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3 **Inference and decision in credal occupancy grids: use case on trajectory**
4 **planning**

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21 Occupancy grids are common tools used in robotics to represent the robot environment,
22 and that may be used to plan trajectories, select additional measurements to acquire, etc.
23 However, deriving information about those occupancy grids from sensor measurements
24 often induce a lot of uncertainty, especially for grid elements that correspond to occluded
25 or far away area from the robot. This means that occupancy information may be quite
26 uncertain and imprecise at some places, while being very accurate at others. Modelling
27 finely this occupancy information is essential to decide the optimal action the robot
28 should take, but a refined modelling of uncertainty often implies a higher computational
29 cost, a prohibitive feature for real-time applications. In this paper, we introduce the
30 notion of credal occupancy grids, using the very general theory of imprecise probabilities
31 to model occupancy uncertainty. We also show how one can perform efficient, real-time
32 inferences with such a model, and show a use-case applying the model to an autonomous
33 vehicle trajectory planning problem.

34 *Keywords:* Occupancy grids and Trajectory planning and Imprecision and Imprecise
35 probabilities

36 **1. Introduction**

37 Occupancy grids are commonly used tools to represent a mobile robot (cars, drones,
38 etc.) environment, especially autonomous ones. Based on a local perception of the

39 vehicle, they are instrumental in solving issues such as obstacle avoidance and short-
40 term trajectory planning, and are particularly suitable in dynamic environments,
41 for instance environments discovered on the fly by the robots (such as in SLAM
42 problems ²⁷) or environments in which moving obstacles evolves ¹⁹. Such grids
43 are composed of multiple cells, which in the most usual settings can be either
44 free or occupied. **Those grids are most of the time obtained from sensor readings**
45 **associated to processing steps that may be peculiar to each sensor, according to**
46 **their nature (cameras, lasers, ...)**. Such occupancy information is therefore prone
47 to be affected by many sources of uncertainties, such as imprecise sensor readings
48 (camera occlusion, numerical precision, ...), noise due to environmental conditions
49 (rain, ...) or faulty sensors. Different frameworks have been proposed to model and
50 reason from such uncertainties, for instance by using probabilistic ^{21,6}, fuzzy ^{28,24,23}
51 or evidential ^{20,33,26,30} occupancy grids.

52 In this paper, we explore how another uncertainty framework, namely impre-
53 cise probabilities, can be used to model uncertainty in occupancy grids. To our
54 knowledge, it is the very first attempt to do so. Imprecise probability consists in
55 extending the classical probabilistic model by considering convex sets of probabil-
56 ities or equivalent models such as lower expectation. This representation formally
57 includes all the other aforementioned representations ¹⁰ (possibilities, probabilities,
58 belief functions), and has the benefit to be fully consistent with classical Bayesian
59 probabilistic modelling, both axiomatically (as it relaxes Bayesian axioms) and for-
60 mally speaking. It can therefore be interpreted either as an uncertainty theory of
61 its own, or as a robustification of the classical probabilistic models. We refer to ²
62 for an introduction to various aspects of the framework, and to Walley's book ³²
63 for a full theoretical account. In the case of cells taking values in the binary space
64 $\mathcal{X} = \{x, \neg x\}$ composed of the states occupied (x in our notation) and free ($\neg x$
65 in our notation), imprecise probabilistic models encode uncertainty by explicitly en-
66 coding imprecision through the use of two boundary measures, therefore allowing
67 to differentiate between what is commonly called aleatoric uncertainty (due to a
68 possible ambiguity and/or random phenomena) and epistemic uncertainty (due to
69 an absence of information).

70 The concept of imprecise probabilistic occupancy grids is introduced in Section 2,
71 where we also discuss the associated challenges in terms of inference and decision.
72 We then consider in Section 3 the specific problem of making inferences for local
73 trajectory planning, proposing a computationally efficient and simple solution to do
74 so. Each step of the method is illustrated using simple examples. Then, in Section 4,
75 for illustrative purposes, we present some results obtained using real occupancy grids
76 coming from PACPUS ¹⁷, an experimental platform developed in our laboratory,
77 dedicated to researches on autonomous vehicles.

78 2. Introducing credal occupancy grids

79 In this section, we will introduce the notion of credal occupancy grids, and will
80 discuss the problem of making general inferences with them. Roughly speaking, such
81 inferences come down to make computations over (pseudo-)Boolean functions where
82 the probabilities of literals are imprecisely specified. We will however not treat this
83 very general issue that is encountered in many fields such as data-bases¹³, game-
84 theory²⁵, but will focus on the most common issue in applications using occupancy
85 grids, that is guiding a moving object through it.

86 For this reason, we will consider from now that our problem concerns a moving
87 robot, and that the robot environment is modelled by a large grid of cells, and that
88 each cell X can take a binary value, occupied (x) or unoccupied ($\neg x$). We assume
89 that when a robot perceives its environment through measurement devices (sensors,
90 cameras), it receives uncertain information about whether a given cell is occupied.
91 Imprecise probabilities³² offer a very generic way to model uncertainty, including
92 most known models of uncertainty such as precise probabilities, belief functions or
93 possibility distributions¹⁰. It also comes with a fully-fledged theory to reason with
94 such uncertainty and make decisions³².

95 In a binary setting such as the occupancy of cell X , any imprecise probabilistic
96 model can be reduced to an interval $[p(x), \bar{p}(x)]$ of the probability to be occupied,
97 as we have that $p(\neg x) = 1 - \bar{p}(x)$ and similarly for the upper bound. **Note that the**
98 **fact that any convex probability set can be reduced to such intervals on singletons**
99 **is only true in the binary case, and is used here as one of the key feature that**
100 **makes our approach tractable.** We can in particular model the following extreme
101 situations:

- 102 • certain occupancy: $[p(x), \bar{p}(x)] = [1, 1]$,
- 103 • certain inoccupancy: $[p(x), \bar{p}(x)] = [0, 0]$,
- 104 • unknown occupancy: $[p(x), \bar{p}(x)] = [0, 1]$,

105 as well as all the intermediate ones, with precise probabilities being retrieved when
106 $p(x) = \bar{p}(x)$. **A credal occupancy grid is pictured in Figure 1, where cells are volun-**
107 **tary of very large size for illustrative purposes. Green cells are likely to be unoccu-**
108 **pied, red ones occupied, and grey/dark ones are in between (i.e., $0.5 \in [p(x), \bar{p}(x)]$).**
109 **The darker the shades, the wider are the corresponding intervals.**

