### Example

User Input	Santa Cecília 2 bedrooms
Input to Judge	<b>User Message</b> Santa Cecília 2 bedrooms <b>Current User Preferences</b> business_context: RENT location: Rua Doutor Rubens Meireles, São Paulo, SP, Brasil max_price: 5700.0 min_bedrooms: 2 <b>What Extractor Did</b> location CHANGED FROM <i>Rua Doutor Rubens Meireles, São Paulo, SP, Brasil</i> TO <i>Santa Cecília, São Paulo – SP, Brasil.</i>

# Chat. Evaluation

## LLM As A Judge

### How We Do It

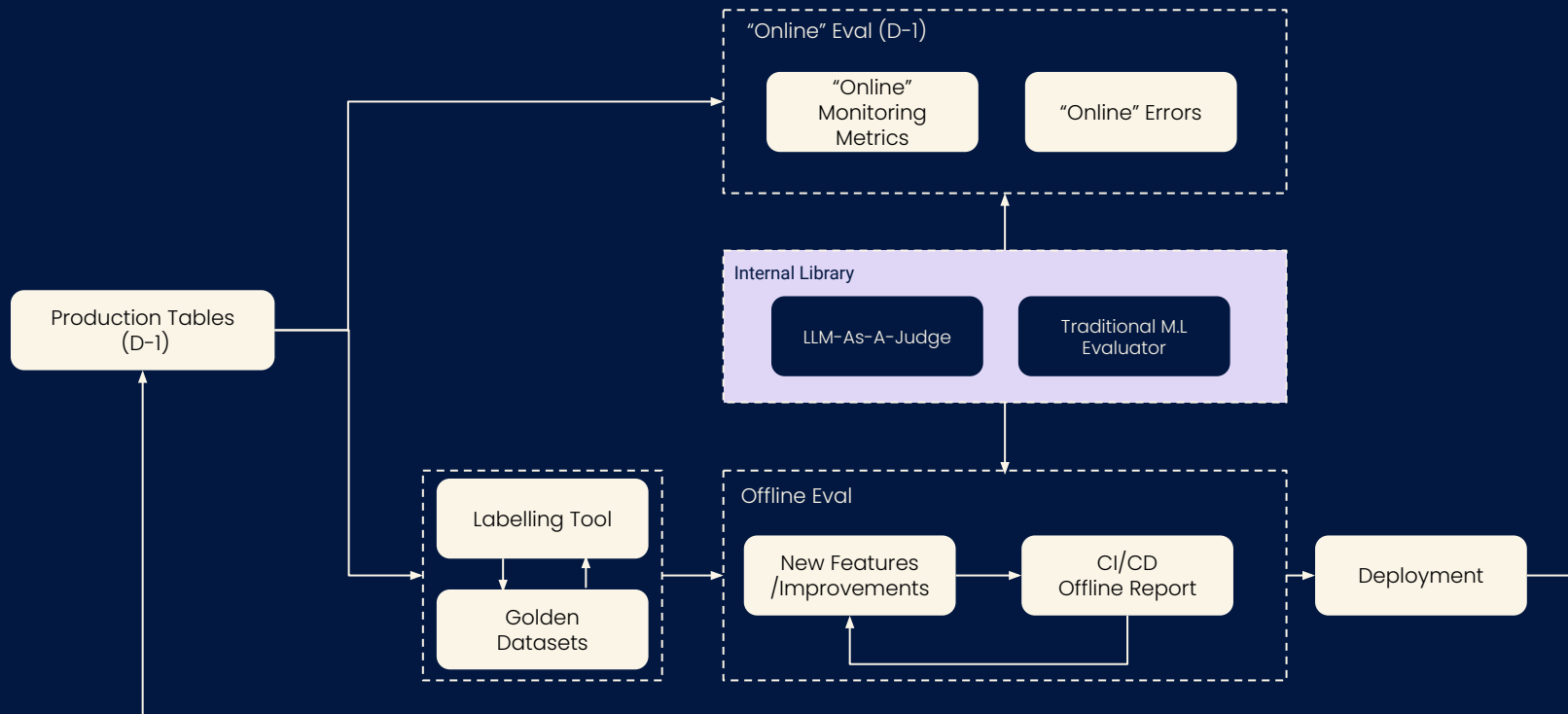
1	<b>Simplify The Task</b> Simplify the original task to make evaluation accurate
2	<b>Chain of Thoughts</b> A list of clear instructions
3	<b>Clear Grading Criteria</b> Clear grading guide to produce final score
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### Example

User Input	Santa Cecília 2 bedrooms	Score	1 (Correct)
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# Chat. Evaluation

## Overall Architecture



# Chat. Solution

## Lessons Learned

### What We Tried

1	"One Prompt to Rule Them All"
2	Granular Approach: <ul style="list-style-type: none"><li>- Break down text into topics;</li><li>- Classify Each Topic;</li><li>- Extraction for Each Topic;</li></ul>
3	Synthetic Datasets

### What Worked Best

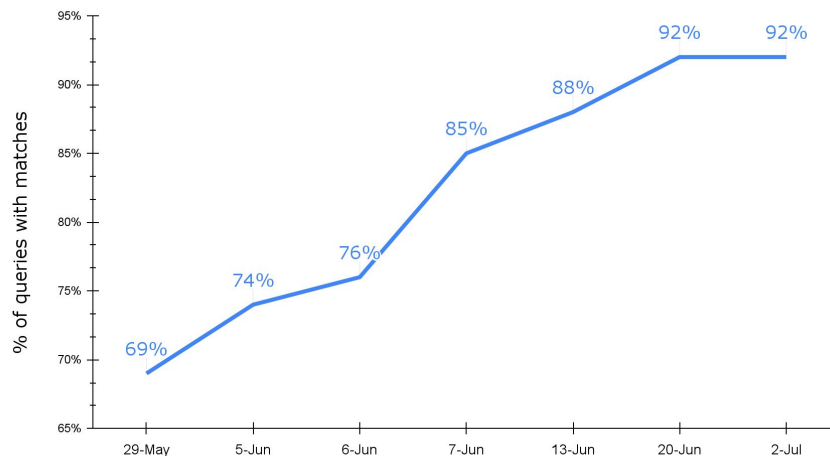
1	Combination of LLM and State Machine
2	Two Steps Approach and Individual Calls For Complex Filters: <ul style="list-style-type: none"><li>- Amenities and Installations</li><li>- Visual Elements</li></ul>
3	Manually Generated Golden Datasets

# Chat. Solution

## Lessons Learned

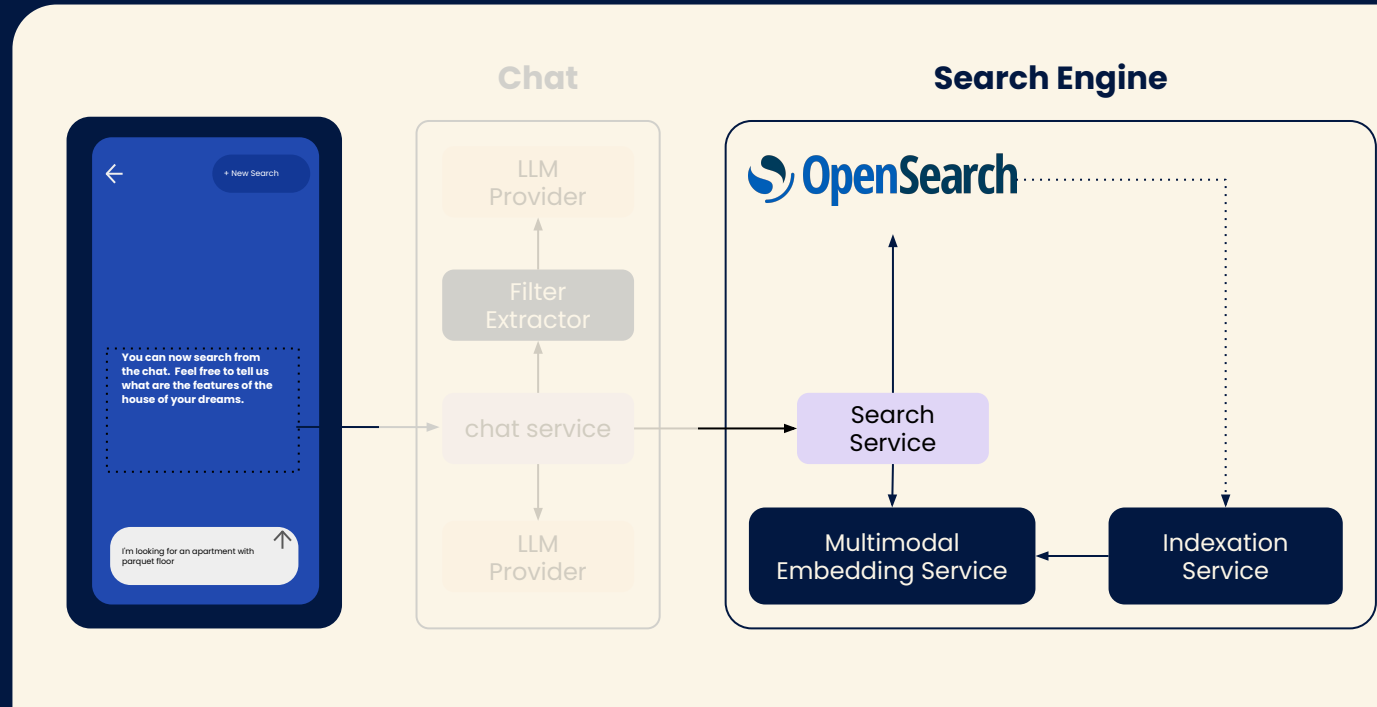
*Right Evaluation Stimulates Virtuous Cycle of Improvements*

