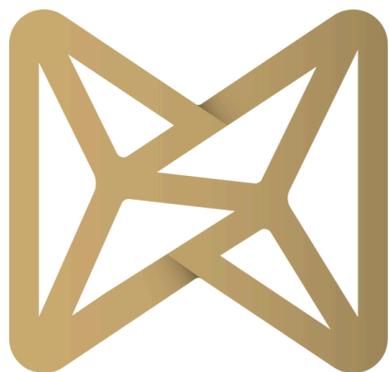


ARTIFICIAL INTELLIGENCE

For AI professionals



OCDS

Optimized Context
Distribution System



**English
version**



**NEURA
KING**

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Summary

OCDS

01

Introduction

02

Limiting factors

- Formulating the request
- Generalization
- Intrinsic conflicts of objectives
- Relevance arbitration
- Neglect of the anthropomorphic cue point
- Computational fatigue
- Instruction saturation
- Choice orientation
- The intelligence factor
- Intelligence versus relevance
- The statistical signature
- The absence of limits

03

OCDS solution

- Definition of OCDS
- OCDS objectives
- Ability to manage limiting factors
- Components of the OCDS

Large language models (LLMs) act as mediators, translating human intentions into tangible actions.

However, this mediation comes up against two problems.

On the one hand, the ability of models to understand and interpret the subtlety of requests, and on the other, the ability of users themselves to clearly formulate their needs, intentions and objectives.

The Optimized Context Dispatching System (OCDS) solves these problems through a multidimensional approach to AI, taking into account both the limits of artificial intelligence and those of humans.

This system optimizes the management of data, content and contexts, ensuring efficient distribution of information to specialized artificial intelligences, while at the same time providing guidance to humans, so that they can correctly implement their intentions.

By fine-tuning the formulation of queries through suggestions of intent, goal and execution frameworks, OCDS improves not only the accuracy of queries, but also the relevance of the resulting responses.

By preventing computational fatigue and increasing AI attentional focus through dynamic dimensioning of context windows, the OCDS promises to improve not only operational performance in various work contexts, but also the user experience.

In fact, the OCDS contributes to the user's skills when interacting with the AI, by facilitating access to appropriate responses and guiding the user towards a fine-tuned expression of his or her needs.

This OCDS-optimized mediation is based on the integrated management of AI's limiting factors. These factors need to be understood in order to understand their effects and the optimization levers accepted by the OCDS.

Limiting factors

Formulating expectations

For many humans, accurately articulating expectations in the face of systems as advanced as AI can be a daunting challenge, especially as our ego prevents us from questioning our inability.

Indeed, using an LLM seems childishly simple, as we only use words to issue instructions.

However, each word conveys a multitude of parameters that can drastically alter the interpretation of queries and the formulation of responses generated by the AI.

Confronted with AI, we are confronted with our lack of knowledge of our own language, and discover our inability to express ourselves with the precision required for good communication.

Since exchanges between humans are intuitive, our approximation is never called into question, whereas exchanges with AI require perfect accuracy.

Limiting factors

Formulating expectations

Precision, finesse and the slightest nuance are essential to ensure that results not only meet expectations, even if these are ill-defined at the time of the query, but also exceed them.

This is what prompt engineering is all about, the fundamentals of which provide a framework, without user intervention, for each and every OCDS query.

But that's not enough, because a phenomenon intrinsic to LLMs is at work in every interaction: generalization.

Limiting factors

Generalization

Today's LLMs, having stored virtually all available data, do not suffer from a lack of information that can be filled by prompt engineering or fine-tuning, but do suffer from an overly dispersed focus.

The problem lies both in the weighting of query interpretation, and in the weighting of each response.

Interpretation and generation are simply the sum of statistical averages across all ingested data.

This means that, when an LLM model is requested, even if it is correctly prompted and fine-tuned, its level of attention linked to a particular objective will be diluted in all circumstances by the weighting effect.

Limiting factors

Generalization

This leads to the need to increase the size of context windows to cancel out this dilution effect through prompt engineering, or to train models on additional, more specific data to improve their behavior, their way of doing things or their relevance.

This is made possible by AI design via OCDS, which integrates an architecture that optimizes the efficiency of any instruction.