Let us now consider a set X_1, \dots, X_m of cells. As they are equivalent to Boolean
variables, any event A concerning these cells (e.g., “at least one cell is occupied”, “ k
consecutive cells are occupied”) can be expressed as a Boolean formula, and in
particular can be put in Disjunctive Normal Form (DNF). This means that we
can express any event in the form of a disjunction $A = \bigvee_{i=1}^j A_i$, where each $A_i =$
 $\bigwedge_{k \in A_i^+} x_k \wedge \bigwedge_{k \in A_i^-} \neg x_k$ is a conjunction of values for the cells (A_i^+ denotes the set of
indices of positive variable, A_i^- the indices of negative one). Such sets are sometimes
called orthopairs⁵ in the literature. When the uncertainty over cells is expressed
by a precise probability, assessing $P(A)$ then amounts to evaluate $P(\bigcup_{i=1}^j A_i)$, a

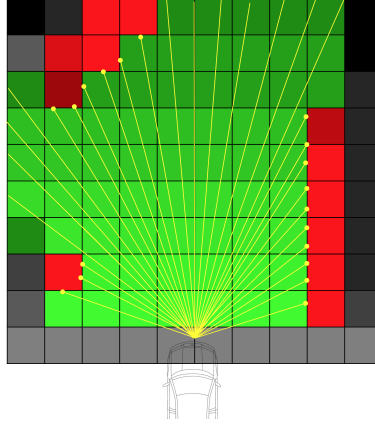


Fig. 1. Credal occupancy grid build from sensor data. Certain occupancy: $[p(x), \bar{p}(x)] = [1, 1]$ in red, certain inoccupancy: $[p(x), \bar{p}(x)] = [0, 0]$ in green, unknown occupancy: $[p(x), \bar{p}(x)] = [0, 1]$ in black. The intermediate states are represented with lower intensity values.

potentially difficult task. One common way to do it is to use the following formula^a

$$P(A) = P(\cup_{i=1}^j A_i) = \sum_{\mathcal{A} \subseteq \{A_1, \dots, A_j\}} -1^{|\mathcal{A}|} P(\cap_{A \in \mathcal{A}} A_i) \quad (1)$$

110 where the second equality simply applies the inclusion/exclusion principle. The
 111 probability of a conjunctive event A_i is

$$P(A_i) = \prod_{k \in A_i^+} p(x_k) \prod_{k \in A_i^-} p(\neg x_k). \quad (2)$$

112 and likewise for intersection of such events, that remain of the same form. Solving
 113 Equation (1), hence making inferences over a probabilistic grid, is then relatively
 114 straightforward when probabilities are precise, as assessing the probabilities of con-
 115 junctions is easy. It should however be noted that there are multiple ways to decom-
 116 pose a given event A into a DNF, such as the use of Binary Decision Diagrams⁴ or of
 117 minimal cuts in reliability theory¹⁶, that can lead to more or less computationally
 118 friendly decompositions, in the sense that the number of terms in the right-hand
 119 side of (2) can grow exponentially. Obtaining compact Boolean representations of
 120 an event A is therefore a whole area research, that is outside of the scope of the
 121 present paper, which is why we will focus on the second part on specific cases for
 122 which efficient decompositions do exist.

123 However, even when one has obtained a decomposition through some means,
 124 the task of solving Equation (2) becomes much more difficult when probabilities

^aNote that in this paper, we will use interchangeably \vee and \cup , or \wedge and \cap , as they have the same meaning.

125 become imprecise, as we then have to solve the equation

$$\underline{P}(A) = \inf_{p(x_i) \in \{\underline{p}(x_i), \bar{p}(x_i)\}} P(A) \quad (3)$$

126 to get the lower bound of the probability of an event A , which is NP-hard in general,
127 as Equation 1 is a multi-linear form of the $p(x_i)$, each constrained to be in an interval
128 (see for instance ³). Indeed, if it is known ¹² that the bound given by Equation 3
129 is obtained in such a case on one of the vertices of the hyper-cube $\times_i [\underline{p}(x_i), \bar{p}(x_i)]$,
130 that is $p(x_i) \in \{\underline{p}(x_i), \bar{p}(x_i)\}$, it remains to find which one, hence to check for 2^m
131 combinations if m is the number of cells. The upper bound can be found similarly,
132 replacing inf by sup, with the same difficulties. This means, in particular, that
133 reasoning over an entire imprecise probabilistic grid and for arbitrary events will be
134 computationally prohibitive and infeasible for real-time applications.

Example 1. Let us consider two cells X_1, X_2 , and the event “one and only one cell is occupied”, that corresponds to a XOR logical gate, that is

$$A = (x_1 \wedge \neg x_2) \vee (x_2 \wedge \neg x_1) = A_1 \cup A_2$$

with $A_1 \cap A_2 = \emptyset$, as each contains opposite values (e.g., x_1 for A_1 , and $\neg x_1$ for A_2). Let us now consider that $p(x_1) \in [0.6, 0.8]$ and $p(x_2) \in [0.3, 0.6]$, we have that $\underline{P}(A)$ is obtained on a combination of extreme points, i.e.,

$$\begin{aligned} \underline{P}(A) &= \inf_{p(x_i) \in \{\underline{p}(x_i), \bar{p}(x_i)\}} p(x_1) (1 - p(x_2)) + (1 - p(x_1)) p(x_2) \\ &= 0.8 \cdot 0.4 + 0.2 \cdot 0.6 = 0.44 \end{aligned}$$

135 obtained for $p(x_1) = 0.8$ and $p(x_2) = 0.6$ (the upper bounds of $p(x_1)$ and $p(x_2)$).