% of users queries with accurate parsing of critical filters



1 Month

# LLM-based Search Assistant



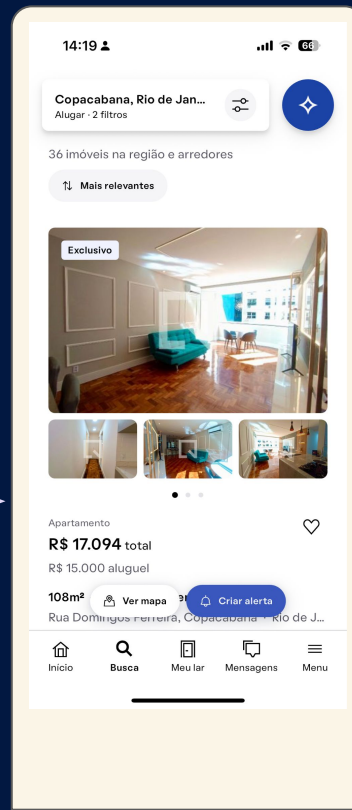
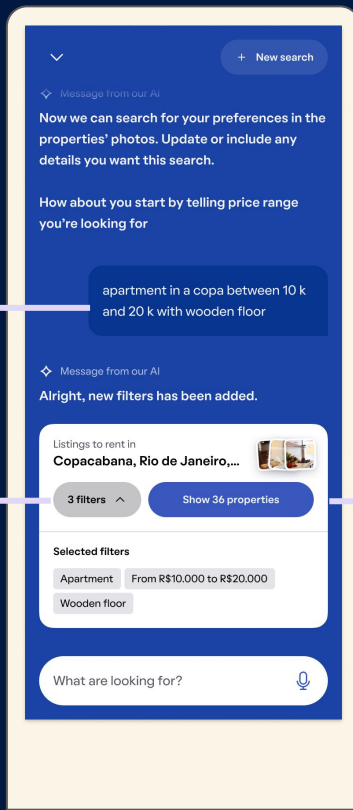
# Search

Before the chat

Query

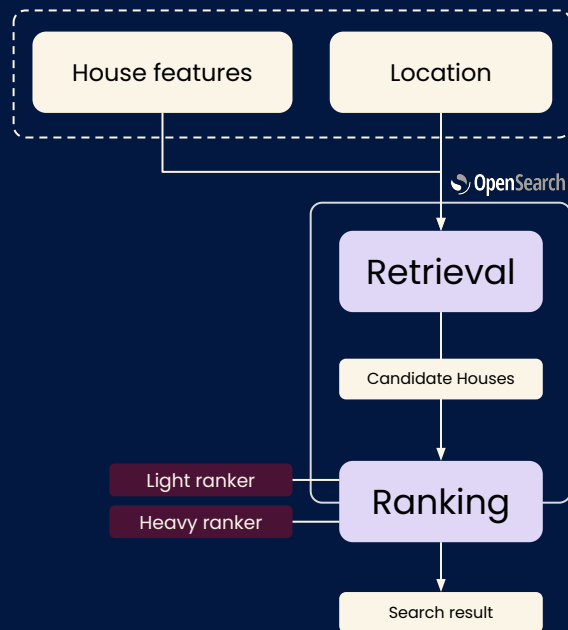


Results



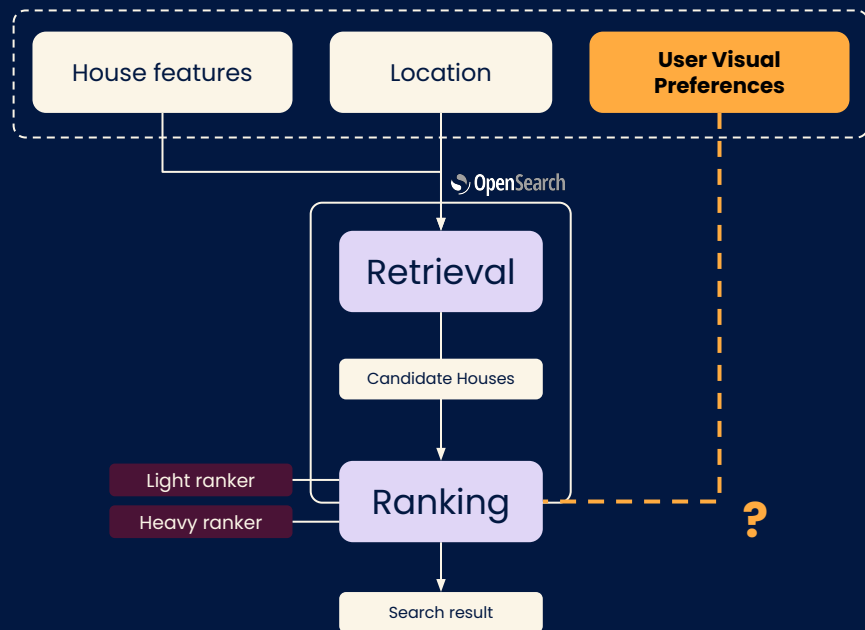
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Before the chat



# Search

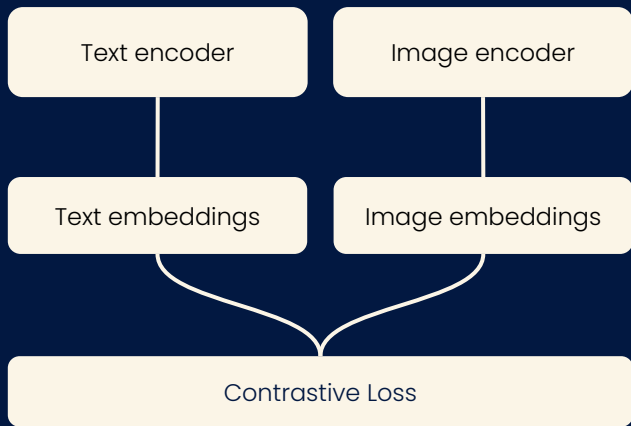
After the chat



# Search

## Multimodal embeddings

"wooden floor"



## OpenAI CLIP

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**Learning Transferable Visual Models From Natural Language Supervision**

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Alec Radford<sup>\*1</sup> Jong Wook Kim<sup>\*1</sup> Chris Hallacy<sup>1</sup> Aditya Ramesh<sup>1</sup> Gabriel Goh<sup>1</sup> Sandhini Agarwal<sup>1</sup>  
Girish Sastry<sup>1</sup> Amanda Askell<sup>1</sup> Pamela Mishkin<sup>1</sup> Jack Clark<sup>1</sup> Gretchen Krueger<sup>1</sup> Ilya Sutskever<sup>1</sup>

## Google SigLIP

**Sigmoid Loss for Language Image Pre-Training**

Xiaohua Zhai\* Basil Mustafa Alexander Kolesnikov Lucas Beyer\*  
Google DeepMind, Zürich, Switzerland  
{xzhai, basilm, akolesnikov, lbeyer}@google.com

## Salesforce BLIP-2

---

**BLIP-2: Bootstrapping Language-Image Pre-training  
with Frozen Image Encoders and Large Language Models**

---

Junnan Li Dongxu Li Silvio Savarese Steven Hoi  
Salesforce Research

# Search

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## Scoring

### User Query

"I'm looking for a house with **wooden floor**, **big windows** and **modern decoration**"

Preferences  
Extractor

**Wooden Floor**

**Big Windows**

**Modern Decoration**

Scoring  
Function

 **House A**  
IMAGES



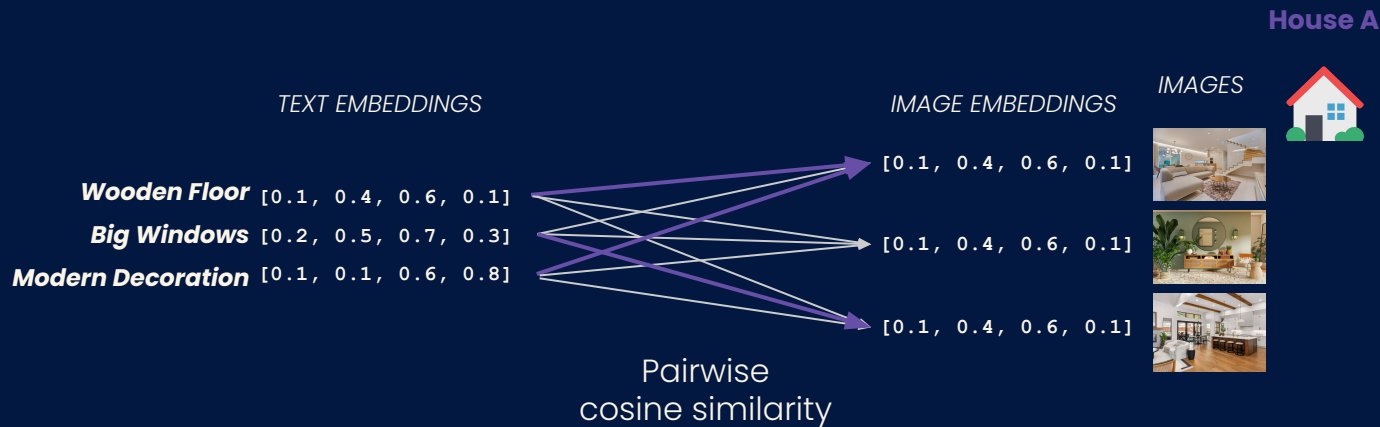
 **House B**  
IMAGES



# Search

---

## Scoring



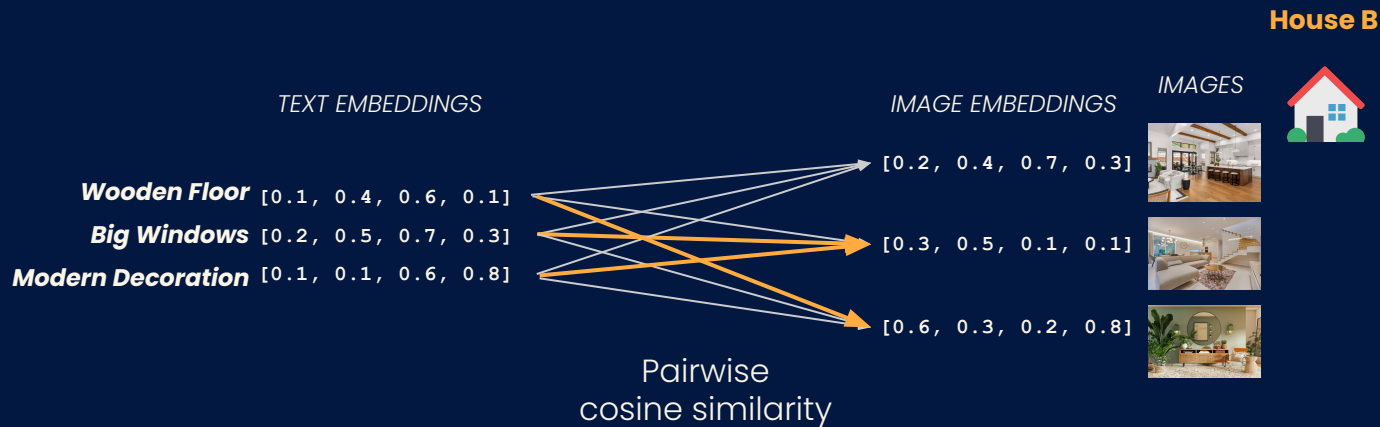
$$\text{IMAGE\_SCORE}_{\text{houseA}} = \text{sum}(\text{max}(\text{cosine}) \text{ group by Visual Preference})$$