But while this is essential, as it helps to reduce the effects of generalization, any query will in any case be confronted with other phenomena and limiting factors which in turn induce a generalist weighting, starting with the factor of goal conflicts.

Limiting factors

Intrinsic goal conflicts

The example of the copywriter:

The copywriter brings together several skills, each of which brings together other specific skills and disciplines.

Skill 1: Target identification:

A good copywriter needs to know how to extract the psychological aspects of a message's potential targets.

This is a skill in its own right, which, to be exploited to its full potential, needs to be applied independently of any other objective, in order to tap into the depth of the task.

Limiting factors

Intrinsic goal conflicts

Skill 2 : the AIDA technique (Attention/ Interest/ Desire/ Action)

This second skill, which already conflicts with the first (target identification), diluting the AI's attentional focus, is itself subject to an attentional conflict between four sub-skills:

- Capturing Attention: involves specific skills relating to capturing and retaining attention.
- Arousing Interest: implies the ability to make logical links between targets and offers aimed at matching offer/need, this involving characterizing the logic of matching links.
- Provoking Desire: implies specific skills for extracting elements of the psyche to act, as required, on frustrations, fears or desires.
- Inciting Action: involves the use of appropriate techniques to trigger action based on elements of psyche, interest and desire.

Limiting factors

Intrinsic goal conflicts

Here, exploiting the full potential of each of the skills involved in what the term Copywriter implies, comes down to a conflict of objectives.

The aim is to capture attention, but also to arouse interest, as much as to provoke desire and incite action.

While humans can intuitively distinguish between the two, giving more or less importance to one objective over another depending on the circumstances, AI is simply incapable of doing so by the very nature of its design.

It reduces its interpretation to the sum of the objectives induced by each of the related skills and sub-skills, by probabilistic supposition, reducing its response to an addition of averages which are themselves sums of other probabilistic averages.

Limiting factors

Intrinsic goal conflicts

In copywriting, as in any other profession, task or service, this phenomenon occurs and requires a fine segmentation of each element in order to extract its particular objectives so that they don't conflict with each other.

This segmentation is made possible by the ESP (Exponential Segmentation Process) method, which OCDS makes possible.

But this, once again, is not enough, as the specificity that characterizes relevance comes directly from the arbitration of a priority scale in the management of these goal conflicts.

An arbitration which, if left to the LLM's free judgment, can only result in a generality resulting from a sum of other generalities themselves defined by a weighted approach; in itself very far from what could be the expected relevance.

Limiting factors

Arbitration of relevance

When formulating a response, LLMs arbitrate the characteristics of relevance for us.

This applies not only to the field of competence, but also to all types of data, be they information, instructions, conditions, etc., etc., etc.

However, the arbitration of conflicting objectives inherent in the characterization of relevance, whatever the field of application, is exclusively a matter for the subjective perception of the applicant.

It is therefore up to the claimant to characterize it himself, in order to restrict the possibilities of interpretation arising from generalization.

This in the knowledge that the claimant is not expert enough to formulate these characteristics, and in the knowledge that this ultimately amounts to characterizing the criteria of his own subjectivity, which is an impossible task.

Limiting factors

Arbitration of relevance

So how do you arbitrate in these conditions?

Well, by relying on benchmarks inspired by human social structures, enabling each person to imagine characteristics of relevance, intuitively recognized by what these benchmarks imply; in this case, frames of reference, such as companies, departments and professions.

This is also what the OCDS proposes through a socially constructed approach replicating the realities of the working world.

Limiting factors

Neglect of the anthropomorphic landmark

Anthropomorphism is the tendency to attribute human characteristics, behaviors and emotions to artificial systems, so as to make them more accessible.

In transforming models, we're only dealing with an entry point for discussion, so the anthropomorphic aspect is neglected.

Yet assigning anthropomorphic characteristics to a job (or department or other standardized framework) also contributes to their accessibility, not through emotional and identification principles, but through the reference point that job anthropomorphism induces.

This makes it possible to pre-frame any query, directing the requester's intentions towards the object of the job, thereby increasing relevance, without having to arbitrate according to subjective criteria, as these are intuitively included in the notions evoked by the term job.