136 More generally, one may be interested not only in computing the lower and
137 upper bounds of some event probabilities, but to compute the lower and upper
138 expected values of some reward/penalty function $f : \times_{k=1}^m \{x_k, \neg x_k\} \rightarrow \mathbb{R}$. Since it
139 is defined on a discrete space, we can always define a partition B_1, \dots, B_k such that
140 f is constant over elements of this partition, i.e. if we denote by \mathbf{x} an assignment
141 vector over cells X_i , $f(\mathbf{x}) = f(\mathbf{x}')$ whenever $\mathbf{x}, \mathbf{x}' \in B_i$ for some $i \in \{1, \dots, k\}$. It
142 then makes sense to denote by f_{B_i} the value of f for all elements included in B_i .
143 Computing the lower expectation of f than amounts to solve the equation

$$\underline{\mathbb{E}}(f) = \inf_{p(x_i) \in \{\underline{p}(x_i), \bar{p}(x_i)\}} \sum_{j=1}^k f_{B_j} P(B_j) \quad (4)$$

144 with each B_j that can be decomposed using (2). As (4) remains a multi-linear form,
145 the problem for solving it is in general not more difficult than the one of finding a
146 lower probability, and its tractability will depend on both the form of f and of the
147 events B_i .

148 **Example 2.** Let us pursue Example 1, by considering a simple game: we get a
149 reward of 2 if the two variables end up with the same value, and suffer a penalty of

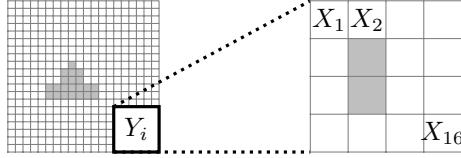


Fig. 2. The metagrid Y_i composed of 16 cells of the credal occupancy grid

150 1 (equivalently, a reward of -1) if they have different values. Our knowledge about
 151 the variables X_1, X_2 remains the same. One may think, for instance, of a game with
 152 two coins with ill-known probabilities of landing head and tail.

We now want to know our lower expected reward, should we play this game. We have $B_1 = (x_1 \wedge x_2) \vee (\neg x_1 \wedge \neg x_2)$ and B_2 its complement, with $f_{B_1} = 2$ and $f_{B_2} = -1$. We must now minimize

$$2(p(x_1) \cdot p(x_2) + p(\neg x_1) \cdot p(\neg x_2)) - (p(\neg x_1) \cdot p(x_2) + p(x_1) \cdot p(\neg x_2))$$

153 which gives $\underline{\mathbb{E}}(f) = -0.86$, obtained for the values $p(x_1) = 0.8$ and $p(x_2) = 0.6$.

154 In the rest of the paper, we will propose a decision model that focuses on partic-
 155 ular types of events, that are of practical interest in robot guidance problems and
 156 are computationally tractable, in the sense that bound (3) can be computed in a
 157 time that is linear in the number of considered cells (or Boolean variables).

158 3. Moving in credal occupancy grid: model, inference and decision

159 Now that we have introduced credal occupancy grids and discussed their main
 160 aspects regarding inference, let us focus on the problem of guiding a moving robot
 161 within such an occupancy grid.

162 From now on, we will also be interested in particular states of subgrids of the
 163 whole occupancy grid, that we will call metagrids. Such metagrids will describe the
 164 successive locations of a robot along a chosen path. Indeed, usually the space occu-
 165 pied by a robot (be it a vehicle, a drone, etc.) is much bigger than a single cell, whose
 166 area is usually related to the smallest zone a robot can perceive with sufficient reli-
 167 ability. As an example, cells of grids for autonomous vehicles are typically squares of a
 168 few decimetres. A metagrid Y_i will be composed of n cells denoted X_1, \dots, X_n , while
 169 a possible path for the robot will always be composed of k metagrids Y_1, \dots, Y_k ,
 170 representing its successive positions. **The concept of metagrid within a grid is shown**
 171 **in the Figure 2 (with a metagrid being made of 16 elementary cells).**

172 Given this, our decision model will be based on the following elements, that we
 173 will detail in different subsections:

- 174 • For each metagrid Y_i , assess the uncertainty over the fact that at least
 175 one cell of the metagrid is occupied: this provides lower/upper bounds
 176 $[\underline{p}(y_i), \bar{p}(y_i)]$ over a new Boolean state (either at least one cell is occupied,

- 177 or none), that we consider as probability bounds of the fact that the robot
178 can move over Y_i .
- 179 • Assess the lower/upper probability of the k mutually exclusive events
180 F_1, \dots, F_k that the robot can move up to the i th metagrid, that is
181 $F_i = \bigwedge_{j=1}^{i-1} \neg y_j \wedge y_i$, corresponding to the event that Y_i is the first occu-
182 pied metagrid.
 - 183 • Pick the trajectory that provides the best expected reward as the robot
184 future path, unless stopping is required because the first metagrids are too
185 likely to be occupied.

186 For each of those steps, we will provide inference tools whose computational com-
187 plexity is fixed and linear with the number of states, hence ensuring that real-time
188 applications of the proposed method is doable. Since they also rely on fixed formu-
189 las, they can also be easily implemented as hardware components, possibly speeding
190 up computations even further.

191 3.1. Inference about individual metagrids

A first inference we want to do is to know, for each metagrid, what is the likelihood of having at least one cell X_i that is occupied, as having one such cell is judged sufficient for the metagrid to be unreachable. In practice, this comes down to assess the probability bounds for the event

$$Y = x_1 \vee x_2 \vee \dots \vee x_n.$$

One advantage of this event is that it satisfies a monotonicity constraint, i.e., it cannot become false if one variable X_i goes from the value $\neg x_i$ to x_i . **It results that the corresponding multi-linear form given by Equation (2) is increasing^b in each variable $p(x_i)$. Previous results about such multi-linear forms¹², applied for instance in¹ to the case of reliability functions, then indicate that $\underline{P}(Y)$ is obtained by computing $P(Y)$ when $p(x_i) = \underline{p}(x_i)$.** Yet it should be noticed that the form $x_1 \vee x_2 \vee \dots \vee x_n$ is not very computationally friendly, as every pair of elements of the disjunction have a non-empty intersection, since no pair of formulas contains opposite values of variables (each formula is only made of positive values). This means that Equation (1) contains a number of terms that factorially increases with n . However, we can re-express Y as a disjunction of non-intersecting events (using, e.g., ordered binary decision diagrams⁴)

$$Y = x_1 \vee (\neg x_1 \wedge x_2) \vee (\neg x_1 \wedge \neg x_2 \wedge x_3) \vee \dots \vee (\bigwedge_{i=1}^{n-1} \neg x_i \bigwedge x_n)$$

192 that counts n different conjunctions that have the advantage to be pairwise disjoint,
193 meaning that we finally get

^bOne can simply consider the partial derivatives $\partial P(A)/\partial p_i$ to check it.

