ROS offers a message passing interface that provides inter-process communication.

A ROS system is composed of nodes, which pass messages, usually in two forms:

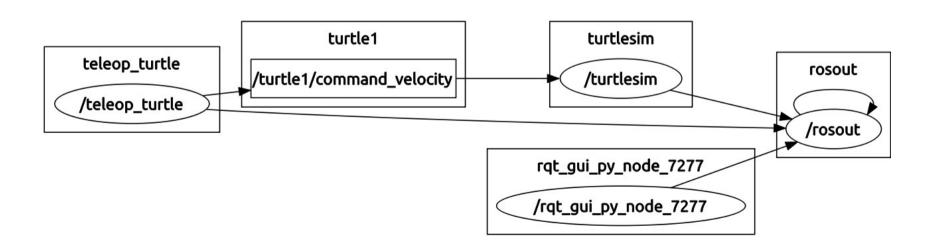
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The actionlib package standardizes the interface for pre-emptable tasks. For example:

- navigation,
- performing a laser scan
- detecting the handle of a door...

Aside from numerous tools, Actionlib provides standard messages for sending task:

- goals
- feedback
- result

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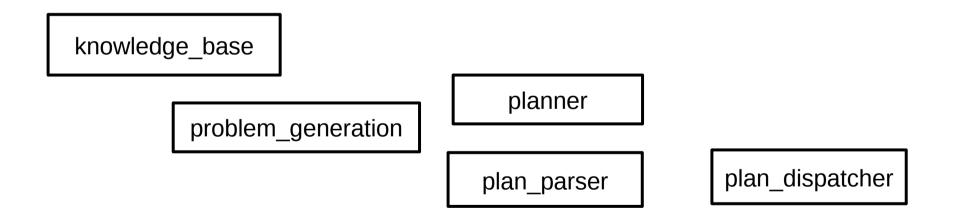
move_base/MoveBaseGoal

```
geometry_msgs/PoseStamped target_pose
std_msgs/Header header
uint32 seq
time stamp
string frame_id
geometry_msgs/Pose pose
geometry_msgs/Point position
float64 x
float64 y
float64 z
geometry_msgs/Quaternion orientation
float64 x
float64 x
float64 y
float64 y
float64 y
float64 y
float64 z
```

ROSPlan Basics

The ROSPlan package provides a standard interface for PDDL planners in ROS.

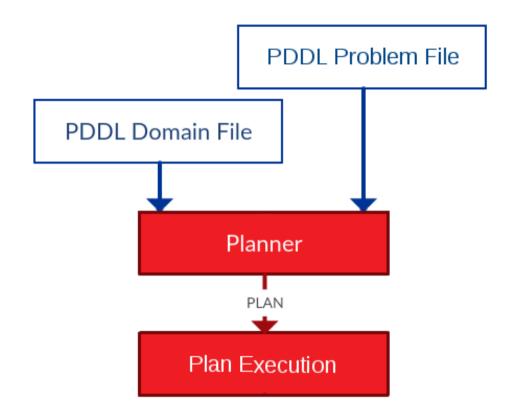
The purpose of the ROSPlan package is to integrate planners within a ROS system without having to write an architecture from scratch.



Plan Execution 1: Very simple Dispatch

The most basic structure.

- The plan is generated.
- The plan is executed.



Plan Execution 1: Very simple Dispatch

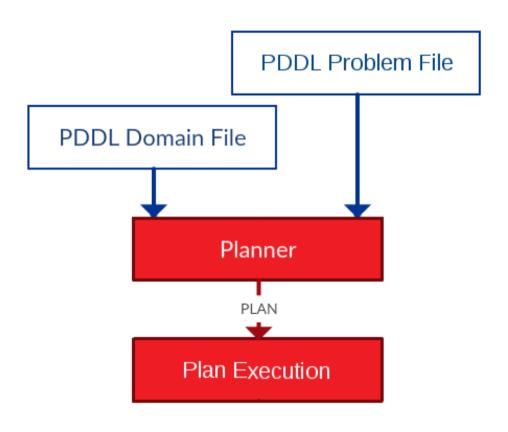
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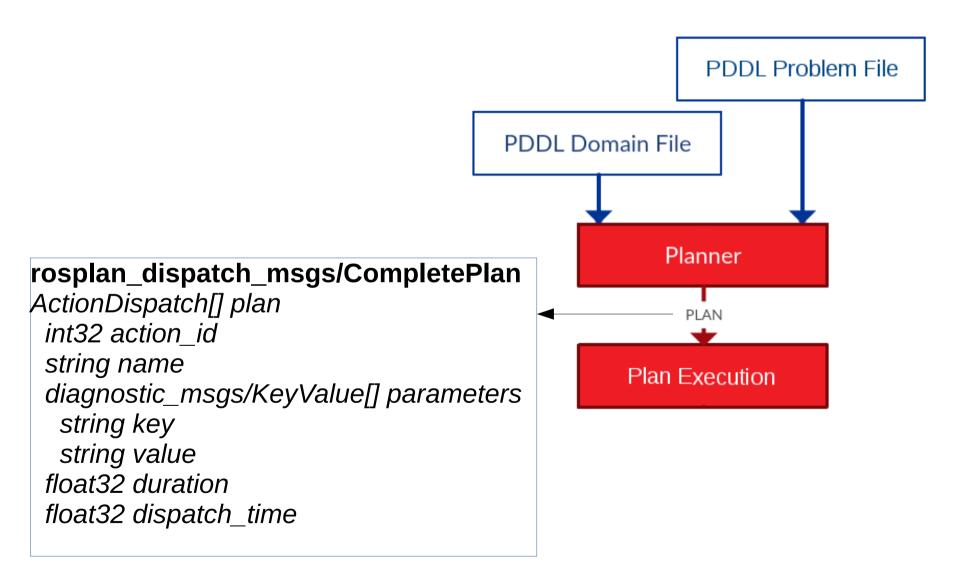
The red boxes are included in ROSPlan. They correspond to ROS nodes.

The domain and problem file can be supplied

- in launch parameters
- as ROS service parameters

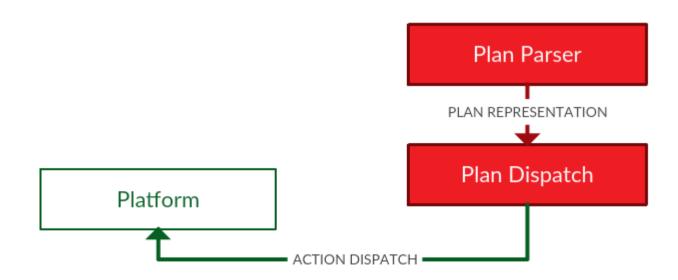


Plan Execution 1: Very simple Dispatch



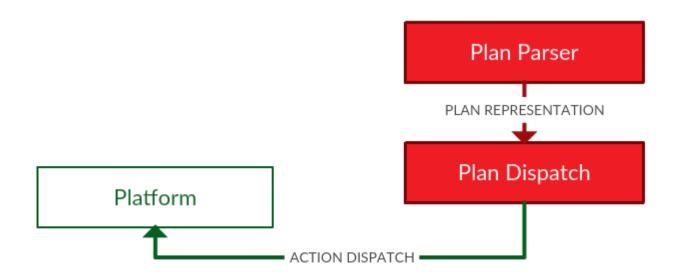
How does the "Plan Execution" ROS node work? There are multiple variants:

- simple sequential execution
- timed execution
- Petri-Net plans
- Conditional Contingent Temporal Constraint Network.
- etc.



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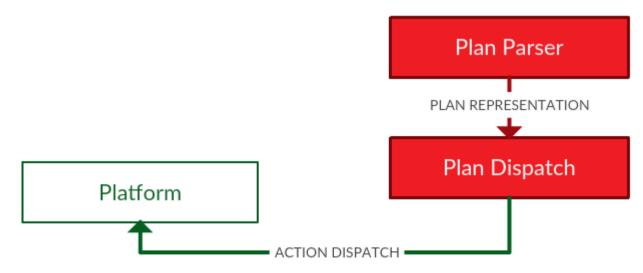
- simple sequential execution
- 1. Take the next action from the plan.
- 2. Send the action to control.
- 3. Wait for the action to complete.
- 4. GOTO 1.



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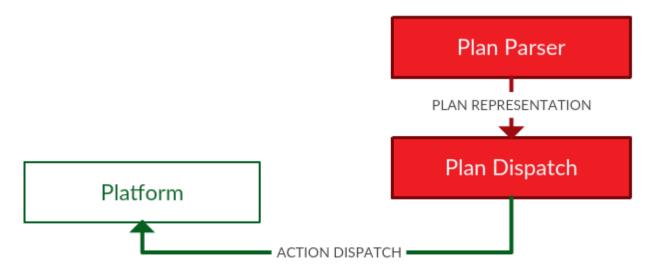
An action in the plan is stored as a ROS message *ActionDispatch*, which corresponds to a PDDL action.



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The *ActionDispatch* message is received by a listening interface node, and becomes a goal for control.