In fact, the term "job" evokes an idea, an unconscious perception of a result that could match our expectations, which we ultimately don't know how to express consciously with sufficient precision to be correctly interpreted, but whose unconscious expression is included in the intuition of the object of the job.

Limiting factors

Neglect of the anthropomorphic landmark

This makes it possible to express the characteristics of the expected subjective relevance, without even mentioning them.

It is therefore essential not to underestimate the importance of anthropomorphism in the context of transforming models, in order to propose user interfaces that structure navigation through elements that are accessible to the user's intuition, so that his choices express his expectations for him.

To this end, the OCDS proposes an anthropomorphic approach that enables virtual replication of corporate, project and business worlds.

But once again, this is not enough, as another phenomenon mitigates the anthropomorphic factor: the computational limits commonly equated with AI fatigue and laziness.

Limiting factors

Computational fatigue

Computational fatigue refers to the decline in AI system performance resulting from over-solicitation, imposing load mitigation.

These episodes of fatigue are unpredictable, frequent (several times a day), can last from a few minutes to several hours, and can only be detected by a significant degradation in relevance.

The uninformed user, when issuing a query during an episode of fatigue, will therefore assume that the use of AI is inappropriate, given the mediocre result.

The AI could have been up to the task five minutes before or five minutes after the request, but not knowing this, the user declares the request inadmissible.

Worse still, when he persists in trying to obtain a relevant result by insisting and repeating himself without obtaining the expected result, he becomes permanently discouraged.

This frustration is all the greater when the prompt engineering work has been done correctly, and all the limiting factors have been considered, but the computational fatigue factor has been forgotten when editing instructions and parameters.

Limiting factors

Computational fatigue

Because computational fatigue doesn't prevent the AI from responding, it prevents it from correctly considering the instructions and all the frameworks it has been given, which are supposed to guarantee relevance.

Thus, the greater the efforts deployed to alleviate limiting factors, resulting in instruction saturation, the more likely it is to produce the opposite effect during episodes of fatigue, as the AI is no longer able to consider all instructions, let alone manage intrinsic conflicts.

At the same time, this leads to an increase in hallucinations, a phenomenon also consubstantial with LLM operation, which consists in producing an answer at all costs, even if it's wrong.

Hence the need to integrate the management of computational fatigue into any interaction with AI on the one hand, and to approach this management through the prism of saturation effects on the other.

Limiting factors

Instruction saturation

In addition to mitigating the effects of fatigue, context volume dosing also prevents attention selection bias.

This other phenomenon is characterized by the inability of transforming models to consider the entire context window, even at full capacity.

Some studies show that around 40% of the context window size is actually considered. Although this percentage is constantly evolving and does not yet represent a consensus, it does shed light on the absence of efficient attention to at least half the window.

More than enough to consider the ability to desaturate on the fly as a fundamental element.

On the one hand, to ensure maximum relevance under the worst possible conditions, thus preventing computational fatigue.

And secondly, to ensure that the AI's focus of attention is established by limiting selection bias.

This results in a systematic level of relevance, contributing to a resilient organization of AI-assisted work, thus ensuring the continuity of processes in action.

However, this on-the-fly desaturation enabled by OCDS once again introduces subjective arbitration by humans.

The latter, remaining the sole judge of the relevance expected at the time of the request, must be able to easily arbitrate his desaturation choices.

Limiting factors

Choice orientation

The user must be able to rely on a segmentation previously established by ESP method, assimilating episodes of computational fatigue and attention selection biases, as the limiting frame of reference for real operational capabilities.

In this way, fine-grained segmentation, the principles of which are postulated in a pre-established environment, will naturally result in context nomenclatures and labels that the user will be able to intuitively recognize when it comes to desaturating a query, identifying at a glance the elements to be activated and/or deactivated.

This, via OCDS, by adding or removing context elements on the fly, with a simple click, enabling the user to adapt the context precisely, quickly and intuitively, to fluctuations in computational fatigue, to AI attention disorders, but also to fluctuations in goal conflicts.

Limiting factors

Choice orientation

It's worth remembering that an increase in the volume of instruction means an increase in goal conflicts.