For query "I'm looking for a house with **wooden floor**, **big windows** and **modern decoration**"

# Search

---

## Scoring



$$\text{IMAGE\_SCORE}_{\text{houseB}} = \text{sum}(\text{max}(\text{cosine}) \text{ group by } \text{Visual Preference})$$

For query "I'm looking for a house with **wooden floor**, **big windows** and **modern decoration**"

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## Scoring

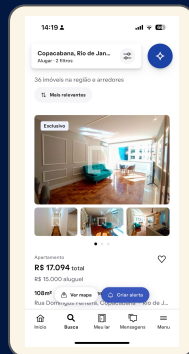
$SCORE_{houseA} = \text{combine}(\text{IMAGE\_SCORE}_{houseA}, \text{HEAVY\_RANKER\_SCORE}_{houseA}, \dots)$

$SCORE_{houseB} = \text{combine}(\text{IMAGE\_SCORE}_{houseB}, \text{HEAVY\_RANKER\_SCORE}_{houseB}, \dots)$

↓

$RESULTS = \text{topK}(\text{rank}(SCORE_{houseA}, SCORE_{houseB}))$

↓



**But...is it  
good at all?**

---



# Search

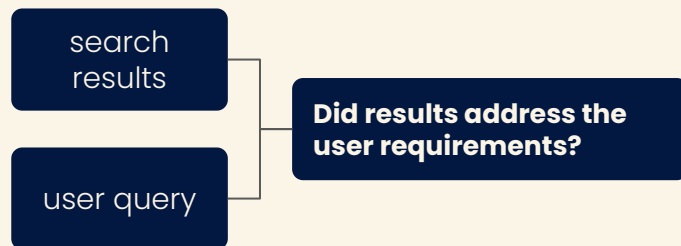
## Evaluation

### Traditional



Overall health of the system

### LLM-as-a-judge



Results (multimodal) explainability

# Search

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## What we did

- Similarity-based image sampling
- Different similarity aggregation strategies
  - $\text{AVG}(\text{SUM}(\text{cosine}))$
  - $\text{AVG}(\text{MAX}(\text{cosine}))$
  - $\text{MAX}(\text{MAX}(\text{cosine}))$

## Future and WIP

- Hybrid Search: full-text + vector search
- House-level vs. image-level embeddings
- Heavy ranker with image features
- Visual features as filter to reduce the search space

# Thank You Team



**We are  
hiring**

---

**Come join our team!**



<https://carreiras.quintoandar.com.br/?lang=en>



An aerial photograph of a blue outdoor court where several children are playing. The children are scattered across the frame, some in motion. Their dark shadows are cast onto the blue surface, indicating a low sun position. In the bottom right corner, a basketball is visible. The text 'Grupo QuintoAndar' is centered in the image in a white, sans-serif font.

# Grupo QuintoAndar

# Agenda

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2. Why a Search Assistant?

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3. What it is

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4. The Chat Component

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5. The Search Component

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6. Final Remarks



# Who are we?

We are QuintoAndar Group, the **largest real estate ecosystem in Latin America.**

Driven by a shared purpose of helping people love where they live, we offer a diverse portfolio of brands and solutions that cover all stages of the living journey.

We develop technologies and innovations to transform and enhance the housing experience as a whole.

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QuintoAndar



# Where are we?

Headquartered in Brazil and with a presence in five other Latin American countries (in addition to a tech hub in Europe), we are a global group that transcends borders.

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QuintoAndar



The QuintoAndar Group currently operates in the following countries: **Brazil, Argentina, Ecuador, Panama, Peru, and Mexico.**

Our team is made up of talented professionals who work from various locations around the world.

# Our Numbers

We have formed the largest real estate group in Latin America, and the numbers we've achieved help to illustrate the scale of our brand.

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QuintoAndar



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**45 million monthly visits to our platforms**



Listings

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Administration

**Over 270,000 contracts under administration**

# What is the Product

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## Chat

Real estate agent would talk to you until they **understand what you need...**

**So does Copilot!**

## Search

Once a real estate agent understands your need, they will **find** the property **tailored** to your needs, prioritizing things most important for **you...**

**Similar as Copilot!**

# Why did we need LLM-based Search Assistant? BEFORE

Search queries are  
filter-based only

The screenshot shows a mobile application interface for searching real estate. At the top, the time is 09:41 and there are icons for signal strength, Wi-Fi, and battery. Below the time is a back arrow and two buttons: 'Alugar' (Rent) and 'Comprar' (Buy). The 'Localização' (Location) section shows a pin icon and the text 'Vila Mariana, São Paulo - SP, Brasil'. The 'Valor' (Value) section has two buttons: 'Valor total' and 'Aluguel' (Rent). Below these are two input fields: 'R\$ 500' and 'R\$ 20.000'. A horizontal slider is positioned below the input fields. The 'Tipos de imóvel' (Property types) section has a checkbox labeled 'Apartamento'. At the bottom, there is a 'Limpar' (Clear) button and a blue button with the text '1386 imóveis'.

Does apartment have wooden floor?

Need to review all photos manually

Is apartment close to supermarkets?

Need to go to the map and check

Me and my husband have 2 kids, we  
need to find nice apartment to fit us all  
close to the good schools

Need to adapt requirements to the filter  
structure

# Why did we need LLM-based Search Assistant? NOW

## Chat

Message from our AI

Now we can search for your preferences in the properties' photos. Update or include any details you want this search.

How about you start by telling price range you're looking for

apartment in a copa between 10 k and 20 k with wooden floor

Message from our AI

Alright, new filters has been added.

Listings to rent in Copacabana, Rio de Janeiro,...

3 filters Show 36 properties

Selected filters

- Apartment From R\$10.000 to R\$20.000
- Wooden floor

What are looking for?

## Search

14:19

Copacabana, Rio de Jan...  
Alugar - 2 filtros

36 imóveis na região e arredores

Mais relevantes

Exclusivo

Apartamento

R\$ 17.094 total  
R\$ 15.000 aluguel

108m² Ver mapa Criar alerta

Rua Domingos Ferreira, Copacabana - Rio de J...

Início Busca Meu lar Mensagens Menu

# LLM-based Search Assistant

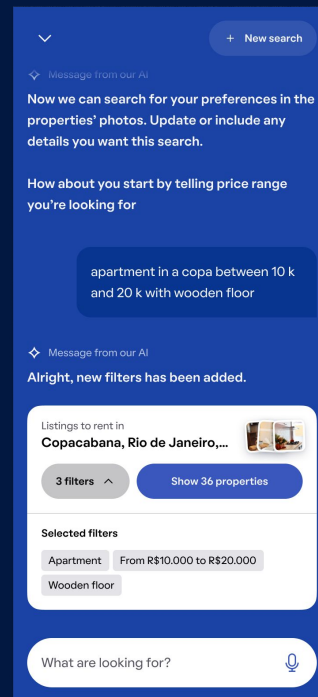
## What it is

### 1 A Data Collector Chat

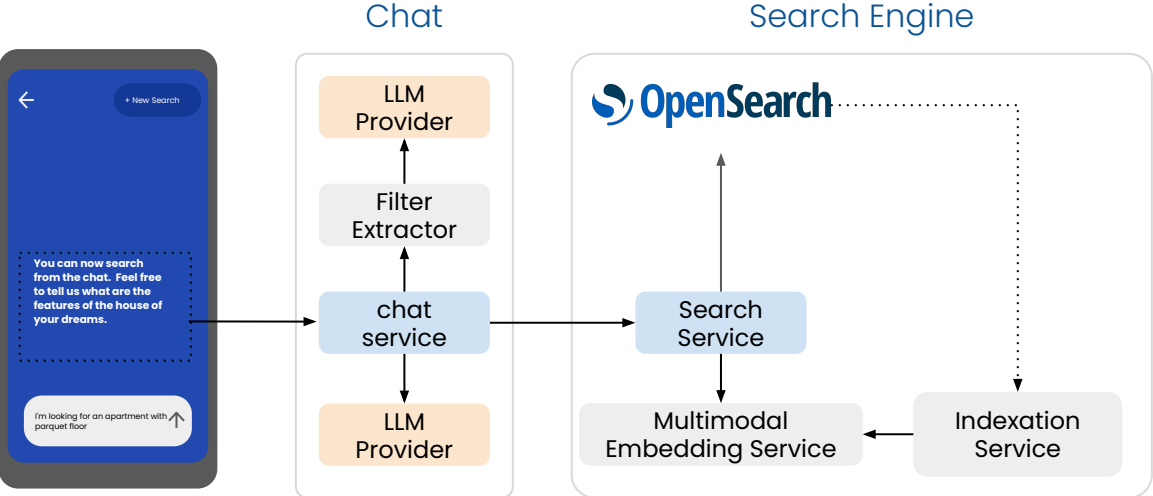
A chat that prompts the user to provide preferences until enough data is gathered to perform a search

### 2 A Search Engine

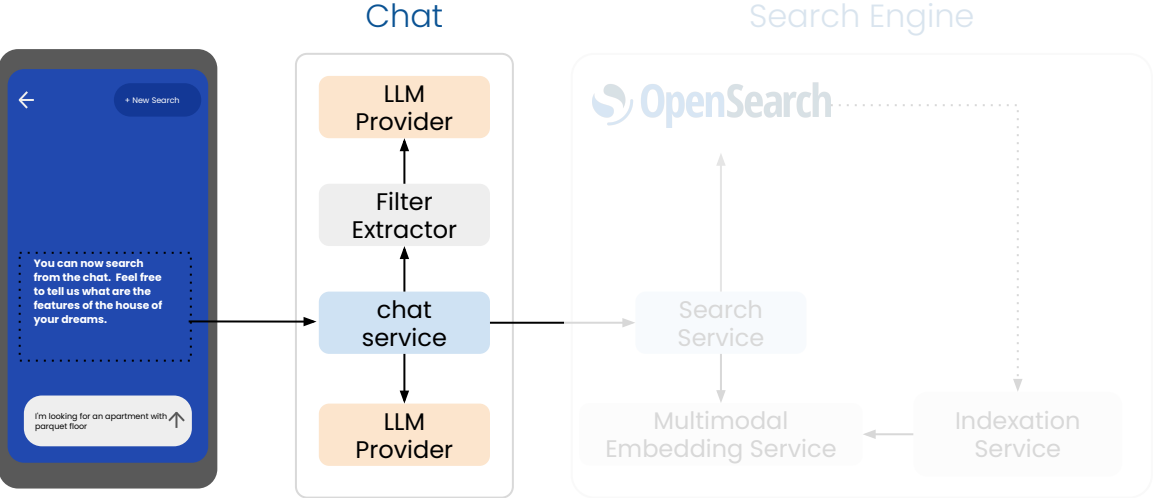
A tool that converts the user's preferences, including visual preferences, into a search.