	X_1	X_2	X_3	X_4
$\underline{p}(x_i)$	0.2	0.1	0	0.6
$\bar{p}(x_i)$	0.2	1	0.1	0.7

Table 1. Example 2: a metagrid with 4 cells

$$\underline{P}(Y) = \sum_{i=1}^n \left(\underline{p}(x_i) \prod_{j=1}^{i-1} \bar{p}(\neg x_j) \right),$$

194 a sum that has a linear number of terms with respect to n . We can similarly obtain
 195 an upper bound $\bar{P}(Y)$, just inverting the bounds over $p(x_i)$ in the equation. The
 196 bounds $[\underline{P}(Y^c), \bar{P}(Y^c)]$ over the event Y^c —“none of the cells of the metagrid are
 197 occupied” can then be obtained by complementation, as we have $\underline{P}(Y^c) = 1 - \bar{P}(Y)$
 198 and $\bar{P}(Y^c) = 1 - \underline{P}(Y)$.

Example 3. Let us consider a metagrid composed of four cells with probability intervals of occupancy given in Table 1. In this case, we have:

$$\begin{aligned} \underline{P}(Y) = & \underline{p}(x_1) + \underline{p}(x_2)\bar{p}(\neg x_1) \\ & + \underline{p}(x_3)\bar{p}(\neg x_1)\bar{p}(\neg x_2) \\ & + \underline{p}(x_4)\bar{p}(\neg x_1)\bar{p}(\neg x_2)\bar{p}(\neg x_3). \end{aligned}$$

Using the fact that $\bar{p}(\neg x_i) = 1 - \underline{p}(x_i)$, we obtain:

$$\begin{aligned} \underline{P}(Y) = & 0.2 + 0.1(1 - 0.2) \\ & + 0(1 - 0.2)(1 - 0.1) \\ & + 0.6(1 - 0.2)(1 - 0.1)(1 - 0) = 0.712 \end{aligned}$$

Similarly,

$$\begin{aligned} \bar{P}(Y) = & \bar{p}(x_1) + \bar{p}(x_2)\underline{p}(\neg x_1) \\ & + \bar{p}(x_3)\underline{p}(\neg x_1)\underline{p}(\neg x_2) \\ & + \bar{p}(x_4)\underline{p}(\neg x_1)\underline{p}(\neg x_2)\underline{p}(\neg x_3). \end{aligned}$$

Thus, we have:

$$\begin{aligned} \bar{P}(Y) = & 0.2 + 1(1 - 0.2) \\ & + 0.1(1 - 0.2)(1 - 1) \\ & + 0.7(1 - 0.2)(1 - 1)(1 - 0.1) = 1, \end{aligned}$$

199 giving a probability interval of occupancy equal to $[0.712, 1]$, what might indicate
 200 that the metagrid is not free. Note that the upper bound is equal to 1 which is quite
 201 natural because it is totally plausible for the second cell to be occupied. Similarly,
 202 the high lower bound is induced by the fact that the fourth cell is probably occupied.

	Y_1	Y_2	Y_3	Y_4
$\underline{P}(y_i)$	0.1	0.3	0.712	0
$\overline{P}(y_i)$	0.2	0.5	1	1

Table 2. Example 3: a trajectory composed of four metagrids

203 3.2. Inferences along a trajectory

Having made inferences over the k metagrids Y_1, \dots, Y_k along a given trajectory, we are now concerned about selecting the path that the robot should take. A first step for this is to assess how far we could go along a given trajectory. Indeed, if one of the first metagrid is almost surely occupied, it is not very useful to know that the last ones are surely free, as we will have encountered an obstacle before them. Hence, what matters is how soon we are likely to encounter an obstacle on a path. With this reasoning in mind, we propose to assess the lower and upper probability bounds over consecutive events F_i ="the i th metagrid is the first non-free", or in variable terms,

$$F_i = \bigwedge_{j=1}^{i-1} \neg y_j \wedge y_i \quad i = 1, k.$$

The event F_i being actually expressible as a Cartesian product of the subspaces $\{y_i, \neg y_i\}$, we have in the probabilistic case that

$$P(F_i) = p(y_i) \prod_{j=1}^{i-1} p(\neg y_j).$$

204 Getting bounds over this probability is then very easy, since if all the terms are
205 independent, it is enough to just minimize each of them. We thus end up with

$$\underline{P}(F_i) = \underline{p}(y_i) \prod_{j=1}^{i-1} \underline{p}(\neg y_j) \quad (5)$$

206 and similarly for $\overline{P}(F_i)$, just switching the bounds. Computing this bound involves
207 at most k products, and is therefore quite efficient again. Note that we compute
208 also the bounds for an additional event $F_{k+1} = \bigwedge_{j=1}^k \neg y_j$ which represents the event
209 "all metagrids are free".

210 **Example 4.** Let us consider a trajectory composed of 4 metagrids which prob-
211 abilities are given in Table 2 (in which the third metagrid could be the one of
212 Example 3).

These values could correspond to the following situation: the first two metagrids are likely to be free, then the sensor detects almost surely an obstacle on the third metagrid, and does not see anything on the last metagrid because of occlusions. We have:

$$F_1 = y_1 \times \{y_2, \neg y_2\} \times \{y_3, \neg y_3\} \times \{y_4, \neg y_4\}$$

	F_1	F_2	F_3	F_4	F_5
$\underline{P}(F_i)$	0.1	0.24	0.28	0	0
$\overline{P}(F_i)$	0.2	0.45	0.63	0.18	0.18

Table 3. Example 3: bounds computation for the F_i

$$F_2 = \neg y_1 \times y_2 \times \{y_3, \neg y_3\} \times \{y_4, \neg y_4\}$$

$$F_3 = \neg y_1 \times \neg y_2 \times y_3 \times \{y_4, \neg y_4\}$$

$$F_4 = \neg y_1 \times \neg y_2 \times \neg y_3 \times y_4$$

$$F_5 = \neg y_1 \times \neg y_2 \times \neg y_3 \times \neg y_4$$

213 Using Esq. (5), we can compute easily the probability bounds of the five events.
214 They are given in Table 3.

It should also be noted that the events F_1, \dots, F_{k+1} actually form a partition of the space $\prod_{i=1}^k \{y_i, \neg y_i\}$ ($F_i \cap F_j = \emptyset$ for any i, j , and $\cup_{i=1}^{k+1} F_i = \prod_{i=1}^k \{y_i, \neg y_i\}$), meaning that they can be interpreted as probability bounds over atoms of a Boolean algebra. This means in particular that the set of intervals

$$[\underline{P}(F_i), \overline{P}(F_i)], \quad i = 1, k$$

215 can be interpreted as probability intervals⁹, a well known imprecise probabilistic
216 model for which efficient inference tools do exist. We will use this fact in the next
217 section, when deciding which path a mobile robot should follow in order to maximize
218 its utility.