How does the "Plan Execution" ROS node work? There are multiple variants:

- simple sequential execution

```
1. Take the next action from the plan.
```

- 2. Send the action to control.
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- 4. GOTO 1.

```
10.01: (observe ip3)
                                            [5.000]
        15.02: (grasp_object box4)
                                            [60.000]
      ActionDispatch
       action id = 0
       name = goto waypoint
       diagnostic msgs/KeyValue[] parameters
        kev = "wp"
        value = "wp0"
       duration = 10.000
       dispatch time = 0.000
                                 Plan Dispatch
Platform
                 ACTION DISPATCH
```

0.000: (goto_waypoint wp0)

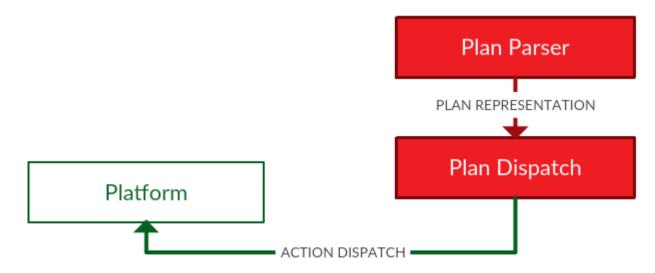
[10.000]

```
move_base/MoveBaseGoal
geometry_msgs/PoseStamped
target_pose
std_msgs/Header header
...
geometry_msgs/Pose pose
geometry_msgs/Point position
float64 x
float64 y
float64 z
geometry_msgs/Quaternion orientation
...
```

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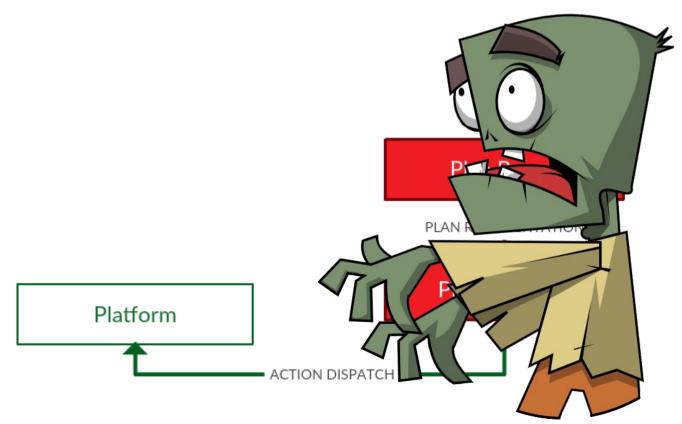
Feedback is returned to the simple dispatcher (action success or failure) through a ROS message *ActionFeedback*.



Plan Execution Failure

This form of simple dispatch has some problems. The robot often exhibits zombie-like behaviour in one of two ways:

- 1. An action fails, and the recovery is handled by control.
- 2. The plan fails, but the robot doesn't notice.



Bad behaviour 1: Action Failure

An action might never terminate. For example:

- a navigation action that cannot find a path to its goal.
- a grasp action that allows retries.

At some point the robot must give up.

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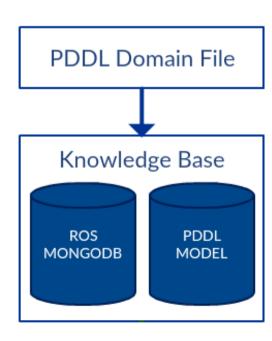
At some point the robot must give up.

If we desire persistent autonomy, then the robot must be able to plan again, from the new current state, without human intervention.

The problem file must be regenerated.

To generate the problem file automatically, the agent must store a model of the world.

In ROSPlan, a PDDL model is stored in a ROS node called the Knowledge Base.



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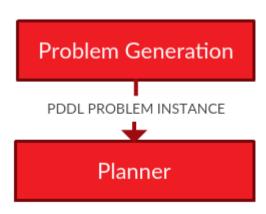
rosplan_knowledge_msgs/KnowledgeItem uint8 INSTANCE=0 uint8 FACT=1 PDDL Domain File uint8 FUNCTION=2 uint8 knowledge_type string instance type string instance_name Knowledge Base string attribute_name diagnostic_msgs/KeyValue[] values ROS **PDDL** string key MONGODB MODEL string value float64 function value bool is_negative

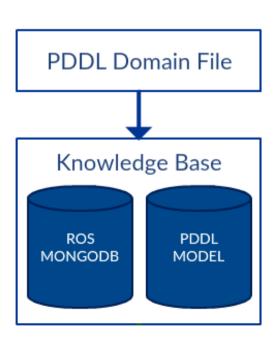
To generate the problem file automatically, the agent must store a model of the world.

In ROSPlan, a PDDL model is stored in a ROS node called the Knowledge Base.

From this the initial state of a new planning problem can be created.

ROSPlan contains a node which will generate a problem file for the ROSPlan planning node.

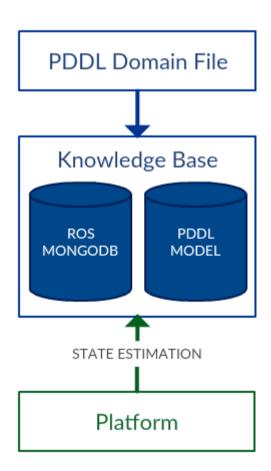




The model must be continuously updated from sensor data.

For example a new ROS node:

- 1. subscribes to odometry data.
- 2. compares odometry to waypoints from the PDDL model.
- 3. adjusts the predicate (robot_at ?r ?wp) in the Knowledge Base.



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PDDL Domain File

nav_msgs/Odometry

std_msgs/Header header string child_frame_id geometry_msgs/PoseWithCovariance pose geometry_msgs/Pose pose geometry_msgs/Point position geometry_msgs/Quaternion orientation float64[36] covariance geometry_msgs/TwistWithCovariance twist geometry_msgs/Twist twist geometry_msgs/Vector3 linear geometry_msgs/Vector3 angular float64[36] covariance

rosplan_knowledge_msgs/KnowledgeItem uint8 INSTANCE=0

uint8 FACT=1
 uint8 FUNCTION=2
 uint8 knowledge_type
 string instance_type
 string instance_name
 string attribute_name
 diagnostic_msgs/KeyValue[] values
 string key
 string value
 float64 function_value
 bool is negative

What happens when the actions succeed, but the plan fails?

This can't always be detected by lower level control.



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PLAN COMPLETE

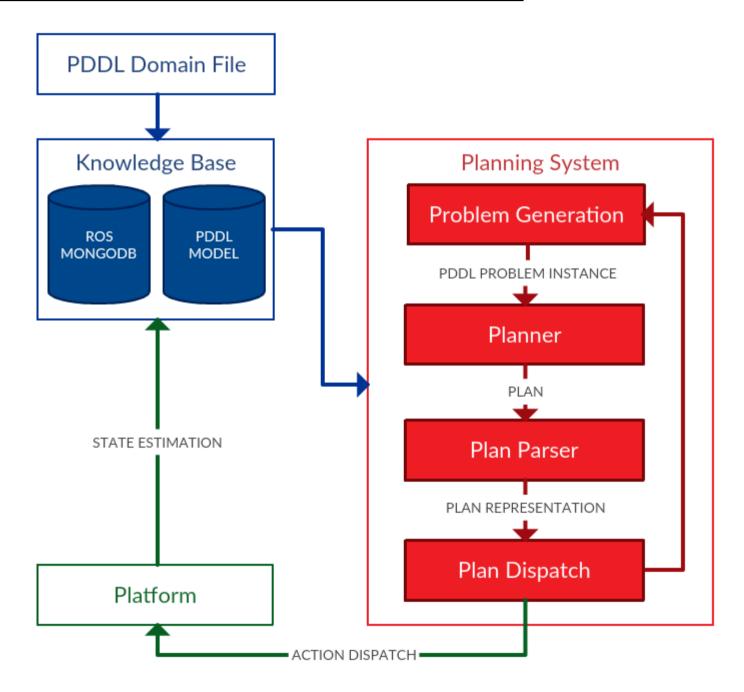


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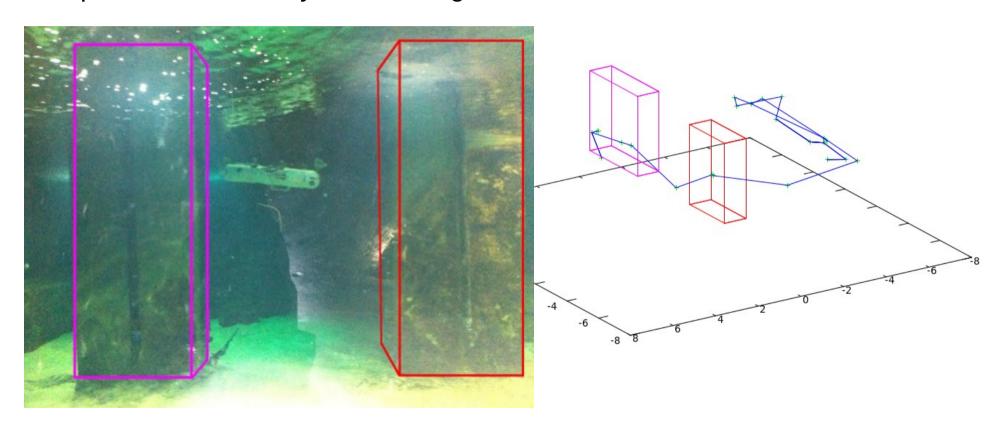




The AUV plans for inspection missions, recording images of pipes and welds.

It navigates through a probabilistic roadmap. The environment is uncertain, and the roadmap might not be correct.

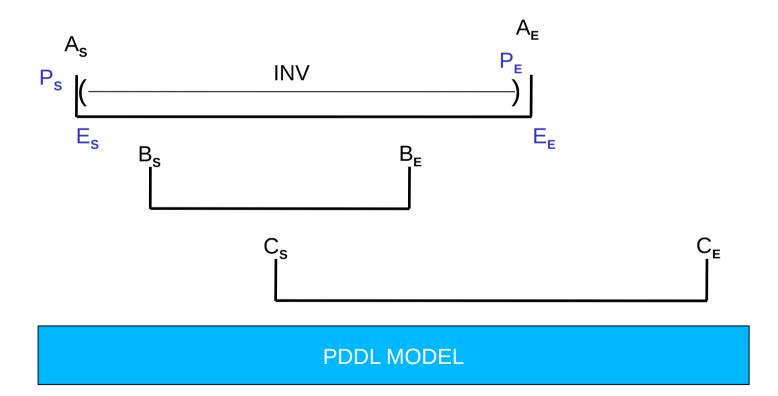
The plan is continuously validated against the model.