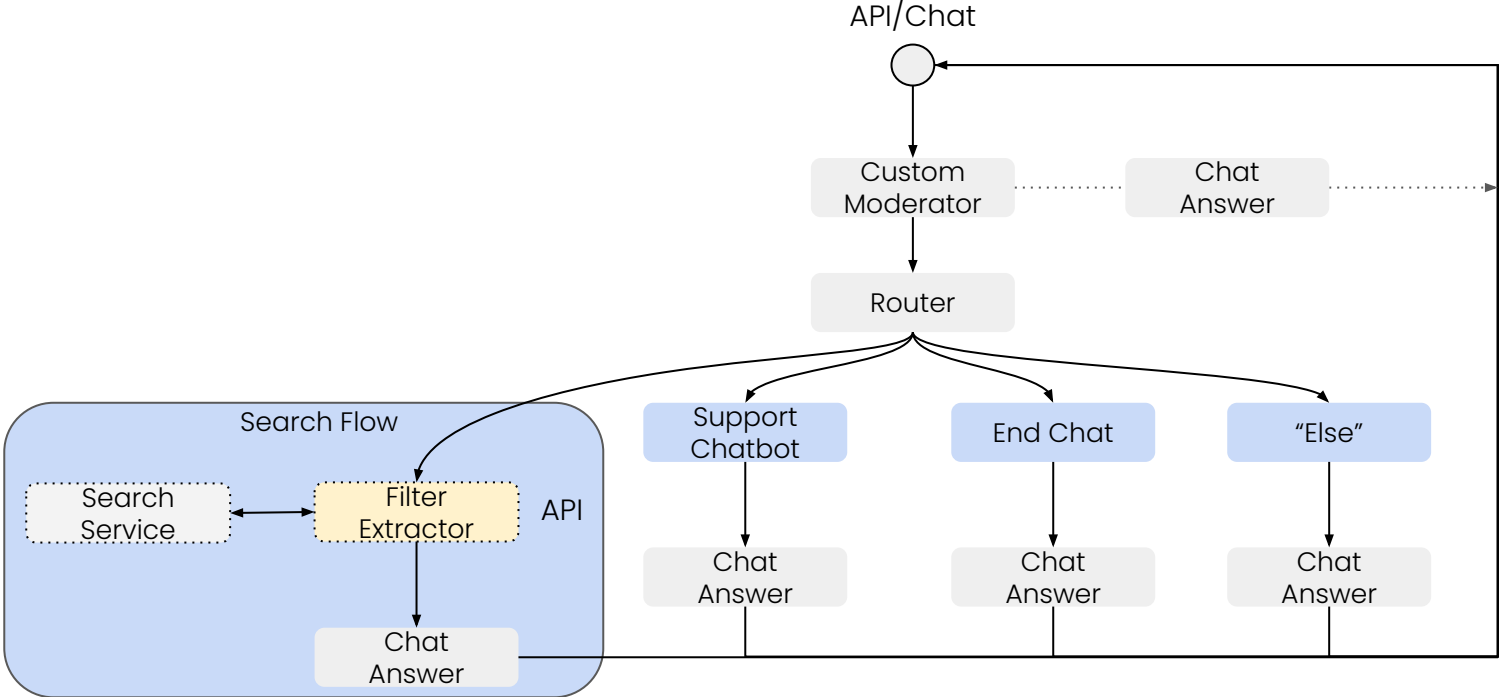
# LLM-based Search Assistant



# LLM-based Search Assistant

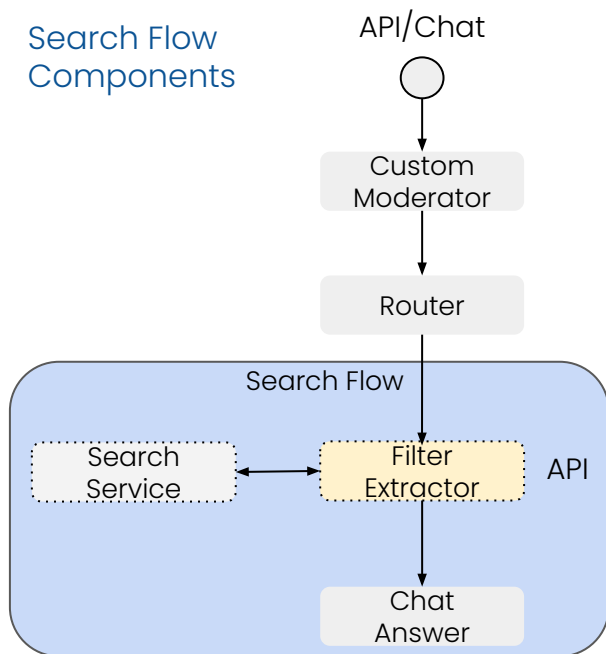


# Chat. Solution



# Chat. Solution

## Search Flow Components



## 1 Filter Extractor

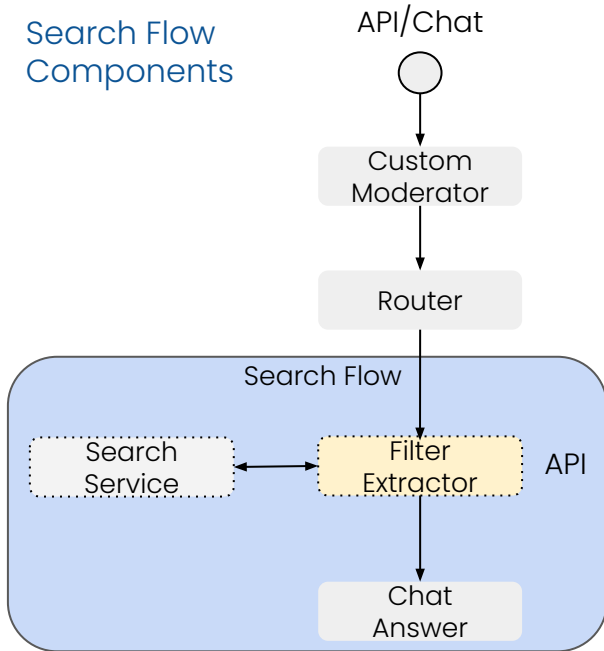
The **heart** of the system, that generate **updated** JSONs with user preferences based on user input. Is the interface with the Search Service.

## 2 Chat Answer

Tracks user preferences and extractor actions, communicates updates from the extractor, and guides the user in providing more data. Has some knowledge about locations.

# Chat. Solution

## Search Flow Components



## 1 Filter Extractor

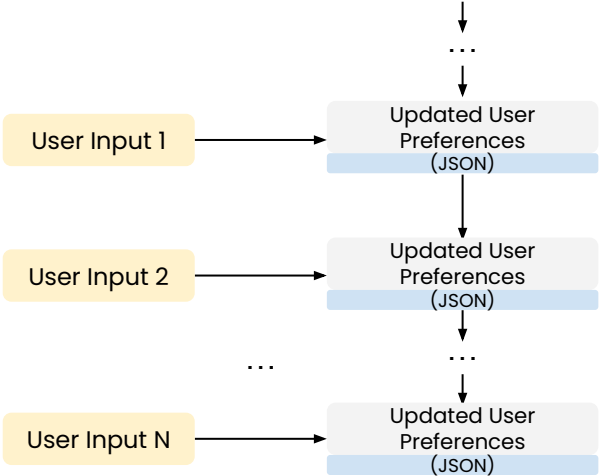
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Tracks user preferences and extractor actions, communicates updates from the extractor, and guides the user in providing more data. Has some knowledge about locations.

# Chat. Solution

## Filter Extractor



Add New JSON Fields (Filters)

Updated JSON Fields (Filters)

Remove JSON Fields (Filters)

# Chat. Solution

## Filter Extractor

1

### 71 Different Filters (Classes)

Property type (House, Apartment, etc)

Business Context (Rent, Sale)

Amenities and Installations

Etc

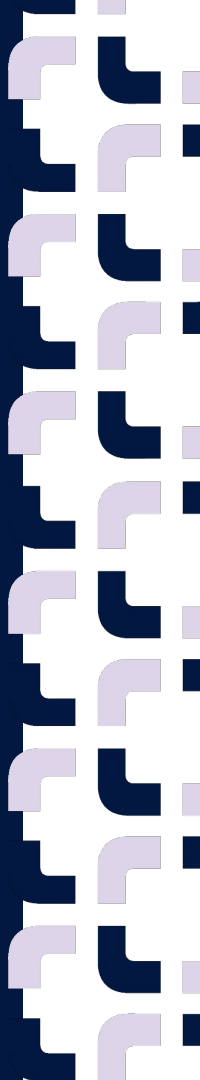
2

### Extract Visual Elements

Characteristics We Can Find in Images

Custom Moderation

Individual Extraction



# Chat. Solution

## Filter Extractor

1

### 71 Different Filters (Classes)

Property type (House, Apartment, etc)

Business Context (Rent, Sale)