219 3.3. Deciding the best trajectory

220 We now consider that we have to choose between several paths τ , each moving
221 over a fixed number of k metagrids whose states are uncertain. To choose the best
222 trajectory, we propose to use a utility function quantifying the fact that a trajectory
223 is usable or not. This utility is defined on the basis of the events F_i .

224 A first remark is that the states or atoms F_i , $i = 1, k + 1$ of our decision space
225 are naturally ordered in terms of increasing utility, in the sense that F_j (the j -th
226 metagrid is the first occupied) happening is worse than F_{j+1} happening. This means,
227 among other things, that the utility function associated to those states should be
228 increasing, i.e., that $u(F_i) \leq u(F_{i+1})$ in any case.

In the case of precise probabilities (we have a precise value $P_j(F_i)$ for each element of a trajectory τ_j), the value of a trajectory would then be its expected utility $\mathbb{E}(\tau_j)$, i.e.

$$\mathbb{E}(\tau_j) = \sum_{i=1}^{k+1} P_j(F_i)u(F_i).$$

229 When the $P(F_j)$'s become imprecise and are only known to belong to some inter-
 230 vals $[\underline{P}(F_j), \overline{P}(F_j)]$, this expectation becomes interval-valued for each trajectory τ_j .
 231 Given the fact that our uncertainty model is expressed as intervals on singletons,
 232 the upper and lower probabilities are 2-monotone and thus we can compute the
 233 lower and upper expected utilities of each trajectory thanks to a Choquet integral
 234 (we refer to ⁹ for the details of the derivation). Moreover, as the utilities are always
 235 ordered in the same way, computing the bounds of the expected utility is simple as
 236 we have:

$$\mathbb{E}(\tau_j) = \sum_{i=1}^{k+1} (u(F_i) - u(F_{i-1})) \underline{P}(\{F_i, \dots, F_{k+1}\}),$$

237 and

$$\underline{P}(\{F_i, \dots, F_{k+1}\}) = \max\left(\sum_{l=i}^{k+1} \underline{p}(F_l), 1 - \sum_{l=1}^{i-1} \overline{p}(F_l)\right),$$

238 with $u(F_0) = 0$. Similarly

$$\overline{\mathbb{E}}(\tau_j) = \sum_{i=1}^{k+1} (u(F_i) - u(F_{i-1})) \overline{P}(\{F_i, \dots, F_{k+1}\}),$$

239 and

$$\overline{P}(\{F_i, \dots, F_{k+1}\}) = \min\left(\sum_{l=i}^{k+1} \overline{p}(F_l), 1 - \sum_{l=1}^{i-1} \underline{p}(F_l)\right).$$

240 Again, due to our assumptions (increasing and ordered utilities along the F_i , that
 241 form a partition), these formulas are fixed and straightforward to compute.

Example 5. Let us consider the utilities given in Table 4. We have chosen to
 fix negative utilities for the two first metagrids, representing a kind of “security
 distance” of at least two metagrids, a negative expected utility then corresponding
 to the fact that if this path is chosen, the mobile robot should preferably brake or
 stop. If we compute the lower and upper bounds for the trajectory of Example 4,
 we have

$$\begin{aligned} \underline{\mathbb{E}}(\tau) &= (-20 - 0) \cdot \underline{P}(\{F_1, \dots, F_5\}) + (-10 - (-20)) \cdot \underline{P}(\{F_2, \dots, F_5\}) + \dots \\ &\quad + (20 - 10) \cdot \underline{P}(\{F_5\}) \\ &= (-20 - 0) \cdot 1 + (-10 - (-20)) \cdot 0.8 + \dots + (20 - 10) \cdot 0 = -8.5 \end{aligned}$$

242 and we finally find $[-8.5, 1]$, which corresponds to the fact that the second metagrid
 243 is likely to be occupied.

244 As each trajectory is characterized by a lower and an upper expectation, there
 245 are several possibilities to make a decision about the best trajectory, as we must now

$u(F_0)$	$u(F_1)$	$u(F_2)$	$u(F_3)$	$u(F_4)$	$u(F_5)$
0	-20	-10	0	10	20

Table 4. Example 3 continuation: utility values

246 compare intervals and no longer point-valued evaluations. Some classical ways ³¹ to
247 do so are the following:

- 248 • Order 1. We can say that a trajectory τ_j is better than a trajectory τ_k
249 ($\tau_j \succ \tau_k$) if and only if $\underline{\mathbb{E}}(\tau_j) \geq \bar{\mathbb{E}}(\tau_k)$.
- 250 • Order 2. We can say that a trajectory τ_j is better than a trajectory τ_k if
251 and only if $\underline{\mathbb{E}}(\tau_j) \geq \underline{\mathbb{E}}(\tau_k)$ and $\bar{\mathbb{E}}(\tau_j) \geq \bar{\mathbb{E}}(\tau_k)$.
- 252 • Order 3. We can say that a trajectory τ_j is better than a trajectory τ_k if
253 and only if $\underline{\mathbb{E}}(\tau_j) \geq \underline{\mathbb{E}}(\tau_k)$.
- 254 • Order 4. We can say that a trajectory τ_j is better than a trajectory τ_k if
255 and only if $\bar{\mathbb{E}}(\tau_j) \geq \bar{\mathbb{E}}(\tau_k)$.

The two first rules provide a partial order on the trajectories allowing for incomparabilities, whereas the two last rules provide a linear order. Rule 3 is a pessimistic rule, it consists in retaining the best trajectory in the worst case, i.e. the trajectory associated to the highest lower expected utility. Rule 4 on the contrary gives the preference to the highest upper expected utility, adopting in this way an optimistic behaviour. When the order is partial (rules 1 and 2), one can determine a set of non-dominated trajectories:

$$T^* = \{\tau_j \mid \nexists \tau_k \text{ such that } \tau_k \succ \tau_j\}$$

256 If this set is composed of more than one trajectory and that a unique trajectory
257 is mandatory, several strategies can then be applied. It is for example possible
258 to postpone the decision by asking complementary information on the navigable
259 space. It is also possible to use additional criteria in the decision process, like the
260 proximity to a reference trajectory (using in this case what is commonly known as
261 lexicographic orders ¹¹).