Thus, the effects of on-the-fly desaturation are not limited to making up for attention deficits and fatigue problems, but also make it possible to increase relevance through an attention velocity effect.

Where desaturation is coupled with the finesse of high-quality prompt engineering, it enables the induction of a large number of notions through the subjective implications inherited from anthropomorphic orientation, all with a minimum of parameters and instructions.

This contributes to both reliability and relevance, while preventing out-of-bounds situations.

However, to implement this triple-benefit finesse, the intelligence factor needs to be considered in its proper light.

Limiting factors

The intelligence factor

The term “artificial intelligence” is often misleading, leading people to believe that the intelligence factor is paramount.

However, none of the factors contributing to the relevance of a result involves intelligence of a useful nature within the framework of a transforming model.

While it's true that there's a relationship between a variety of information (remembering that it's systematically smoothed and weighted), bringing out the term intelligence through the ability to weave links between this information, relevance is much more than that.

When we ask an LLM to carry out a task, we're not asking him to make connections that we equate with a form of reasoning, no, we're asking him to make the connection between the rough draft of our intentions and the vague idea of our expectations in subjective terms of result.

This certainly relies on a certain level of intelligence based on the size of the AI model, as this size is largely equated with superior reasoning skills.

But beyond a certain threshold, the ability to reason no longer has anything to do with relevance, and no longer has a sufficient impact on the quality of the result.

Limiting factors

The intelligence factor

For, whatever they may be, LLMs are subject to the accumulation of the aforementioned limiting factors, which no technological advance can resolve, all the less so as the subjective human factor is omnipresent.

As a result, when relevance comes into play, it becomes inappropriate to base expectations solely on the supposed intelligence of a transforming model, as much as on a single lever, such as fine-tuning or prompt engineering.

Because the usefulness, relevance and reliability of an LLM are based on the aggregation of multiple factors, each from multiple perspectives, each involving the arbitration of subjective characteristics, the latter requiring the dynamic intervention of humans, who are the sole judges of the relevance of a result in the face of expectations that they themselves are unable to define with sufficient precision.

All this, again and again, under computational constraints and the influence of attention selection biases, each of which can have a counter-productive effect on expectations.

This underlines the importance of not confusing “intelligence” with “relevance”, so as to be able to orchestrate and direct the full potential of LLMs in the right direction, namely that of relevance.

Limiting factors

Intelligence versus relevance

LLM models, with their vast knowledge, are like omniscient oracles, gifted with clairvoyance, erudite in all things.

But even an oracle can't give relevant answers if the requests don't specify in detail the reduction of the field of interpretation, the desired direction of the answer, the exhaustive context, the interwoven objectives and the expected behavioral nuances in the management of priorities, which themselves vary according to uncontrollable subjective criteria, impossible to anticipate and even less to characterize without recourse to tacitly induced notions.

As these oracles are perpetually confronted with conflicts (requiring subjective arbitration) introduced by both the user and the prompt engineer, fine-tuning and pre-training by unsupervised deep learning can never be relevant, despite their intelligence.

For the expression of this intelligence, outside a framework limited to a clearly defined intention, is no more than a generalized assertion whose reliability rests on our confidence in this expression.

On the other hand, too much intelligence, based on these generalist modalities and the ability to reason, has the opposite effect.

Limiting factors

Intelligence versus relevance

Indeed, an intelligence of this type can make so many links of possible interpretations for each word making up instructions, that it becomes impossible to focus attention as desired, so high is the complexity.

By thus increasing Intrinsic goal conflicts tenfold, and drastically complicating the characterization of expected relevance, intelligence in itself generates more problems than it solves.

Because when we decide to trust it with elements we don't master, we're not only taking the risk of assuming responsibility for a mediocre generality that offers no profitability and therefore no utility.

We are also surrendering the sovereignty of our decisions, and erasing the specificity of our judgment of relevance in favor of uniformity, by accepting without understanding that subjective criteria of relevance are dictated to us.

Limiting factors

Intelligence versus pertinence

Even if technological advances were to solve the problem of computational fatigue, as well as the problem of selection bias, this would in no way resolve the need for desaturation aimed at exacerbating certain objective priorities rather than others, the relevance of which can only be judged by the operator.