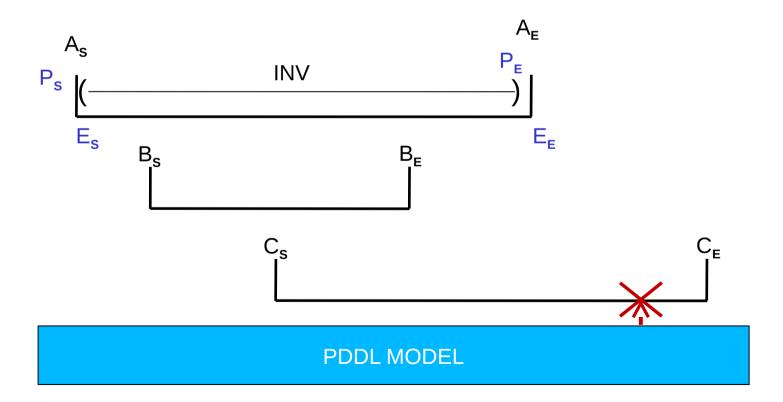
The planned inspection path is shown on the right. The AUV will move around to the other side of the pillars before inspecting the pipes on their facing sides.

After spotting an obstruction between the pillars, the AUV should re-plan early.

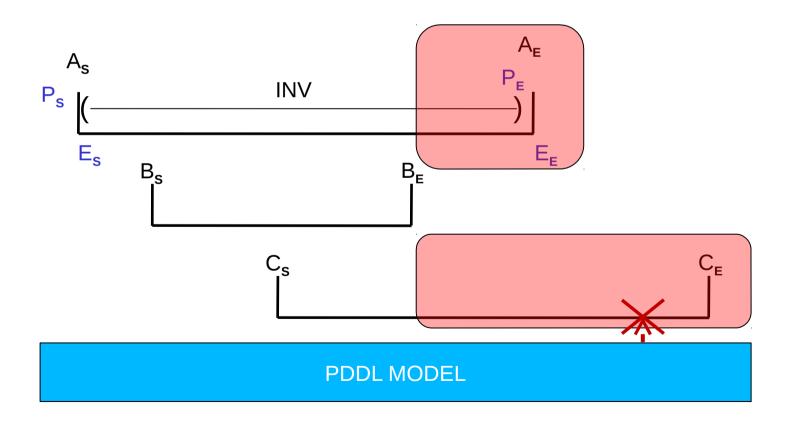
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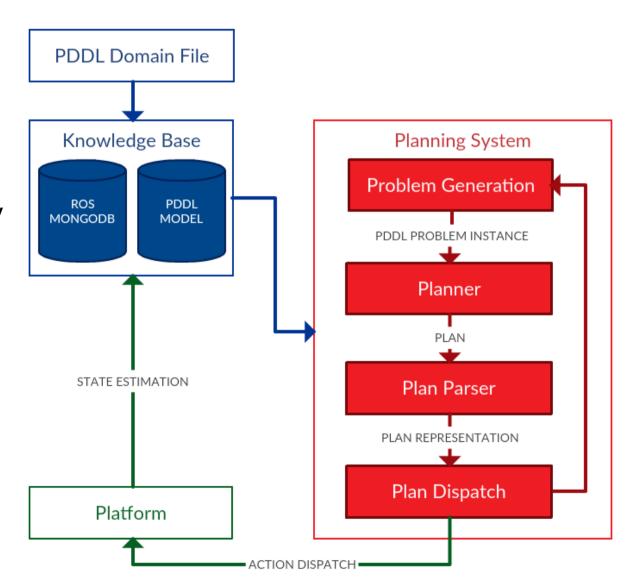
ROSPlan validates using VAL. [Fox et al. 2005]



ROSPlan: Default Configuration

Now the system is more complex:

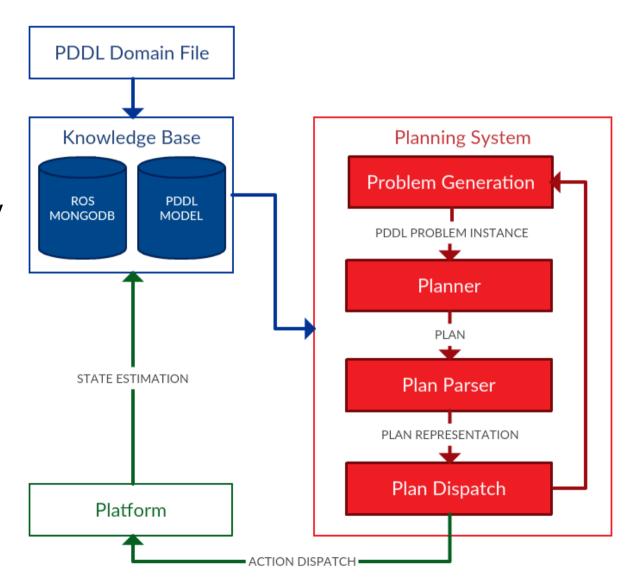
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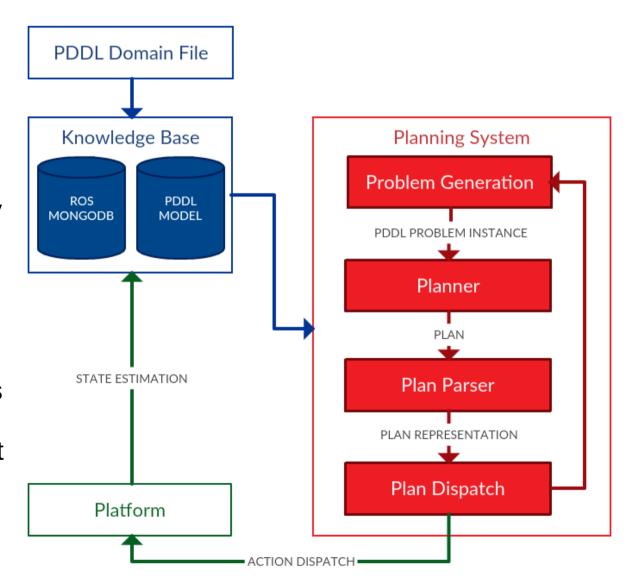
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ROSPlan: Default Configuration

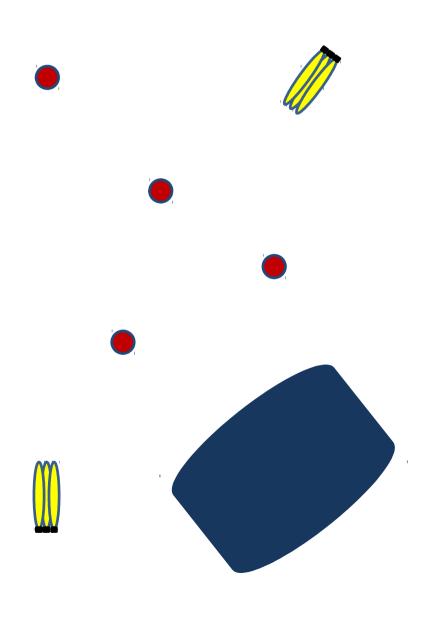
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- PDDL model is continuously updated from sensor data.
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- feedback on action success and failure.
- the plan is validated against the current model.



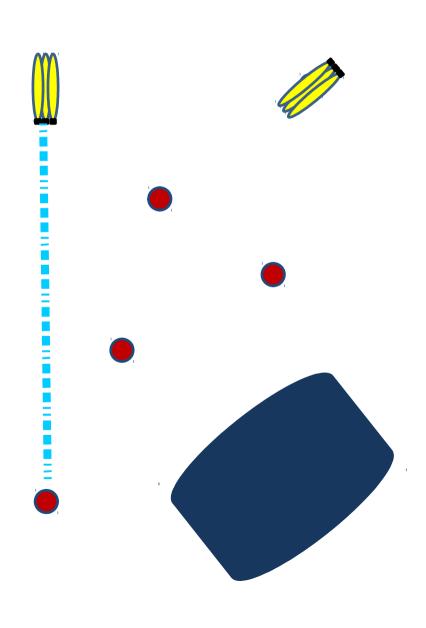
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- battery power and consumption,
- direction of sea current, or traffic flow.