262 **Example 6.** Let us suppose that we have 5 possible trajectories, whose lower and
263 upper expected utilities are given in Table 5 and represented in Figure 3. Using Rule
264 1, there are three maximal elements in the partial order induced by the intervals
265 (τ_2 , τ_4 , and τ_5). Two maximal elements are found using Rule 2 (τ_4 and τ_5). The
266 pessimistic rule 3 leads to the choice of τ_4 , whereas Rule 4 chooses τ_5 .

267 4. Illustrative application

268 As a proof of concept, we experiment our approach using real data, issued from the
269 platform PACPUS ¹⁷ developed in our lab. The objective of PACPUS is to provide

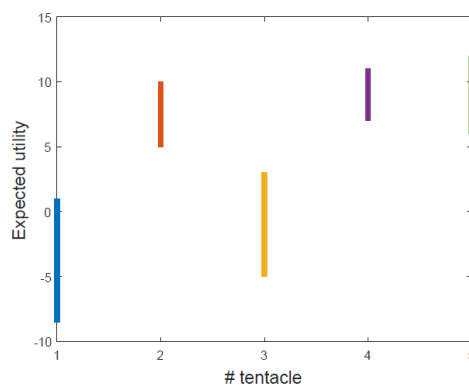


Fig. 3. Representation of the expected utilities of the trajectories

	τ_1	τ_2	τ_3	τ_4	τ_5
$\underline{\mathbb{E}}(\tau_j)$	-8.5	5	-5	7	6
$\overline{\mathbb{E}}(\tau_j)$	1	10	3	11	12

Table 5. Bounds of expected utilities of the trajectories

270 tools and resources for experimenting on intelligent vehicles. We use a Lidar as a
 271 perception sensor. This sensor can distinguish between free and occupied space and
 272 model it in 2D (x,y coordinates) with respect to the vehicle bodyframe. We used the
 273 **credal** grids generated by a C++ code¹⁹ with data acquired on our experimental
 274 vehicle (cf Figure 4). **We refer to the provided references for further details about**
 275 **the grid acquisition.** We consider a set of 40 different grids (or images). Each grid
 276 of 20*50 meters is built with uniform cells of size 0.1*0.1 meters. Each grid is repre-
 277 sented as an image in which one pixel corresponds to one cell, the green color shows
 278 the free cells (usable), the red one shows the occupied cells, while the black repre-
 279 sents unexplored cells (unknown). The color intensity reflects the certainty degree.
 280 **For each image (or grid), we generated n possible trajectories, as represented in**
 281 **Figure 5.** The shapes of the trajectories are clothoids, that are generated following
 282 the approach proposed by Mouhagir *et al.*²². The number of generated trajectories
 283 depends on internal states of ego-vehicle (speed and yaw rate). This type of trajec-
 284 tory called “tentacle” is indeed well suited to local planning. The final aim is then to
 285 automatically select the best trajectory, or “tentacle”. In the following we consider
 286 $n = 5$ trajectories. Generating such a finite set of pre-computed trajectories is quite
 287 common when needing real-time decision for objects having a high velocity (rockets,
 288 cars, etc.), as it speeds up the decision process. In this case, exploring all solutions



Fig. 4. Experimental vehicle

289 and trajectories may simply be too costly, even with efficient algorithms at hand.

290 Each trajectory is composed of several metagrids, each of them are defined as a
 291 square encompassing a circle of 3 meters diameter (30*30 cells). The security distance
 292 is fixed to 15 meters which is equivalent to 5 metagrids along a trajectory. The
 293 red circles indicate that the distance of the vehicle to the metagrid is less than the
 294 security distance. Each cell X of a metagrid is characterized by a basic belief mass
 295 assignment (bba) m on the frame $\mathcal{X} = \{x, \neg x\}$, where x stand for “occupied” and $\neg x$
 296 for “free”, that can be easily transformed into lower/upper probabilistic bounds^c.
 297 This means that for each cell, we retrieve three masses $m(\{x\}), m(\{\neg x\}), m(\mathcal{X})$.
 298 Each metagrid, initially of size 30*30, was transformed into metagrids of size 6*6
 299 by averaging the masses of adjacent cells.

300 To have access to a ground truth and to be able to compare methods for choosing
 301 the best trajectory, we have used two human “experts” (in this case, experienced
 302 drivers from the laboratory) to label the possible trajectories. An example of some
 303 evaluations given by one expert is given in Table 6. The instructions given to the
 304 experts were to assign a rank to the proposed trajectories, with the convention
 305 that 0 means that the trajectory is not at all acceptable (i.e., could lead to an
 306 accident), that rank 1 is the best rank, and that the same rank can be given to several
 307 trajectories if the expert is not able to distinguish them in terms of drivability. For
 308 example, in Table 6, for grid 200, trajectory τ_5 is declared unacceptable by the
 309 expert, and τ_3 is preferred to τ_2 , which is in turned preferred to τ_1 and τ_4 , without
 310 any preference between these two last trajectories. In image 209, τ_4 and τ_5 are
 311 unacceptable, τ_2 and τ_3 are equally preferred, and τ_1 is in the third position.

To apply our method, we convert the evidential grids (which we simply use as
 an estimation/learning tool) into imprecise probability grids in the following a way:
 each cell of a metagrid is characterized by an interval of probability $[p(x), \bar{p}(x)]$ such
 that:

$$\underline{p}(x) = m(\{x\}),$$

^cWe consider in this paper only normal bbas so that $m(\emptyset) = 0$ for any cell of the grid, so we can just treat them as our way to obtain probability bounds, without considering their potential semantic within evidence theory.