So, although transformer models can be described as artificial intelligence systems, their form of intelligence is of little use in the quest for performance, even less so when compared with what relevance obtained by process and limiting factor consideration can bring.

This is true of all models based on attention mechanisms, as these operate on statistical patterns.

Limiting factors

The statistical signature

LLM models are not only forced to generalize by their limitations in context and computation, but they also do so on the wrong basis, since the conflicts introduced by training or by the user are themselves constituted by a generalist weighting.

Thus, no relevance can be expected from an LLM simply by trusting its intelligence.

A relevant answer is only relevant by statistical inadvertence, and not by the expression of a mastered logic contributing to the accomplishment of a requested task.

This is because LLM models respond on the basis of statistical patterns, themselves derived from other statistical patterns whose conflicts have been dealt with by generalization.

Limiting factors

The statistical signature

We see here the signature of unsupervised deep learning, which is essential for increasing intelligence in the general sense, but which prevents any specificity and therefore any relevance.

This accumulation of difficulties leads to a reduction in the depth of answers, and systematically raises the question of relevance to objectives, intentions and expectations.

So, in all circumstances, we need to rely not on the usefulness of superior intelligence, but on its limits, in order to draw out its true potential, which is quite sufficient to overturn work and societal paradigms.

But not without the help of humans, who wish to remain in control of what they produce with the assistance of AI.

Limiting factors

Lack of limits

Managing limiting factors and their interdependencies, as well as managing context dosages and anthropomorphism parameters, requires a unified multi-perspective management system built around these constraints.

This, in an environment that replicates human realities and norms in order to induce the subjective implications necessary for the cues that guide humans in their tasks with AI.

For, whatever the level of intelligence of a language model (LLM), it is, and will remain, incapable of providing perfectly relevant answers, as long as its operation is not framed by predefined limits.

These limits need to be dynamically adjustable, allowing the AI to focus on certain objectives rather than others, while at the same time mitigating context saturation where necessary, to ensure a satisfactory match between expectation and result in all circumstances.

Limiting factors

Lack of limits

Only if all the above conditions are met can an LLM be a relevant mediator in the fulfillment of our intentions, transposed into tangible tasks.

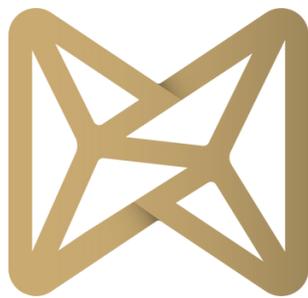
At this point, the intelligence of a model becomes almost secondary, because at this stage of understanding, the criterion of operating costs becomes more important than that of intelligence in the choice of model.

This is because, when limiting factors are considered at their true value and integrated accordingly, they enable us to obtain from a supposedly less intelligent model, the equivalent of what a so-called more intelligent model is capable of producing in terms of relevance.

The difference is that a model considered less intelligent costs between 10 and 100 times less for a similar error rate, all things considered with regard to the problem of hallucination.

The latter boils down to an information deficit related to the volume of model parameters, which can be filled by dynamically adjustable segmentation.

Solution



Optimized Context
Distribution System

OCDS

AI

All the issues raised can be summed up in a single obligation: to bring together two interlocutors (human / AI) in a pre-established environment, framed by norms, tacitly accepted undertones, objectives whose priorities are underpinned by the execution environment, and based on anthropomorphic landmarks that induce implicit notions essential to desaturation and increased focus of attention.

This is achieved by integrating the fundamental element of all-round limitation, in order to establish a zone of concordance conducive to systematic relevance, admitting variations arising from the applicant's subjectivity.

Definition of OCDS

The OCDS for Optimized Context Distribution System is a content management system for the systematic, transversal and multidimensional integration of generative AI into management applications and integrated software packages, based on the categorized management of data, content and contexts dedicated to AI, thus ensuring optimal distribution to specialized anthropomorphic AI, through an approach that considers the intrinsic limits of generative AI, just as much as the cognitive limits of human beings.