Amenities and Installations

Etc

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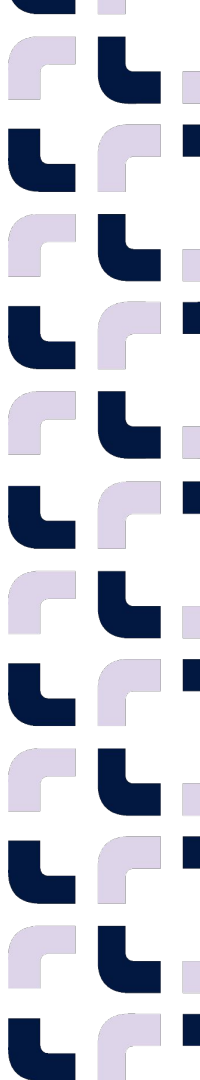
```
{  
  "property_type": "apartment",  
  "max_price": 3000,  
  "context": "rent",  
  "bedrooms": 3,  
  "location": "Sao Paulo, SP, Brazil",  
  "visual_search": ["modern decor"],  
}
```

# Chat. Solution

## Filter Extractor

### User **Current** Preferences

```
{  
  "property_type": "apartment",  
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# Chat. Solution

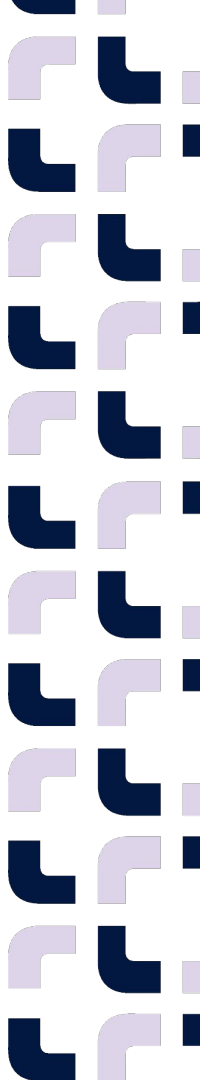
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```

### User Textual Input

*"Actually, 2 bedrooms and industrial style."*



# Chat. Solution

## Filter Extractor

### User **Current** Preferences

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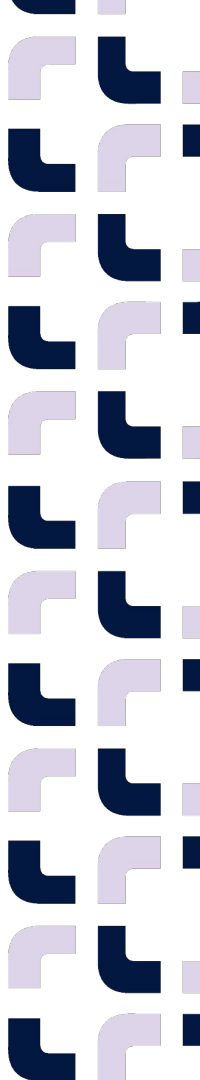
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*"Actually, 2 bedrooms and industrial style."*

Filter Classifier

Filter Extractor

Two Steps  
Dynamic  
Extraction



# Chat. Solution

## Filter Extractor

### User **Current** Preferences

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Filter Classifier

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Two Steps  
Dynamic  
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**LLM Call: Detects Preferences Mentioned by the User**  
[bedrooms, visual search]

# Chat. Solution

## Filter Extractor

### User **Current** Preferences

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"Actually, 2 bedrooms and industrial style."

Filter Classifier

Filter Extractor

Two Steps  
Dynamic  
Extraction

**LLM Call: Detects Preferences Mentioned by the User**  
[bedrooms, visual search]

**LLM Call: Updates user JSON**  
Given the current user filters and input, updates **only the detected preferences**

# Chat. Solution

## Filter Extractor

### User **Current** Preferences

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### User Textual Input

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Filter Classifier

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Two Steps  
Dynamic  
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**LLM Call: Detects Preferences Mentioned by the User**  
[bedrooms, visual search]

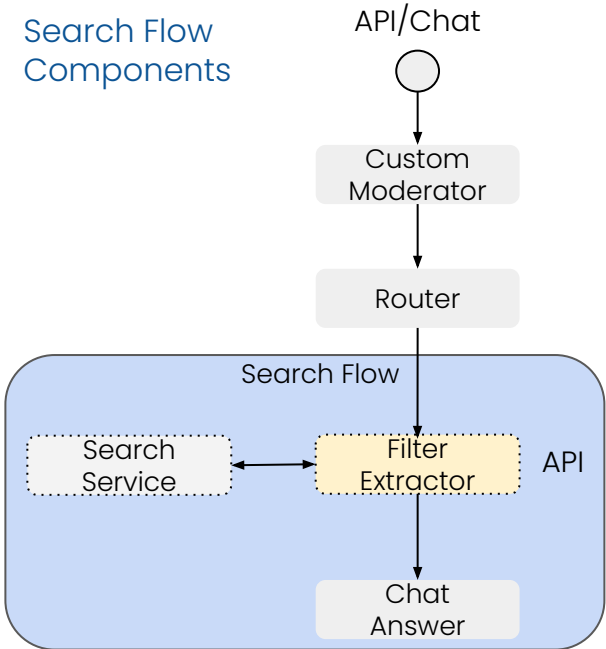
**LLM Call: Updates user JSON**  
Given the current user filters and input, updates **only the detected preferences**

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  "bedrooms": 2,  
  "location": "Sao Paulo, SP, Brazil",  
  "visual_search": ["industrial decor"]  
}
```

**Updated  
User  
Preferences**

# Chat. Solution

## Search Flow Components



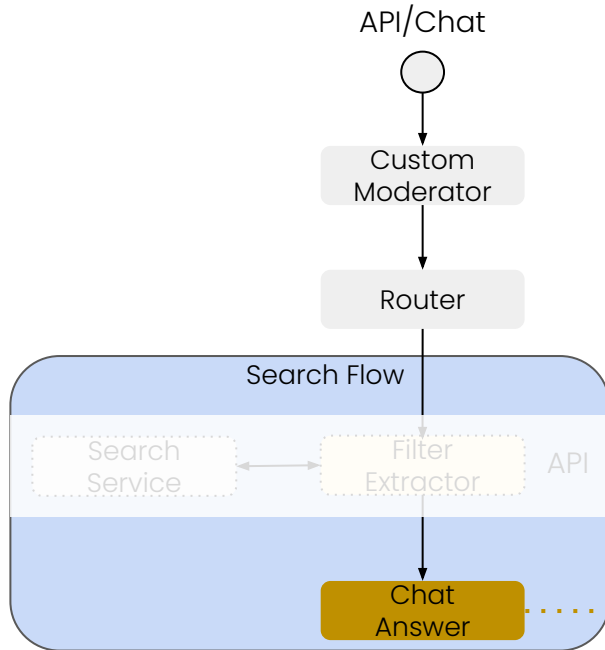
### 1 Filter Extractor

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### 2 Chat Answer

Tracks user preferences and extractor actions, communicates updates from the extractor, and guides the user in providing more data. Has some knowledge about locations.

# Chat. Solution



## Chat Answer Prompt

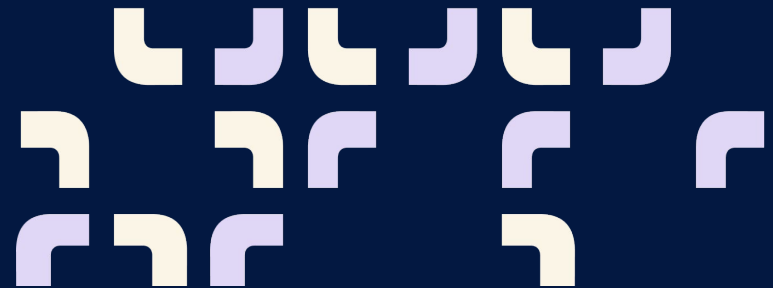
### Filters Section

- Knows The **Chat History**
- Knows **Extractor Actions**
- Communicate Changes in the Filters

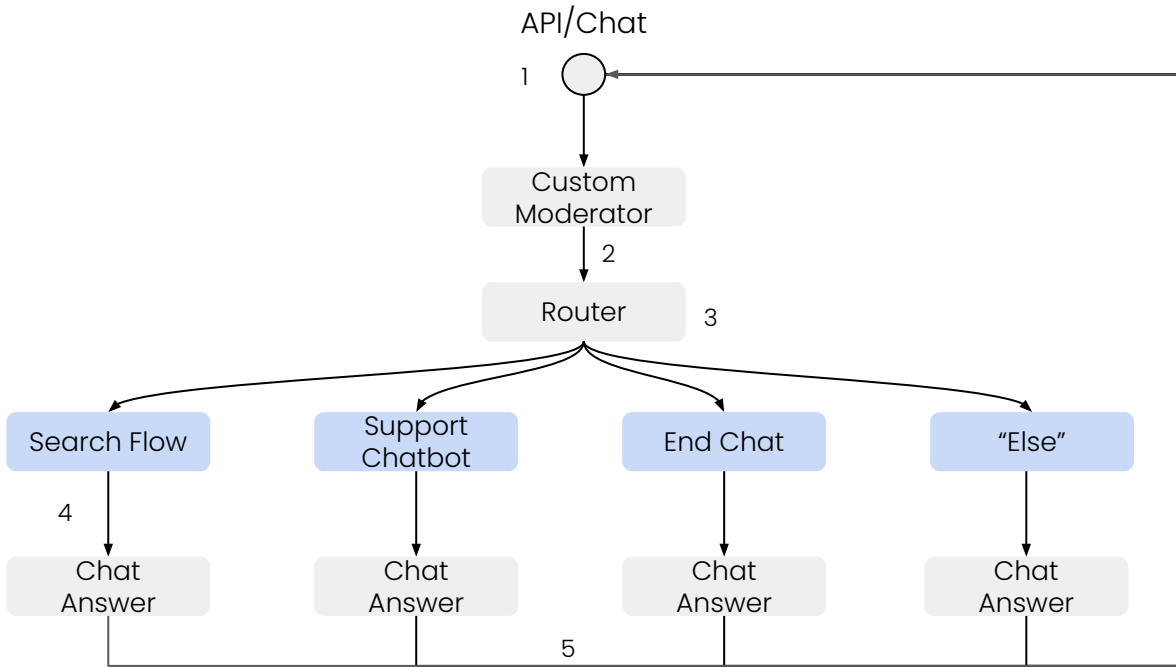
### Location Section

Handles, with restrictions, users' location questions.

But...is it good at all?