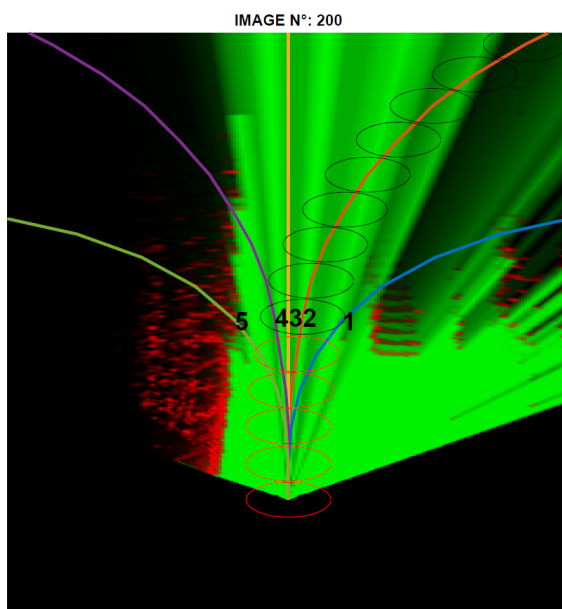


Fig. 5. A credal grid and five possible trajectories

Grid	τ_1	τ_2	τ_3	τ_4	τ_5
200	3	2	1	3	0
209	2	1	1	0	0

Table 6. Example of trajectory evaluation by an expert

and

$$\bar{p}(x) = m(\{x\}) + m(\{x, \neg x\}).$$

312

313 The decision is based on 12 metagrids per trajectory which corresponds in av-
 314 erage to what can be visually evaluated by the expert. As it is partly outside of
 315 what can be seen by the Lidar, the first metagrid is not taken into account in the
 316 decision process. We have fixed arbitrarily the values of the utility function to -5
 317 for the first four metagrids, and to values linearly spaced between 10 and 70 for the
 318 following ones.

319 As a baseline to compare our method, we also convert the evidential grids into
 320 binary grids and use them as follows:

321 (1) A cell is occupied if the middle of the interval $[\underline{p}(x); \bar{p}(x)]$ is greater than

322 0.5.

- 323 (2) A metagrid is free if none of the cells that make it up are occupied,
 324 (3) If the rank of the first occupied metagrid is less or equal to 4, then the
 325 trajectory is declared unacceptable.
 326 (4) The further away is the first metagrid occupied along a trajectory, the
 327 better is the trajectory.

328 The reason for choosing such a baseline is that it is very simple (hence easily usable
 329 by an autonomous car or any mobile robot), but retains very little of our initial, rich
 330 information. A key question is therefore to check that retaining such a rich (but
 331 computationally more demanding) information does bring some practical advan-
 332 tage. The methods are evaluated according to the two tasks performed during the
 333 decision: deciding if a trajectory is acceptable or not and ordering of the remaining
 334 trajectories. The methods are thus evaluated according to two different criteria.

For the first task, we use the traditional F_β measure which is defined by:

$$F_\beta = \frac{(1 + \beta^2)TP}{(1 + \beta^2)TP + \beta^2FN + FP},$$

335 where TP stands for the number of true positives, FN for false negatives and FP for
 336 false positives. In the task of recognizing acceptable trajectories, the false negative
 337 refer to acceptable trajectories which are wrongly classified as unacceptable, whereas
 338 the false positives refer to unacceptable trajectories which are wrongly declared as
 339 acceptable. The last error being much more serious and dangerous for a driver than
 340 the former, we use a value of $\beta = 0.5$ which penalizes more the false positives than
 341 the false negatives. Two possible rules have been explored in the experiments:

- 342 • Rule 1. trajectory τ_j is classified as acceptable if $\underline{\mathbb{E}}(\tau_j) > 0$;
 343 • Rule 2. trajectory τ_j is classified as acceptable if $\overline{\mathbb{E}}(\tau_j) > 0$.

344 For the second task, we need a criterion to judge the relevance of the trajec-
 345 tory ordering. As explained before, the order relations on the set of trajectories
 346 obtained using our method are either total preorders (orders 3 and 4) or partial
 347 orders (orders 1 and 2). On the other hand, the evaluations of the experts, express-
 348 ing their preference about the trajectories with possible indifference, lead to total
 349 preorders. **A first way to compare the results is to use** a general measure to evaluate
 350 the discrepancy between preorders, as partial or total orders are special cases of
 351 preorders. For this purpose, we use a distance measure between preorders proposed
 352 in ¹⁵. Let us use the following notations: $\tau_j \succ \tau_k$ denotes the fact that τ_j is strictly
 353 preferred to τ_k , $\tau_j \approx \tau_k$ that τ_j and τ_k are indifferent, and $\tau_j ? \tau_k$ means that τ_j and
 354 τ_k are incomparable. The distance between two preorders is defined as the sum of
 355 the distances between all pairs of trajectories, using the values indicated in Table
 356 7. These values have been arbitrarily chosen in a set of values respecting axiomatic
 357 and common sense rules.

358 **For Orders 3 and 4, and for the binary method, as they lead to total preorders,**
 359 **there is a second way of comparing the results: if indecision is not allowed, each**

	$\tau_j \approx \tau_k$	$\tau_j \succ \tau_k$	$\tau_j \sim \tau_k$	$\tau_k \succ \tau_j$
$\tau_j \approx \tau_k$	0	1	4/3	1
$\tau_j \succ \tau_k$	1	0	4/3	5/3
$\tau_j \sim \tau_k$	4/3	4/3	0	4/3
$\tau_k \succ \tau_j$	1	5/3	4/3	0

Table 7. Values of the distance between two preorders

360 method can be forced to select a best trajectory i.e. a trajectory which is ranked
 361 first (there may be multiple ones in case of indifference) in the preorder. We propose
 362 in this case to evaluate each method by an accuracy score computed as follows. Let
 363 $\hat{\tau}_i$ denote the prediction of a method. For each predicted trajectory, the individual
 364 accuracy is obtained as:

$$acc_i = \begin{cases} \frac{1}{r_i} & \text{if } \hat{\tau}_i \text{ is acceptable for the expert} \\ 0 & \text{else,} \end{cases}$$

365 where r_i denote the rank of $\hat{\tau}_i$ in the expert order. The total accuracy Acc is obtained
 366 as the mean of the individual accuracies.

367 It must be noticed that, in contrast with the IP method, the binary method
 368 often provides several trajectories equally ranked at the first place because the
 369 order depends only on the number of metagrids on the trajectories supposed to
 370 be free. In case of a tie, we propose thus two strategies: either to retain the best
 371 rank among the set of best trajectories (which gives clearly an advantage to the
 372 binary method) or to break the tie by randomly choosing a trajectory in the best
 373 trajectories, which seems fairer for the comparison, as in principle we do not have
 374 access to the expert “ground truth”.