OCDS Solution



OCDS objectives

Specific OCDS objectives include :

- Optimizing user queries: by proposing intent suggestions based on the contexts provided and usage frameworks, the OCDS helps users to formulate more precise queries, thereby increasing the relevance of results.
- Improved performance: by streamlining the distribution of information to specialized artificial intelligences, OCDS aims to maximize operational efficiency and reduce processing errors.
- Increased user satisfaction: by guaranteeing more intuitive interactions tailored to users' needs, OCDS enhances user satisfaction and engagement in their interactions with AI systems, thanks in particular to the relevance of responses resulting from streamlined distribution of information to specialized AIs.

OCDS Solution



OCDS objectives

Specific OCDS objectives include :

- Adaptability to changing needs: OCDS stands out for its ability to adapt to changing needs, responding effectively to user requirements and adapting to technological advances. This ensures continuity of operational performance in AI-assisted organizations, and reliable thresholds of relevance in the answers provided.
- Flexibility in model choice: the OCDS allows anyone to choose their own transforming model provider, as well as the parameters relating to temperature (determinism and creativity), and the maximum volume of input, output and/or global tokens.

In short, the OCDS establishes an environment where artificial intelligence can truly serve users.

On the one hand, through the performance and flexibility levers induced by the exploitation of LLM-type artificial intelligence, and on the other, by transforming approximate requests into precise results, in line with the demands of the professional world.

Ability to manage limiting factors :

OCDS enables :

- calibrate on-the-fly context activation and deactivation to adjust the AI's attentional focus, by decongesting the instructional context from lower-priority elements depending on the task at hand. The choice of relevance level can thus be adjusted by desaturation combined with a simultaneously induced focus on a single objective.
- direct the addressing of queries by department, business line, task and sub-task, in order to induce a pre-framing of queries, which, through the business line and department approach, remains intuitive for the user. At the same time, the suggestions and orientations inherent in the interfaces teach the user the right query approach to adopt in order to achieve optimum relevance.
- departmentalize the processing of queries through a socially constructed approach, understood by humans, enabling them to refine their choices of AI interlocutor according to the needs they are aware of, but do not know how to formulate with the necessary precision.

Ability to manage limiting factors :

OCDS enables :

- exploit business segmentations resulting from ESP extraction, translated into disciplines, tasks and related sub-tasks. This is achieved through specialized AI team members accompanying any anthropomorphic AI, each evolving in a wider context. This enables relevance to be achieved beyond expectations, through the effect of attention velocity on a single task.
- the construction and allocation of so-called “global” support teams, to particular execution environments, again through segmentation and subdivision. These teams can be accessed at any time, regardless of the pages visited, so that hyper-specialization is at your fingertips. This is achieved without having to invoke other contexts, and without having to change environments, as contexts adjust themselves without human intervention.

Ability to manage limiting factors :

OCDS enables :

- segment the distribution of contexts of a variable nature, such as appointments, stocks and other moving flows impossible to integrate into fine-tuning given their variability. This hyper-segmentation of variable elements is essential, as the influence of selection bias is very strong in these circumstances.
- compartmentalize contexts by content type, so as to restrict understanding and interpretation to the exclusive object implied by the content typologies. This is similar to the way in which appointments represent a type of content, but in this case the partitioning of other types of content is predefined and can be refined according to the particular needs of segmentation by type.

OCDS Features

In project mode

Query intent outlook :

Variations in perspectives are pre-integrated into the OCDS, enabling the following queries to be processed:

- Queries whose intentions are shared both by the frame's intervention context and by interlocutors not belonging to this frame, invoking shared unified contexts for public front-end and private internal uses.
- Requests whose intentions can only emanate from users actively participating in the execution framework, as a member with a particular role, job or task assignments, invoking contexts restricted to the connected user, always within the reference framework.
- Requests whose intentions can only originate from disconnected users, not belonging to the execution frame, but interacting with it, invoking the related interpretation contexts, but subject to the editorial policy of the reference frame of the requested environment.

OCDS Features

In project mode

Global interpretation values:

Global interpretation values are contexts propagated to all AIs involved in a dedicated “project” environment.

These global values include alignment and editorial orientation.

Disconnected general contexts :

Disconnected general contexts enable the orientation of intentions to be adjusted so as to give the right perspective to task objectives. These contexts are propagated to all publicly accessible AIs, without the need for an account.