# Chat. Evaluation



1: The user Input

2: If the input was moderated or not

3: The Router Predictions

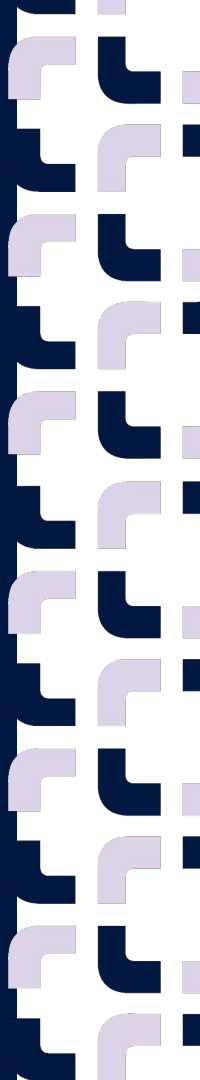
4: Extracted Filters

5: Chat Answers

+ LLM Adopted Prompts

# Chat. Evaluation

Chat Component	Validation Type	Eval Dataset	Evaluator
Router	Offline/CICD	Golden Dataset	Classical M.L Metrics
	Online	Production Dataset	LLM As A Judge
Filter Extractor	Offline/CICD	Golden Dataset	Classical M.L Metrics
	Online	Production Dataset	LLM As A Judge
Visual Components	Offline/CICD	Golden Dataset	LLM As A judge
	Online	Production Dataset	
Chat Answers	Offline/CICD	Golden Dataset	LLM As A Judge
	Online	Production Dataset	



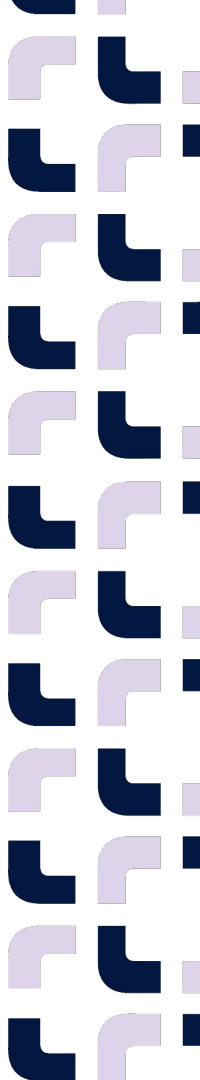
# Chat. Evaluation

## Classical ML Evaluation

- ✓ Objective/Deterministic Tasks, such as Classification (Filter Extractor, Router)
- ✓ Used Offline Only (CI/CD)
- ✓ More Granular/Detailed metrics (Filter-level)

## LLM As a Judge Evaluation

- ✓ Subjective/Open-Ended Tasks, such as Conversation (Chat Answers)
- ✓ Used Online and Offline (CI/CD)
- ✓ General Metrics



# Chat. Evaluation

## Classical ML Evaluation

### Example of Filter Extractor Metrics

Filter Group	Filter Category	F1	Precision	Recall
property_type	condominium	0.909	0.968	0.857
property_type	apartment	0.970	0.963	0.978
business_context	rent	0.991	0.988	0.994
business_context	sale	0.981	0.981	0.981

## LLM As a Judge Evaluation

**User Input:** Santa Cecilia 2 bedrooms

<b>Score</b>	1 (Correct)
<b>Score Reason</b>	<ul style="list-style-type: none"><li>- The LLM correctly updated the location filter to 'Santa Cecilia, São Paulo - SP, Brasil'</li><li>- Already Existing filter for 2 bedrooms (min_bedrooms: 2), so no change was needed there.</li></ul>

# Chat. Evaluation

## LLM As A Judge

### How We Do It

1

#### **Simplify The Task**

Simplify the original task to make evaluation accurate

2

#### **Chain of Thoughts**

A list of clear instructions

3

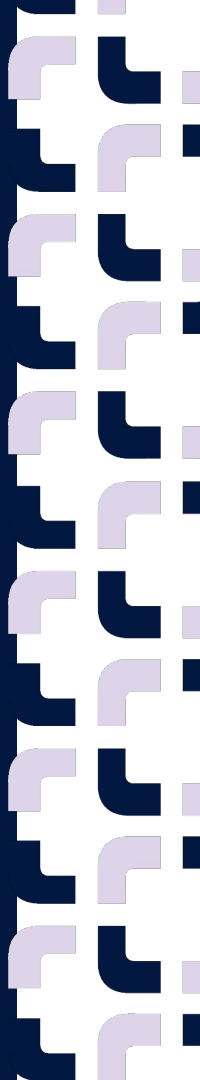
#### **Clear Grading Criteria**

Clear grading guide to produce final score

4

#### **Score Reason**

Ask the LLM to Produce a reason for the scoring



# Chat. Evaluation

## LLM As A Judge

### How We Do It

1

#### Simplify The Task

Simplify the original task to make evaluation accurate

2

#### Chain of Thoughts

A list of clear instructions

3

#### Clear Grading Criteria

Clear grading guide to produce final score

4

#### Score Reason

Ask the LLM to Produce a reason for the scoring

### Example

User Input	Santa Cecília 2 bedrooms
Input to Judge	<b>User Message</b> Santa Cecília 2 bedrooms
	<b>Current User Preferences</b> <b>business_context:</b> RENT <b>location:</b> Rua Doutor Rubens Meireles, São Paulo, SP, Brasil <b>max_price:</b> 5700.0 <b>min_bedrooms:</b> 2
	<b>What Extractor Did</b> <b>location</b> CHANGED FROM <i>Rua Doutor Rubens Meireles, São Paulo, SP, Brasil</i> TO <i>Santa Cecilia, Sã Paulo - SP, Brasil.</i>

# Chat. Evaluation

## LLM As A Judge

### How We Do It

1

#### Simplify The Task

Simplify the original task to make evaluation accurate

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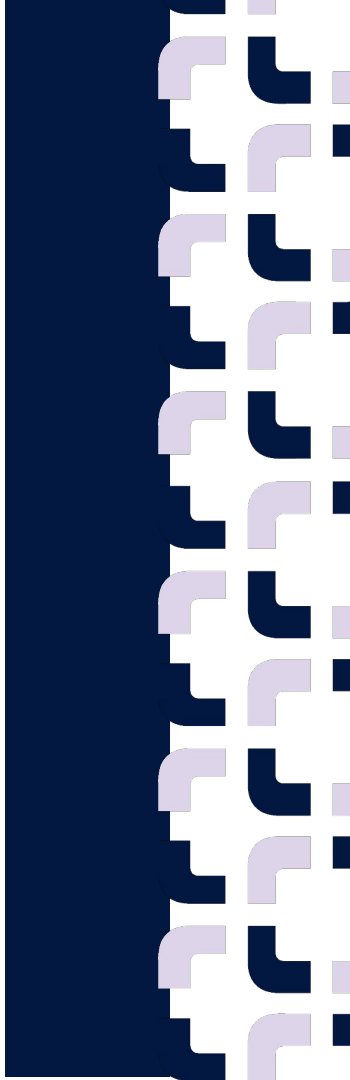
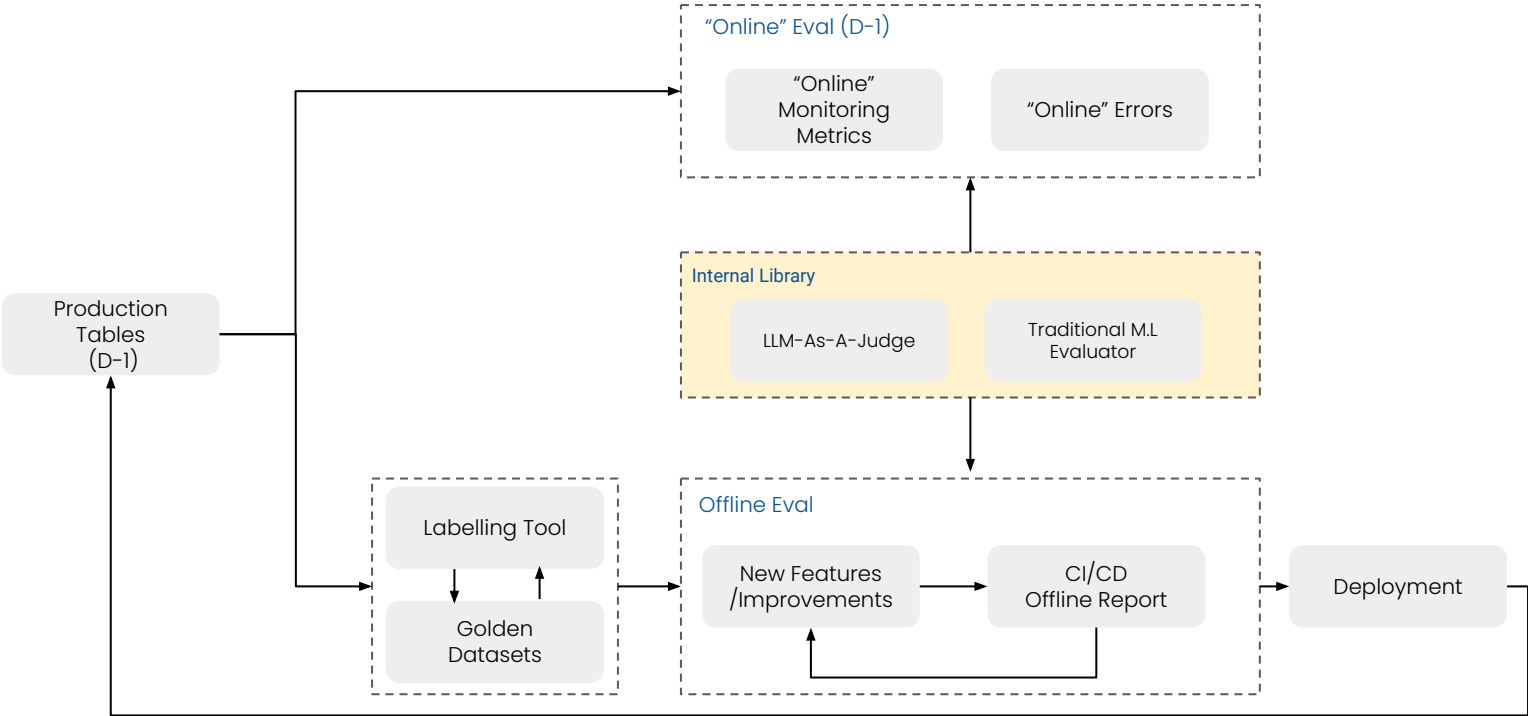
### Example

User Input	Santa Cecília 2 bedrooms
Input to Judge	<b>User Message</b> Santa Cecília 2 bedrooms
	<b>Current User Preferences</b> <b>business_context:</b> RENT <b>location:</b> Rua Doutor Rubens Meireles, São Paulo, SP, Brasil <b>max_price:</b> 5700.0 <b>min_bedrooms:</b> 2
	<b>What Extractor Did</b> <b>location</b> CHANGED FROM <i>Rua Doutor Rubens Meireles, São Paulo, SP, Brasil</i> TO <i>Santa Cecilia, Sã Paulo - SP, Brasil.</i>

Score	1 (Correct)
Score Reason	The LLM correctly updated the location filter to 'Santa Cecilia, São Paulo - SP, Brasil'  Already Existing filter for 2 bedrooms (min_bedrooms: 2), so no change was needed there.