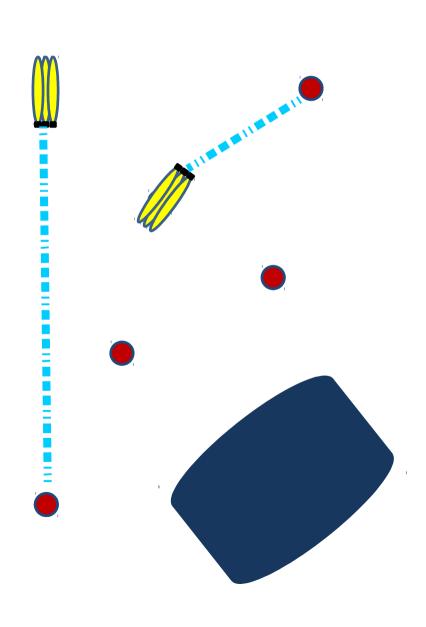
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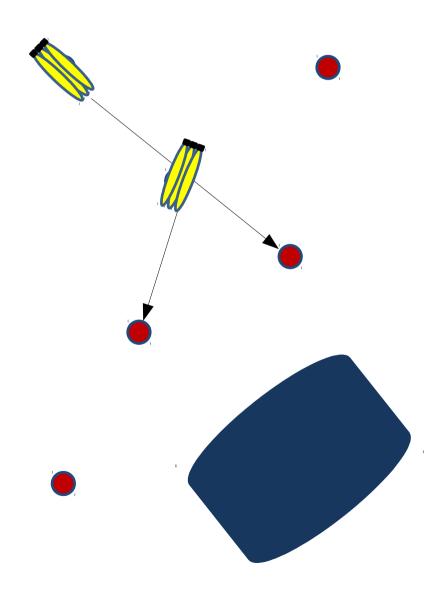
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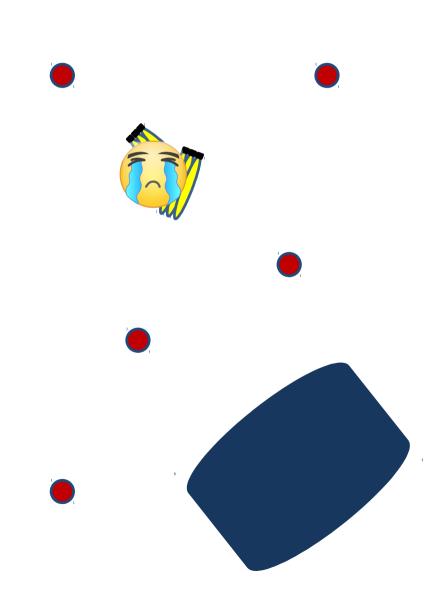


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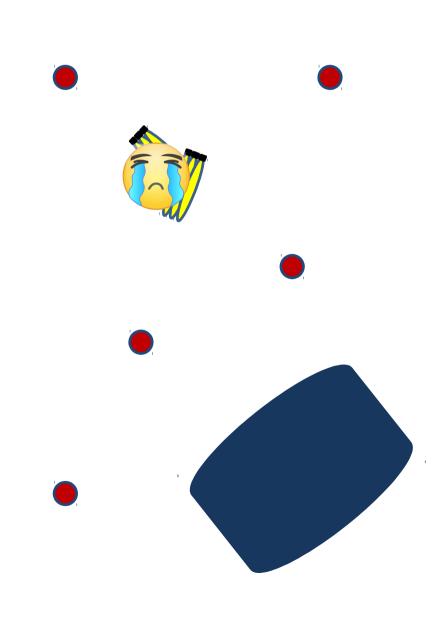
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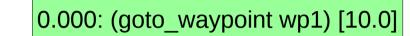
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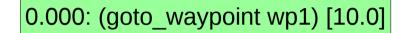


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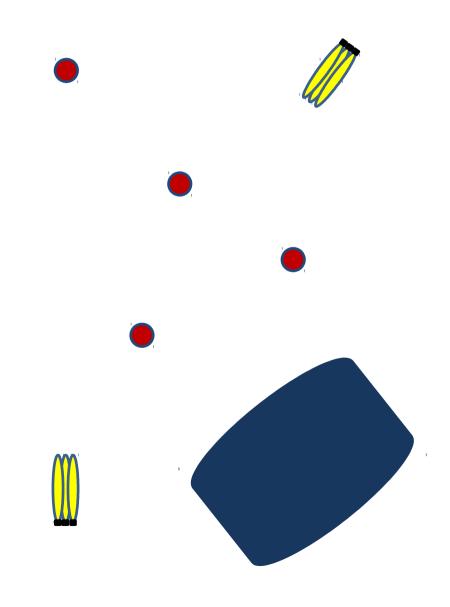
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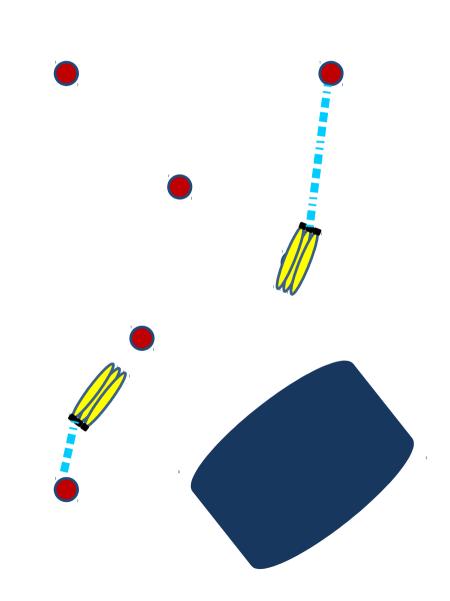
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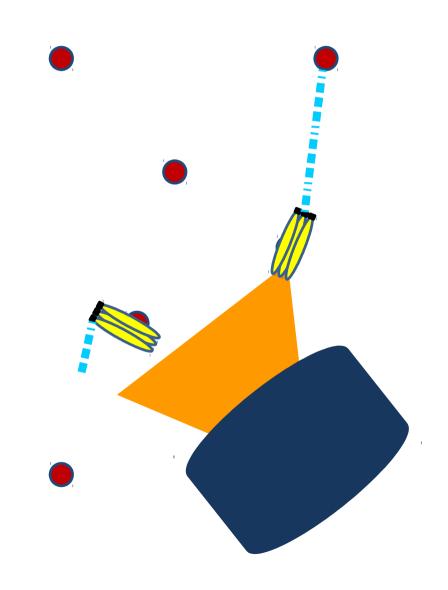
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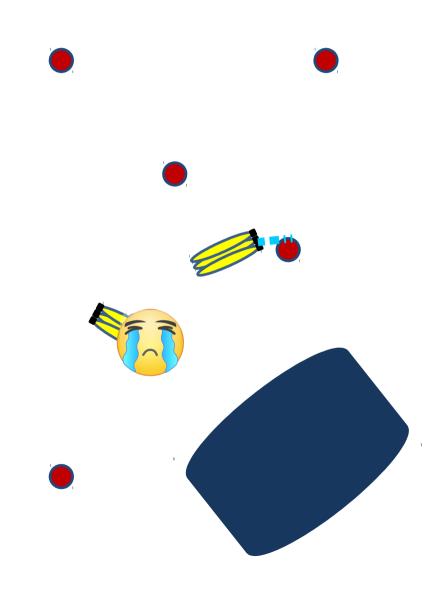
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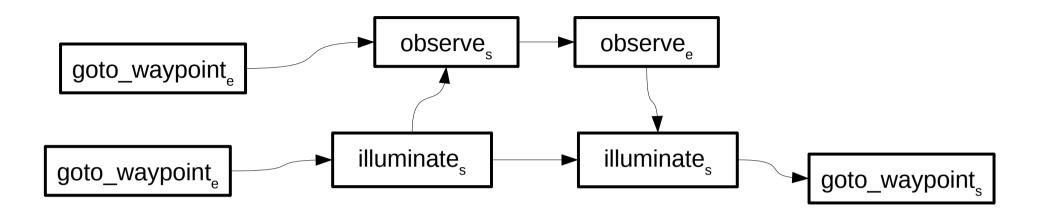


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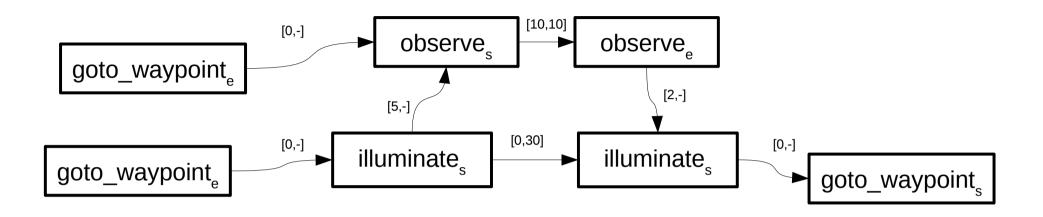




The temporal plan in which every action and duration can be controlled could be represented as a Simple Temporal Network.

The real upper and lower bounds, and ordering constraints on actions can be represented explicitly.

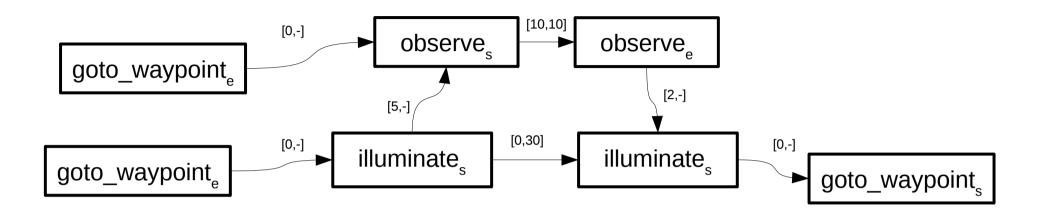
With this representation, the system is able to dispatch actions at times to maintain the consistency of the STN.