375 Results are presented in Table 8,9, and 10. In Table 8 is presented the value of
 376 F_β averaged on the 40 images for the two rules and the binary approach. We can see
 377 that the best score for F_β is achieved using Rule 2. This rule consists in eliminating
 378 trajectories for which the utility is for sure less than zero. This confirms that using
 379 negative utilities for the first metagrids is a useful feature, as it is an efficient filter.
 380 Note that results of our method and the binary one are not very different. As future
 381 works, we could try to optimize/change utilities so that they provide optimal F_β
 382 on a training set, yet this would significantly increase the method complexity, with
 383 an unclear benefit.

384 Much more differences are found in the second task. Table 9 presents the results
 385 obtained for the ordering task (after using Rule 2 for selecting the acceptable trajec-
 386 tories). It gives the average distance between the expert orders and the automatic
 387 orders. It can be seen that, for both experts, the order obtained using Order 4 leads
 388 to a smallest distance with respect to the expert order and that it outperforms the

389 simple binary method. Interestingly, this indicates that once the undesirable (unac-
 390 ceptable) trajectories have been removed from the possible choices, the optimistic
 391 behaviour seems to be in very good accordance with the observed expert behaviours.
 392 Order 1 seem to be too conservative, as could be reasonably expected, while orders
 393 2 and 3 end up in similar distances. It should however be emphasized that we are
 394 systematically comparing all orders to total preorders, meaning that it is hard, from
 395 our experimental setting, to assess the utility of the incomparabilities induced by
 396 orders 1 and 2, in particular the refine an imprecise selection. Exploring this aspect
 397 is the matter of future methodological and experimental work, for example to allow
 398 experts to express such incomparabilities.

399 In Table 10, we compare the results of the task consisting in choosing only one
 400 trajectory. We report three results for the simple binary method: the maximum ac-
 401 curacy which corresponds to breaking ties in choosing systematically the trajectory
 402 associated to the best result (the one ranked highest by the expert), the minimum
 403 accuracy which corresponds to choosing systematically the worst result and, finally,
 404 a random guess among the possible best trajectories. Without surprise, the results
 405 of the binary method in which the maximum accuracy is retained gives the best
 406 results but it may be seen that Order 4 outperforms the random guess and pro-
 407 vides results which are close to maximum accuracy. Another thing is that the span
 408 between the minimum and maximum accuracies can be quite large, thus indicating
 409 that a refined modelling of uncertainty may be helpful ot better discriminate the
 410 trajectories.

Expert	F_β (rule 1)	F_β (rule 2)	F_β (binary)
1	0,8934	0,9118	0,9034
2	0,8768	0,9460	0,9429

Table 8. Classification unacceptable/acceptable: average F_β for the three methods

Expert	Order 1	Order 2	Order 3	Order 4	Binary
1	9,7	6,31	6,85	2,81	6,84
2	9,86	6,4	6,2	3,61	7,32

Table 9. Ordering results: mean distance between the expert and the proposed order

Expert	Order 3	Order 4	Binary (min)	Binary (random)	Binary (max)
1	0,6995	0.9125	0,5372	0.7855	0.9251
2	0,6663	0,8792	0,4422	0,6446	0,9625

Table 10. **Best trajectory results: accuracy of the methods**

411 5. Conclusion

412 In this article, we have introduced the notion of credal occupancy grids, that to
413 the best of our knowledge was never studied before. The advantage of such grids is
414 their flexibility in terms of uncertainty modelling, as well as their consistency with
415 traditional probabilistic models, that they extend. To show how such grids could
416 be used in practice, we have proposed a model to make cautious inferences for
417 robot trajectory planning from uncertain information provided in the form of such
418 credal occupancy grids. The proposed model allows one to accurately represent
419 the available information while controlling the computational complexity by the
420 use of particular events of the decision space. In particular, the proposed method is
421 relatively simple and makes very clear assumptions about the uncertainty modelling
422 and reasoning parts, as well as about the decision process. This has in our opinion
423 two key advantages: it makes the whole method more acceptable and explainable to
424 third parties, and it is easy to revisit, question, or modify the different components
425 of the method.

426 We have illustrated the behaviour of the proposed approach using simple ex-
427 amples, and have tested it using real data, in the context of autonomous vehicles,
428 comparing it favourably with a simple baseline approach. These first results indeed
429 show that the approach is interesting thanks to a greater flexibility in the decision
430 process. To completely validate the approach, a greater number of experts and a
431 larger number of grids and situations in the experimental part would be needed.
432 Future research could include also the automatic learning of the utility function
433 and the integration of other criteria in the decision process like the similarity to a
434 reference trajectory.

435 We also plan to augment the expressivity of the method, for example by bet-
436 ter differentiating cell occupancy information, distinguishing between completely
437 usable cells, not-fully usable cells (e.g. for vehicles, side-walks, emergency lines)
438 and completely unusable cells (with obstacles). Such distinctions could be impor-
439 tant elements to deal with complex situations possibly leading to accidents, but
440 would increase the method complexity. Another important avenue of research is
441 how dependence information could be embedded in the inferences. Indeed, so far
442 we have considered the cells and their uncertainty model to be independent, which
443 is an acceptable simplifying assumption in first approximation, but is not true in
444 general.

445 Finally, while we considered here the problem of making real-time inferences
446 on a pre-selected number of trajectories by using DNF Boolean formulas, it would
447 be interesting to investigate other ways to handle either the planning problem or
448 to obtain the normal forms of the formulas, that could prove useful in those cases
449 where computational time should remain acceptable but is not constrained by real-
450 time and by physical constraints induced by velocity and limiting the number of
451 trajectories one could consider (e.g., slow moving robots in risky environments). For
452 instance, one could consider finding an arbitrary optimal sequence of cells as a tra-
453 jectory from point A to point B , taking inspiration from recent works on inferences
454 in HMM⁸ or from works extending PODMP¹⁴ to the imprecise framework. Con-
455 cerning Boolean formulas, we mainly used DNF formulas and mentioned BDDs as
456 another way to obtain compact representations of Boolean functions, but it would
457 interesting to make a general exploration of the interplay between different ways of
458 compiling semantically equivalent Boolean formulas⁷ and their corresponding com-
459 putational complexity, notably those compilations that have an efficient imprecise
460 counterpart such as the recent Sentential Decision Diagrams¹⁸.

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