# Chat. Evaluation

## Overall Architecture



# Chat. Solution

## Lessons Learned

### What We Tried

1	"One Prompt to Rule Them All"
2	Granular Approach: <ul style="list-style-type: none"><li>- Break down text into topics;</li><li>- Classify Each Topic;</li><li>- Extraction for Each Topic;</li></ul>
3	Synthetic Datasets

### What Worked Best

1	Combination of LLM and State Machine
2	Two Steps Approach and Individual Calls For Complex Filters: <ul style="list-style-type: none"><li>- Amenities and Installations</li><li>- Visual Elements</li></ul>
3	Manually Generated Golden Datasets

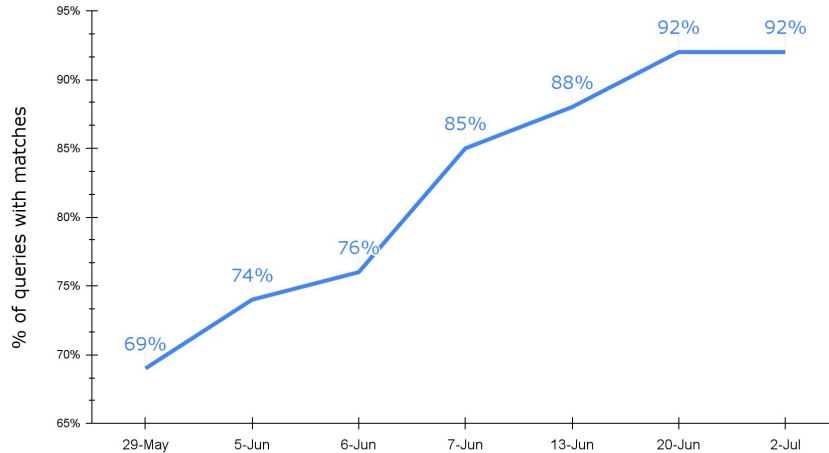


# Chat. Solution

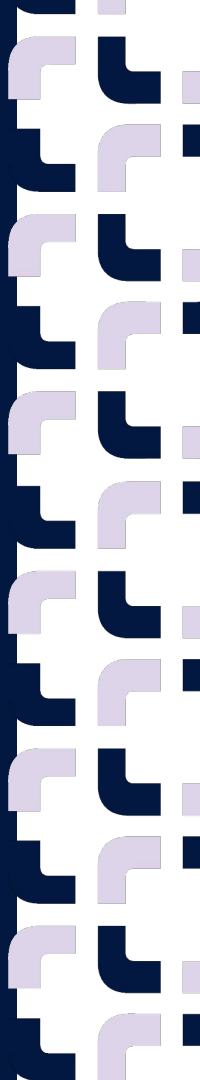
## Lessons Learned

*Right Evaluation Stimulates Virtuous Cycle of Improvements*

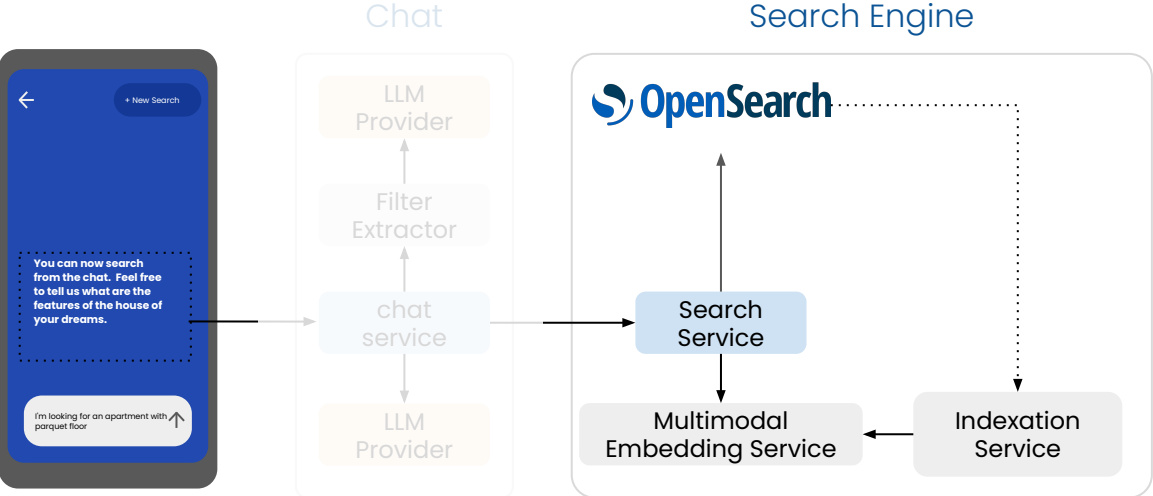
% of users queries with accurate parsing of critical filters



1 Month



# LLM-based Search Assistant

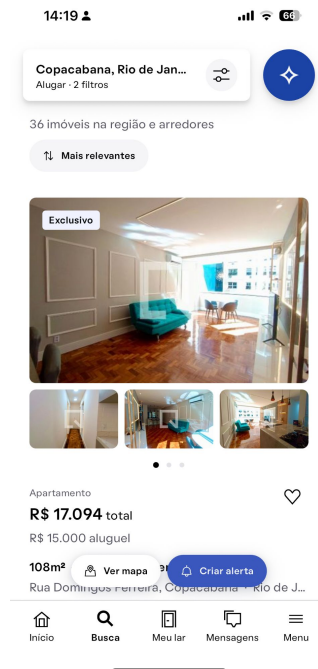
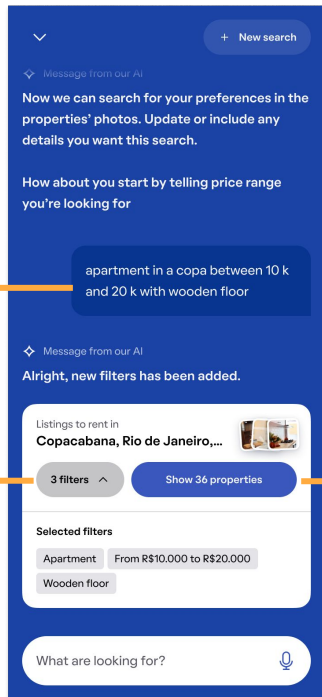


# Search

Query

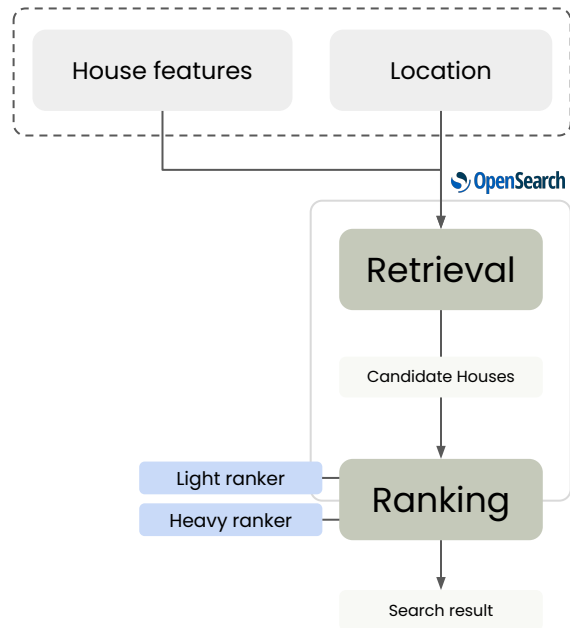


Results



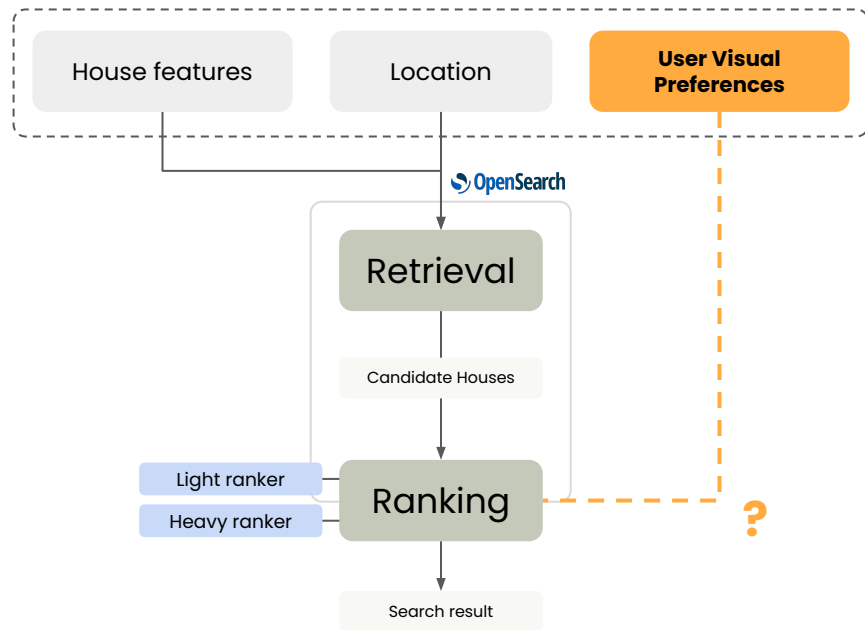
# Search

Before the chat



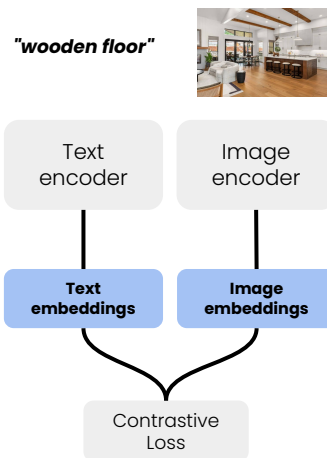
# Search

After the chat



# Search

## Multimodal embeddings



## OpenAI CLIP

### Learning Transferable Visual Models From Natural Language Supervision

Alec Radford<sup>\*1</sup> Jong Wook Kim<sup>\*1</sup> Chris Hallacy<sup>1</sup> Aditya Ramesh<sup>1</sup> Gabriel Goh<sup>1</sup> Sandhini Agarwal<sup>1</sup>  
Girish Sastry<sup>1</sup> Amanda Askell<sup>1</sup> Pamela Mishkin<sup>1</sup> Jack Clark<sup>1</sup> Gretchen Krueger<sup>1</sup> Ilya Sutskever<sup>1</sup>