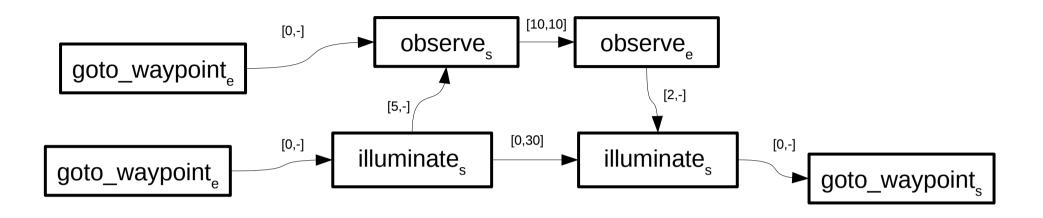
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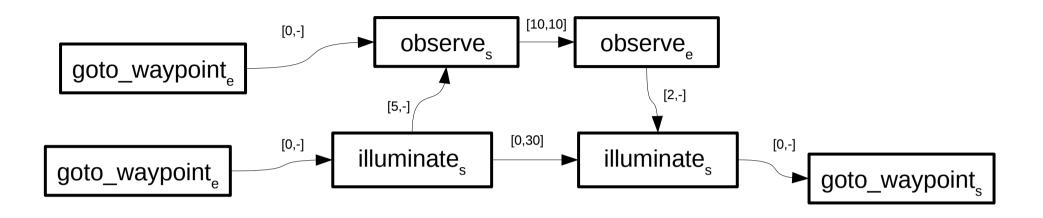


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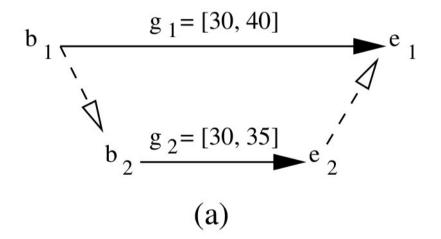
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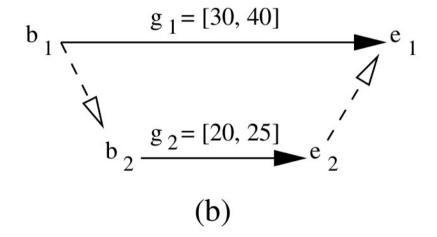
The Simple Temporal Problem under Uncertainty (STPU) described by a TPN might be strongly, weakly, or dynamically controllable. [Ciamatti, Micheli et al. 2016]

STPUs: Strong controllability

An STPU is strongly controllable iff:

- the agent can commit to a time for all activated time-points,
- such that for any possible time for received time points,
- the temporal constraints are not violated.

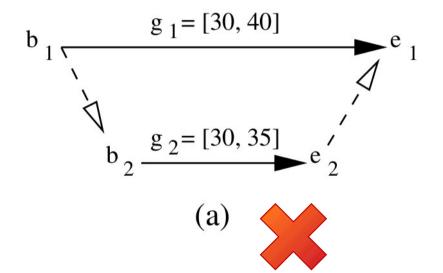


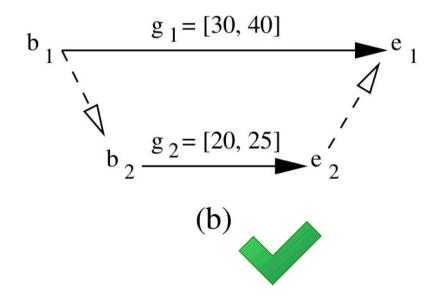


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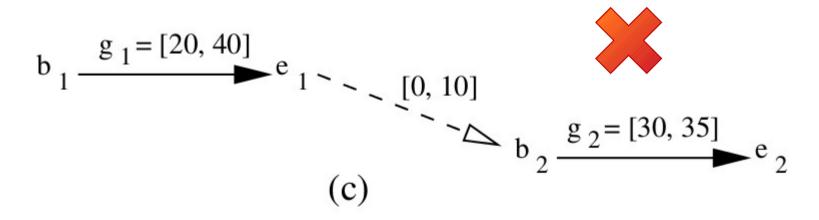


Setting t(b1) == t(b2) will always obey the temporal constraints.

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The STPU is not strongly controllable, but it is obviously executable. We need dynamic controllability.

STPUs: Dynamic controllability

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In this case, the agent does not have to commit to a time for any activated time points in advance.

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$$b_{1} \xrightarrow{g_{1} = [20, 40]} e_{1} - [0, 10]$$

$$b_{2} \xrightarrow{g_{2} = [30, 35]} e_{2}$$
(c)

STPUs: Dynamic controllability

Not all problems will have solutions which have any kind of controllability. This does not mean they are impossible.

To reason about these kinds of issues we need to use a plan representation sufficient to capture the controllable and uncontrollable durations, causal orderings, and temporal constraints.

$$b_{1} \xrightarrow{g_{1} = [20, 40]} e_{1} - [0, 10]$$

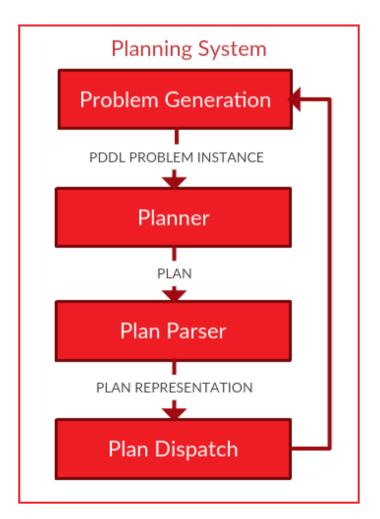
$$b_{2} \xrightarrow{g_{2} = [30, 35]} e_{2}$$
(c)

Plan dispatch in ROSPlan

To reason about these kinds of issues we need to use a plan representation sufficient to capture the controllable and uncontrollable durations, causal orderings, and temporal constraints.

The representation of a plan is coupled with the choice of dispatcher.

The problem generation and planner are not necessarily bound by the choice of representation.



Plan Execution 3: Conditional Dispatch

Uncertainty and lack of knowledge is a huge part of AI Planning for Robotics.

- Actions might fail or succeed.
- The effects of an action can be non-deterministic.
- The environment is dynamic and changing.
- The environment is often initially full of unknowns.

The domain model is *always* incomplete as well as inaccurate.



- The environment is dynamic and changing.
- The environment is often initially full of unknowns.

- Fully-Observable Non-deterministic planning.
- Partially-observable
 Markov decision
 Process.
- Conditional
 Planning with
 Contingent Planners.
 (e.g. ROSPlan with
 Contingent-FF)



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- Partially-observable
 Markov decision
 Process.
- Conditional
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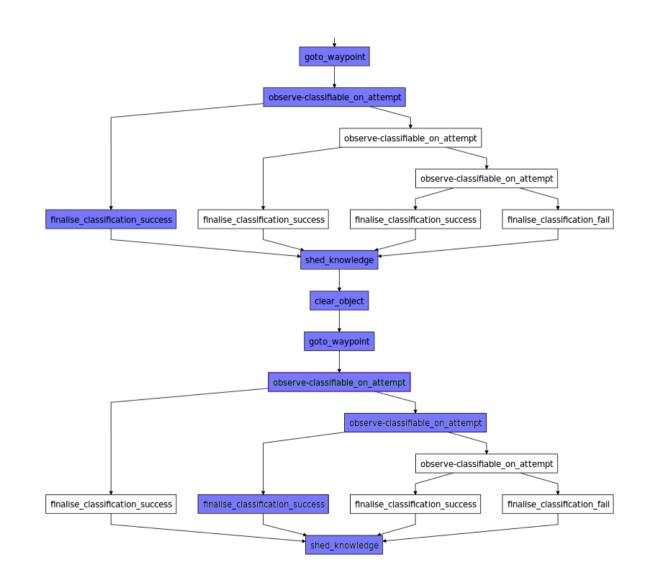
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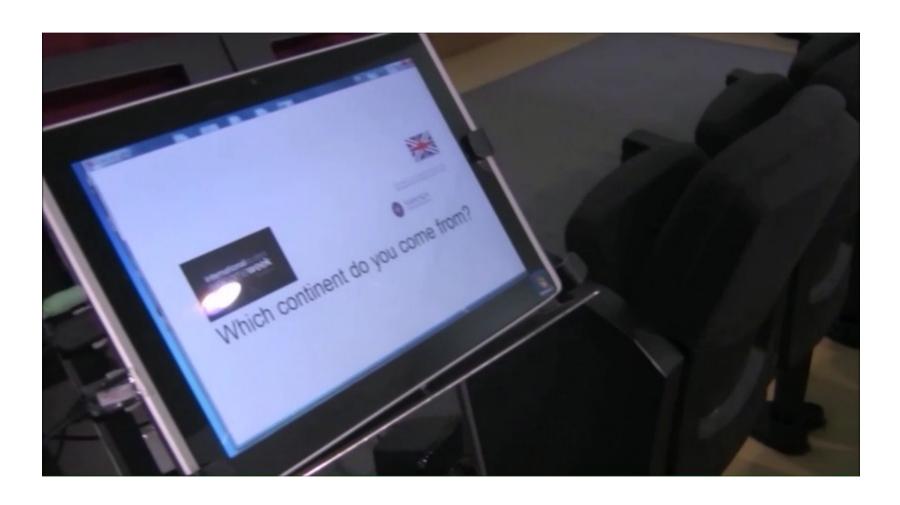
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Human Robot Interaction is filled with uncertainties.



Plan Execution 4: Temporal and Conditional Dispatch together

Robotics domains require a combination of temporal and conditional reasoning. Combining these two kinds of uncertainty can result in very complex structures.