OCDS

Features

In project mode

Segmentation by content type :

For variable feeds :

- Appointments
- Planning
- Stock

For intention orientations:

- Strategies
- Notes and memos
- Social content
- Editorial content
- Email content
- Training
- Frequently asked questions

* Non-exhaustive: directly linked to the ability to choose the categories and types of contexts to be considered by AIs individually or through the general “project” framework.

In project and personal mode

Personal contexts:

Personal contexts are propagated only to the current user. In this way, elements specific to the user are known to all AIs visited by that user, without affecting the initial parameters of the AIs.

The latter receive elements with different parameters according to the users who consult them. This allows the variability needed to adjust intentions by explicit preferences.

General contexts :

So-called “general” contexts are information and/or skills that are imposed globally for any user (logged-in or not) acting within the dedicated environment.

This is the case whatever the perspective of the query, always within the reference frame of global interpretation values. These general contexts are systematically considered.

OCDS

Features

In project and personal mode

Anthropomorphic AIs

In an OCDS-type management interface, each AI has its own characteristics and parameters, which operate within a global reference framework known as a “project”.

Anthropomorphic features :

Profile

- Name
- Age
- Gender
- Profession
- Main service
- Description
- Place of work

Expression :

- Quality of writing or speaking
- Style
- Register

Framing

- Open-ended prompt
- Discussion starter

OCDS

Features

In project and personal mode

Anthropomorphic AIs

Anthropomorphic features :

Scope

- Intervention context
- Type of public / Audience
- Objectives or tasks to be accomplished
- Role to be played by this AI
- Posture in conflict situations

Skills

- Embedded
- Specific

Knowledge

- Embedded
- Specific

Alignment

- Alignment criteria

Other parameters :

- Fournisseur API
- Choix du modèle fournisseur
- Choix du modèle fine-tunné
- Input limite
- Output limite
- Max sentence

OCDS

Features

In project and personal mode

Anthropomorphic AIs

AI team members

Each AI can be accompanied by team members, each with their own anthropomorphic characteristics, each of which is oriented by the intentions of the main AI, i.e. the one accompanied by the team members.

Team members act as employees under the authority of an AI's intentions, within the general framework of the “project”.

Team members can be added for independent purposes, or added chronologically, leading to a process in which the responses of the main AI are intended to be passed on in whole or in part to the first team member, whose responses are in turn intended to be passed on to the next team member, and so on, making it possible to go into extreme depth in terms of the relevance sought.

This process is based on the ESP method, which can be used by the Jaris team.

In project and personal mode

Anthropomorphic AIs



The Jaris team

The artificial intelligences that make up TEAM Jaris systematically accompany any artificial intelligence as architects collaborating on its parameterization.

TEAM Jaris AIs also act as employees of the main AI, but incorporate not only the latter's intentions, but also all its parameters. This allows Team Jaris AIs to incrementally refine the parameters of the main AI.

Accompanying teams

Accompanying teams are groupings of departmentalized AIs that incorporate the reference frames of the project as well as the reference frames of the anthropomorphic AIs used by the user.

On any other page, companion teams incorporate only the frames of reference of the global execution context known as the “project”.

These teams can be customized by business department, discipline and task.

This allows the user to compose his own environment according to his most frequent needs, while remaining within the limiting framework of the global environment.

In project and personal mode

The incremental expander

Enables deep distribution on the fly by suggesting AIs specifically dedicated to particular tasks, favoring the focus on objectives induced by proposing the right AI interlocutor.

The incremental expander makes it possible to go beyond the limits of length and depth of any content by systematically regenerating, on demand, via the selection of words, zones, sentences or passages, other queries that are reconstructed in a new context, that of the selected content or text.

The proposals made by opening a dialog box guide the user's choice in selecting the right AI interlocutor, i.e. one whose parameters and objectives are focused on a single element of intent, thus guaranteeing optimal relevance of the query and the expected relevance, as thought by the requester.

The AIs called upon in the incremental expander also integrate the general references as well as the references and characteristics of the main AI in use.

This translates into significant gains in terms of relevance, speed and efficiency, while offering an enriched and intuitive user experience.



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