## Google SigLIP

### Sigmoid Loss for Language Image Pre-Training

Xiaohua Zhai\* Basil Mustafa Alexander Kolesnikov Lucas Beyer\*  
Google DeepMind, Zürich, Switzerland

{xzhai, basilm, akolesnikov, lbeyer}@google.com

## Salesforce BLIP-2

### BLIP-2: Bootstrapping Language-Image Pre-training with Frozen Image Encoders and Large Language Models

Junnan Li Dongxu Li Silvio Savarese Steven Hoi  
Salesforce Research

# Search

## Scoring

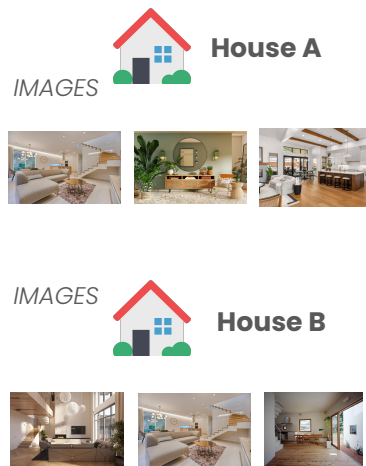
User Query

"I'm looking for a house with **wooden floor**, **big windows** and **modern decoration**"

Preferences  
Extractor

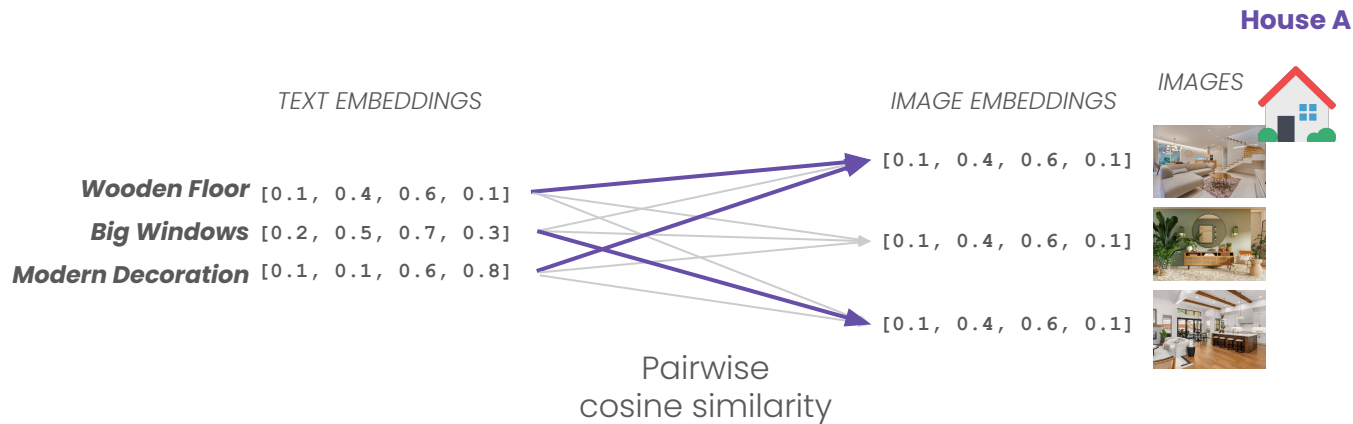
**Wooden Floor**  
**Big Windows**  
**Modern Decoration**

Scoring  
Function



# Search

## Scoring

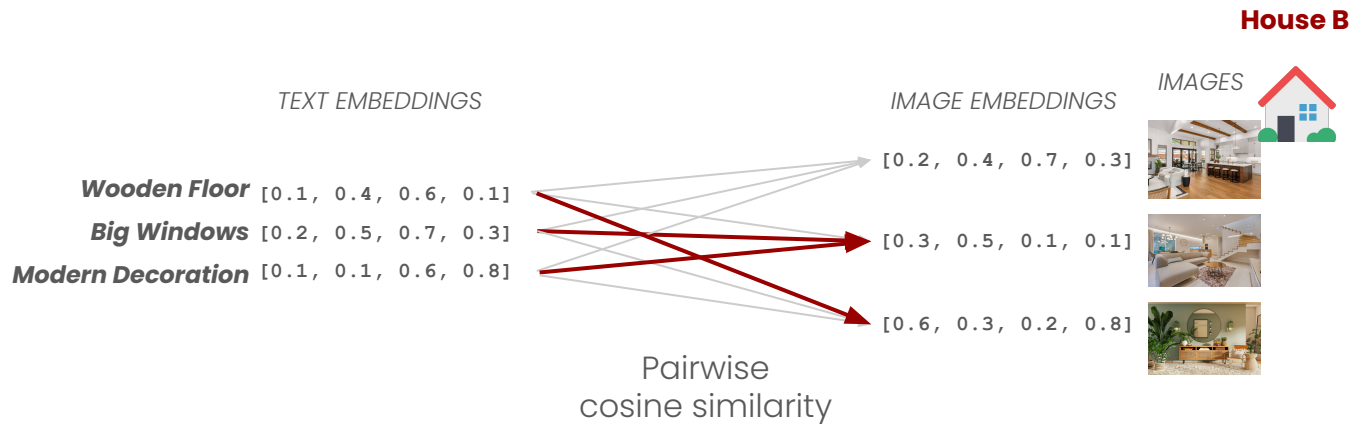


$$\text{IMAGE\_SCORE}_{\text{houseA}} = \text{sum}(\text{max}(\text{cosine}) \text{ group by Visual Preference})$$

For query "I'm looking for a house with **wooden floor**, **big windows** and **modern decoration**"

# Search

## Scoring



$$\text{IMAGE\_SCORE}_{\text{houseB}} = \text{sum}(\text{max}(\text{cosine}) \text{ group by } \text{Visual Preference})$$

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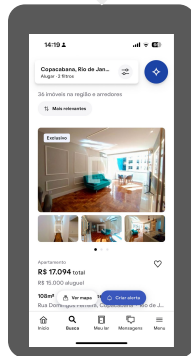
# Search

## Scoring

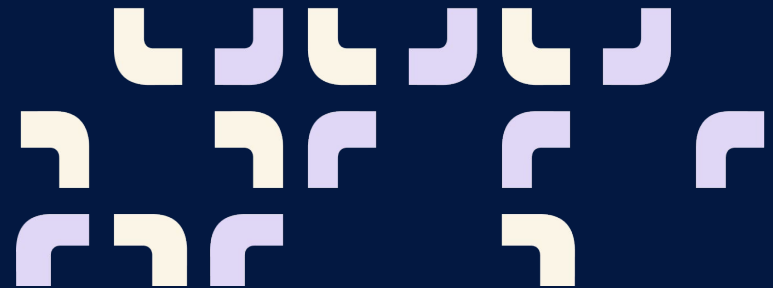
$SCORE_{houseA} = \text{combine}(\text{IMAGE\_SCORE}_{houseA}, \text{HEAVY\_RANKER\_SCORE}_{houseA}, \dots)$

$SCORE_{houseB} = \text{combine}(\text{IMAGE\_SCORE}_{houseB}, \text{HEAVY\_RANKER\_SCORE}_{houseB}, \dots)$

$RESULTS = \text{topK}(\text{rank}(SCORE_{houseA}, SCORE_{houseB}))$



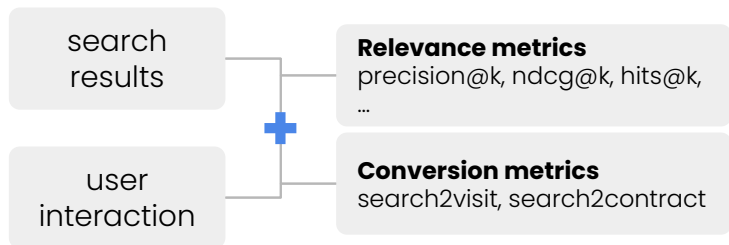
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# Search

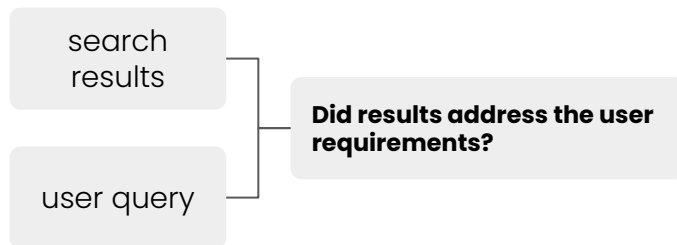
## Evaluation

### Traditional



Overall health of the system

### LLM-as-a-judge



Results (multimodal) explainability

# Search

---

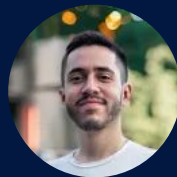
## What we did

- Similarity-based image sampling
- Different similarity aggregation strategies
  - $\text{AVG}(\text{SUM}(\text{cosine}))$
  - $\text{AVG}(\text{MAX}(\text{cosine}))$
  - $\text{MAX}(\text{MAX}(\text{cosine}))$

## Future and WIP

- Hybrid Search: full-text + vector search
- House-level vs. image-level embeddings
- Heavy ranker with image features
- Visual features as filter to reduce the search space

# Thank You Team



**We are  
hiring**

---

**Come join our team!**



<https://carreiras.quintoandar.com.br/?lang=en>



An aerial photograph of a blue outdoor court where several children are playing. The children are scattered across the frame, some in motion. Their dark shadows are cast onto the blue surface, indicating a low sun position. In the bottom right corner, a basketball is visible. The text 'Grupo QuintoAndar' is centered in the image in a white, sans-serif font.

# Grupo QuintoAndar