There are plan formalisms designed to describe these, e.g.:

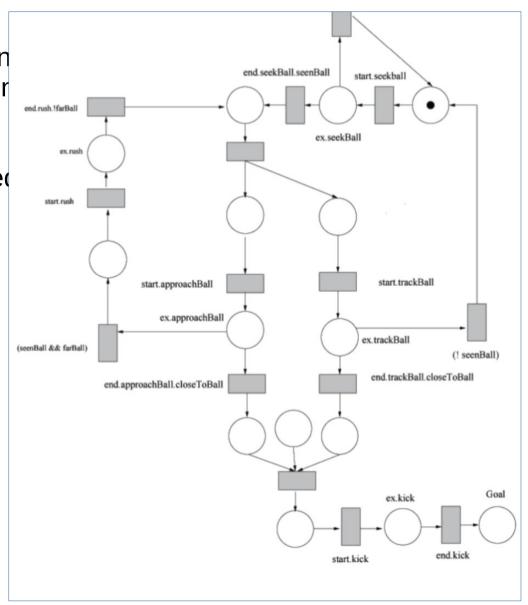
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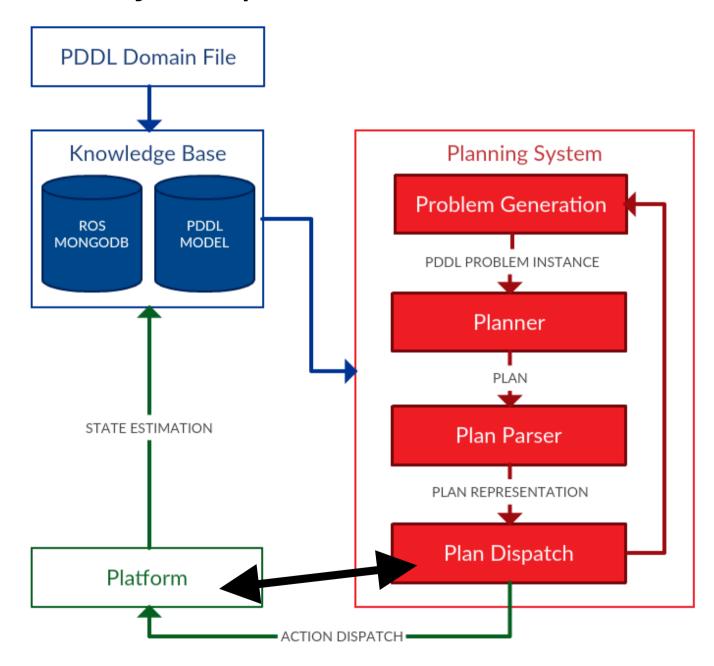
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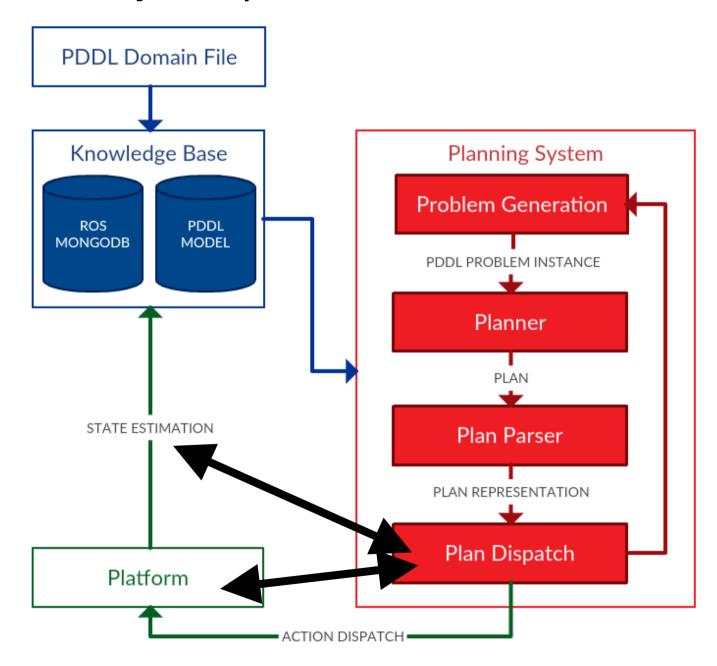
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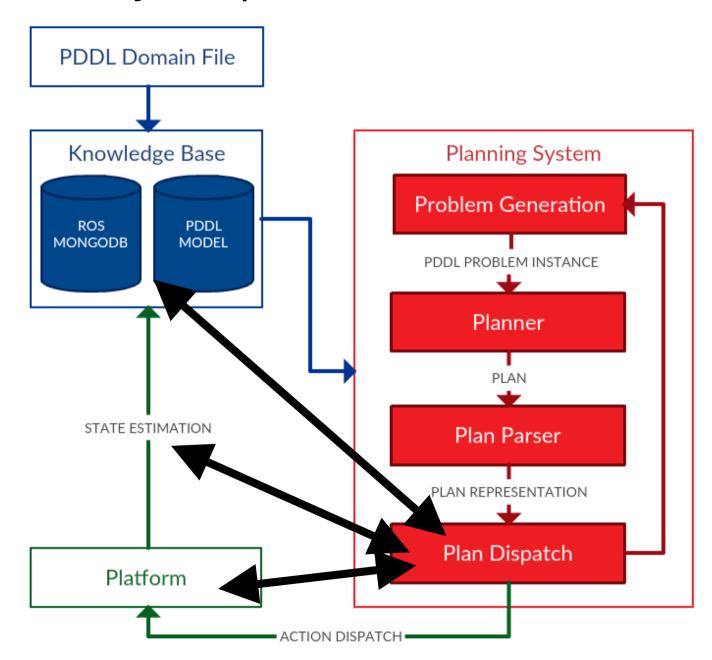
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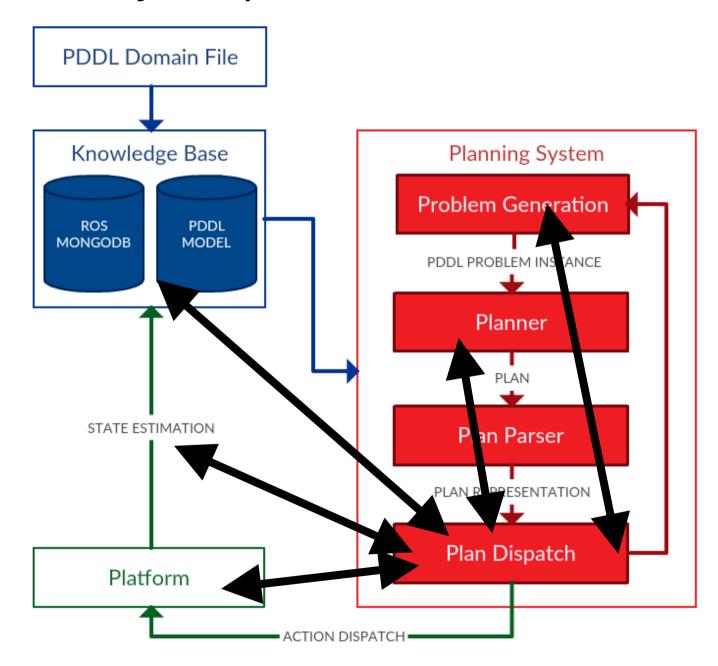
- GOLOG plans. [Claßen et al., 2012]
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ROSPlan is integrated with the PNPRos library for the representation and execution of Petri-Net plans. [Sanelli et al. 2017]



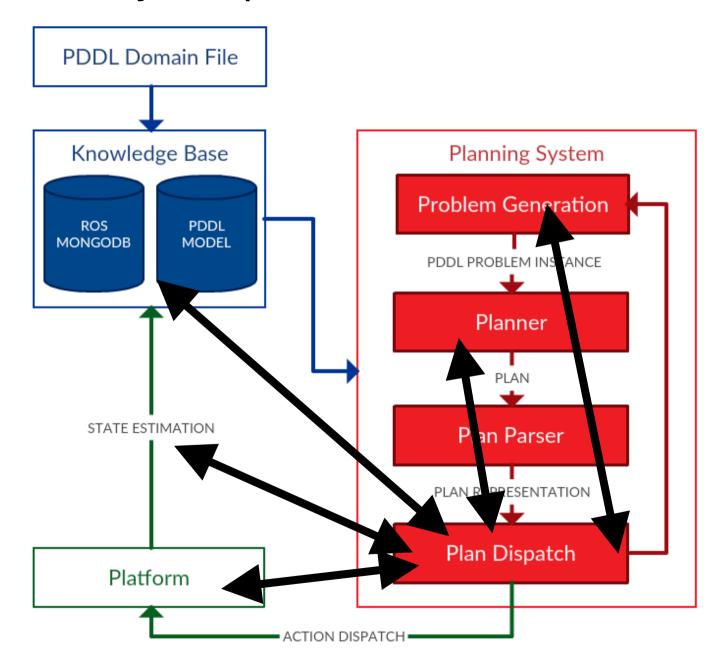






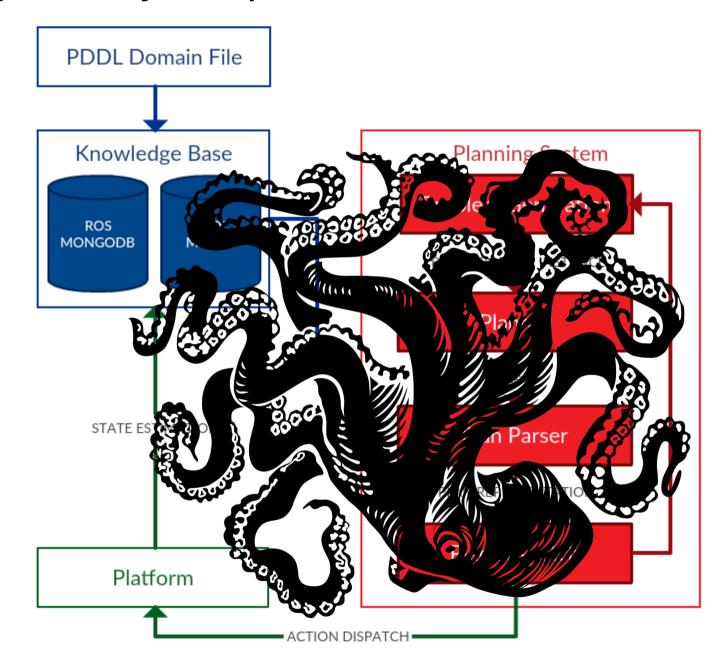
Plan Execution depends upon many components in the system. Changing any one of which will change the robot behaviour, and change the criteria under which the plan will succeed or fail.

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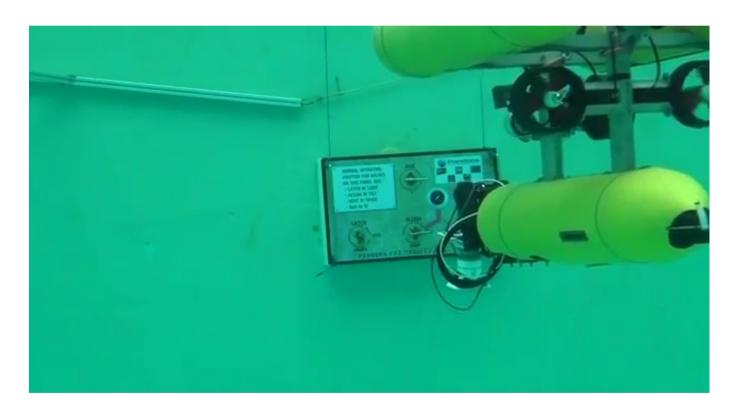
The behaviour of a robot should not be restricted to only one plan.

In a persistently autonomous system, the domain model, the planning process, and the plan are frequently revisited.

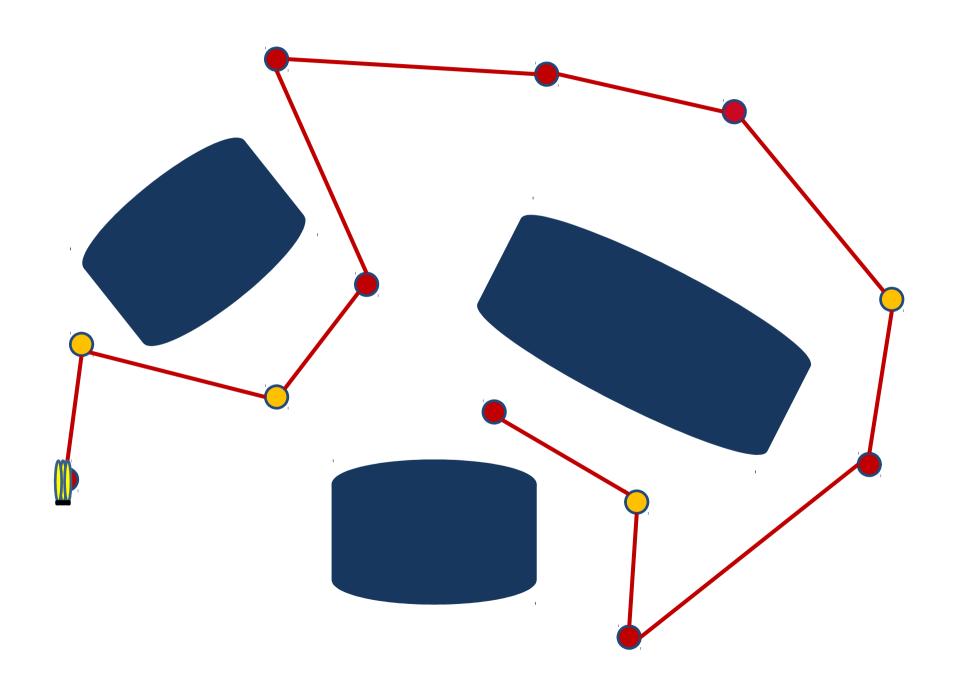
There is no "waterfall" sequence of boxes.

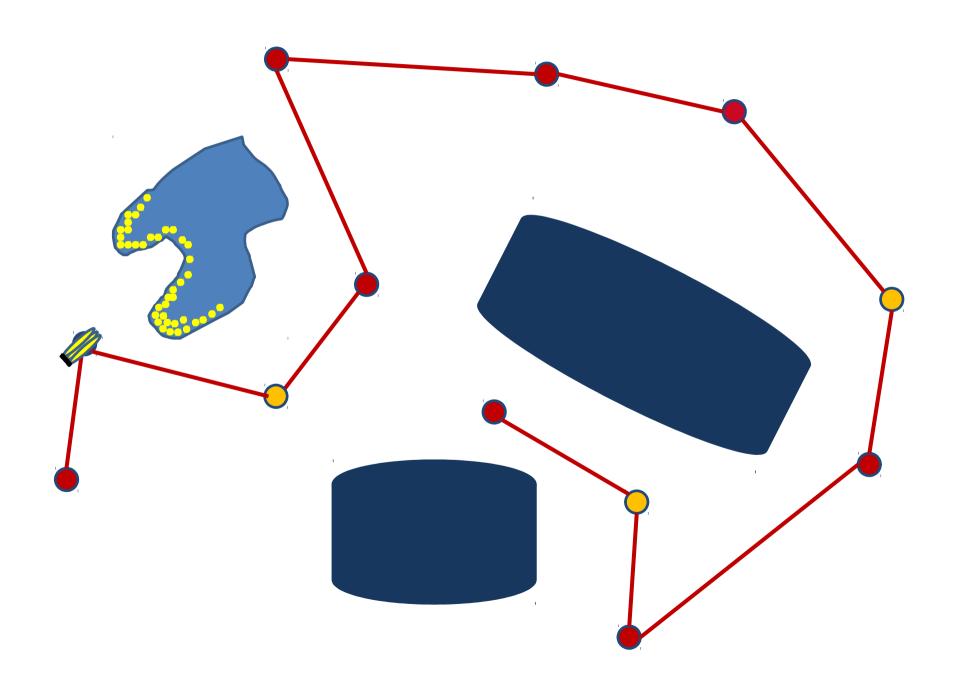
Example of multiple plans: What about unknowns in the environment?

One very common and simple scenario with robots is planning a search scenario. For tracking targets, tidying household objects, or interacting with people.

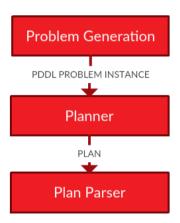


How do you plan from future situations that you can't predict?

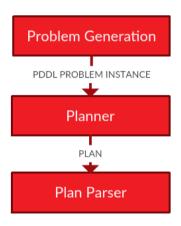


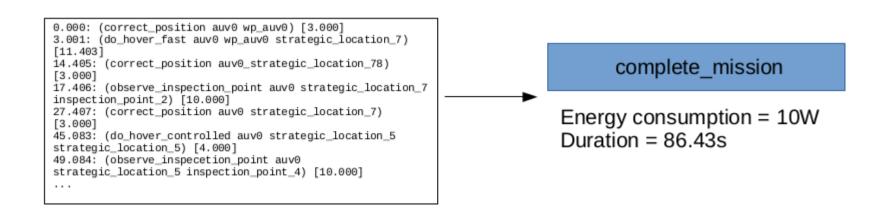


For each task we generate a tactical plan.

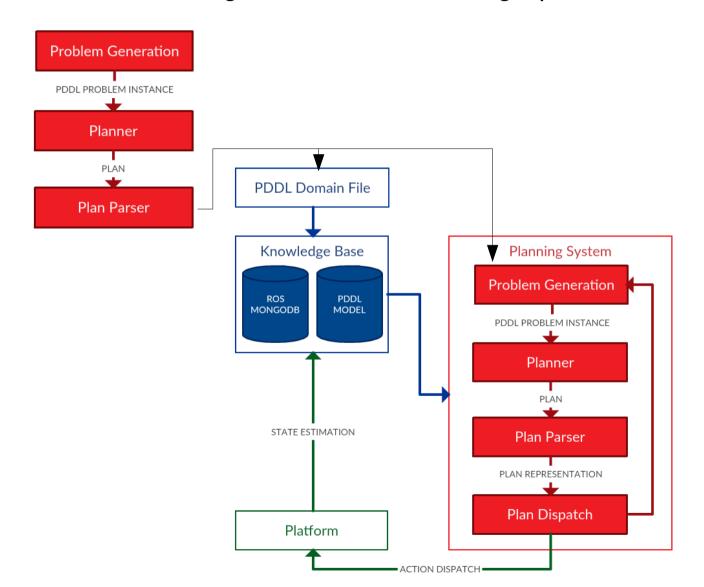


For each task we generate a *tactical plan*. The time and resource constraints are used in the generation of the strategic problem.

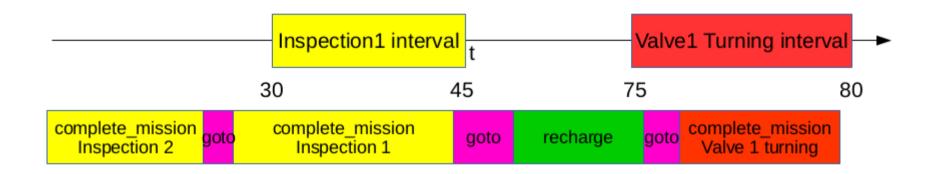




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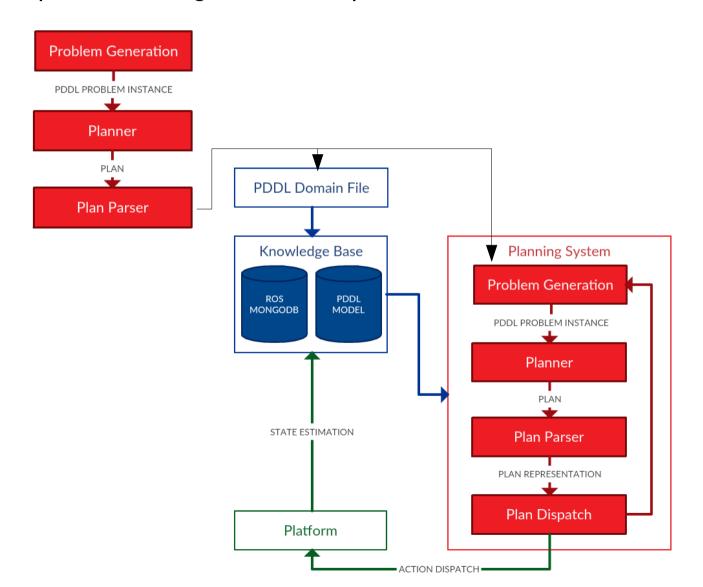


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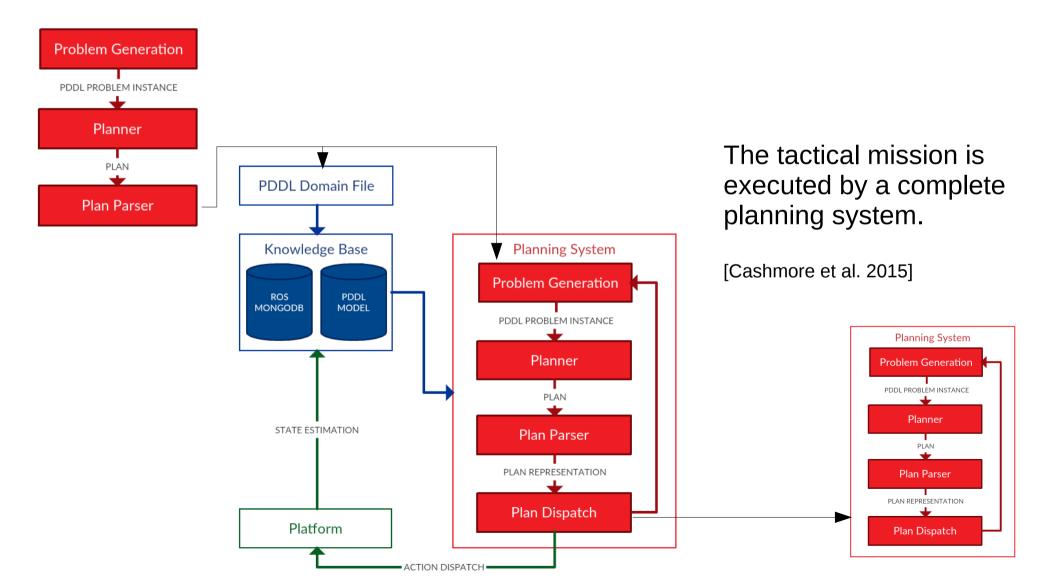


A strategic plan is generated that does not violate the time and resource constraints of the whole mission.

When an abstract "complete_mission" action is dispatched, the tactical problem is regenerated, replanned, and executed.



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There might also be unknowns that we don't expect to discover.

For example, new opportunities are found during execution, and the robot should exploit them.

High Impact Low-Probability Events (HILPs)

- the probability distribution is unknown
- cannot be anticipated
- our example is chain following

If you see an unexpected chain, it's a good idea to investigate...

| 2011 Banπ | 5 of 10 lines parted. |
|--------------------|--|
| 2011 Volve | 2 of 9 lines parted |
| 2011 Gryphon Alpha | 4 of 10 lines parted, vessel drifted a |
| | distance, riser broken |

3 lines parted between 2008 and 2010. 2010 Jubarte 2009 Nan Hai Fa Xian

4 of 8 lines parted; vessel drifted a

distance, riser broken

2009 Hai Yang Shi You Entire yoke mooring column

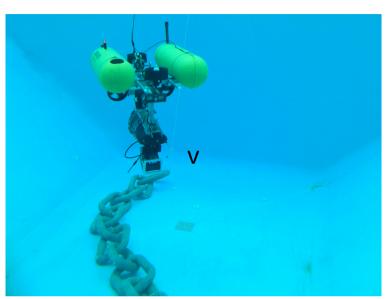
collapsed; vessel adrift, riser broken.

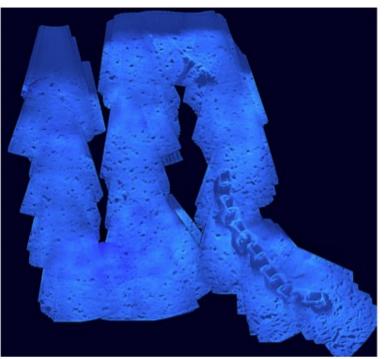
2006 Liuhua (N.H.S.L.) 7 of 10 lines parted; vessel drifted a

distance, riser broken.

3 (+2) of 9 lines parted, no damage to 2002 Girassol buoy

offloading lines (2 later)

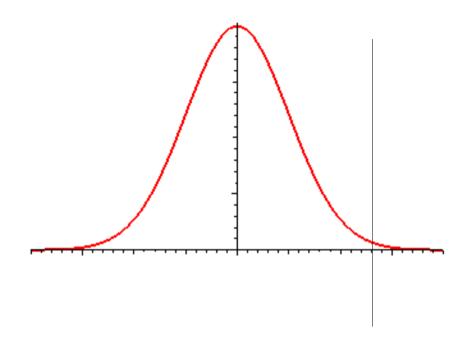




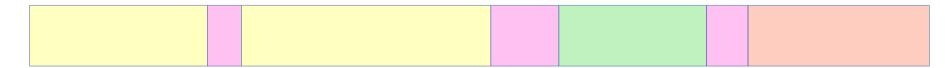
In PANDORA we planned and executed missions over long-term horizons (days or weeks)

Our planning strategy was based on the assumption that actions have durations normally distributed around the mean.

To build a robust plan we therefore used estimated durations for the actions that were 95th percentile of the normal distribution.



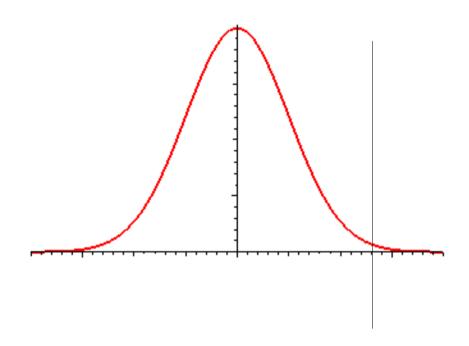
The resulting overestimation of actions builds a free time window



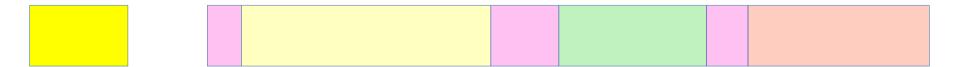
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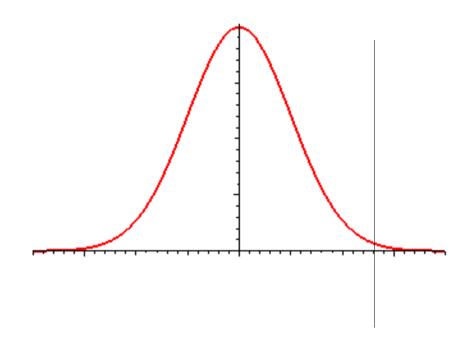
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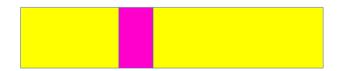
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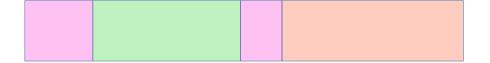
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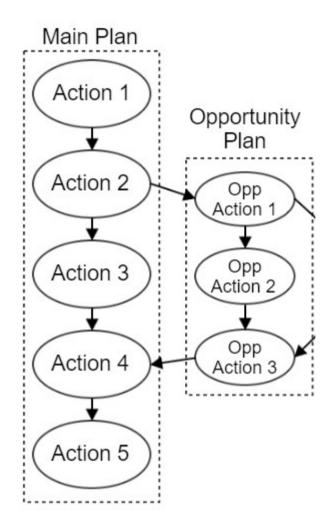
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New plans are generated for the opportunistic goals and the goal of returning to the tail of the current plan.

If the new plan fits inside the free time window, then it is immediately executed.



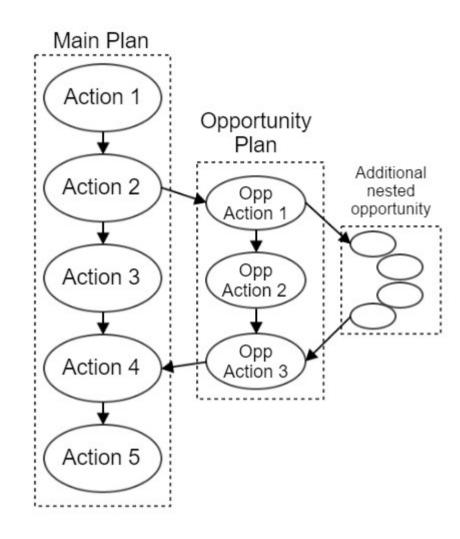
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The approach is recursive

If an opportunity is spotted during the execution of a plan fragment, then the currently executing plan can be pushed onto the stack and a new plan can be executed.

[Cashmore et al. 2015]

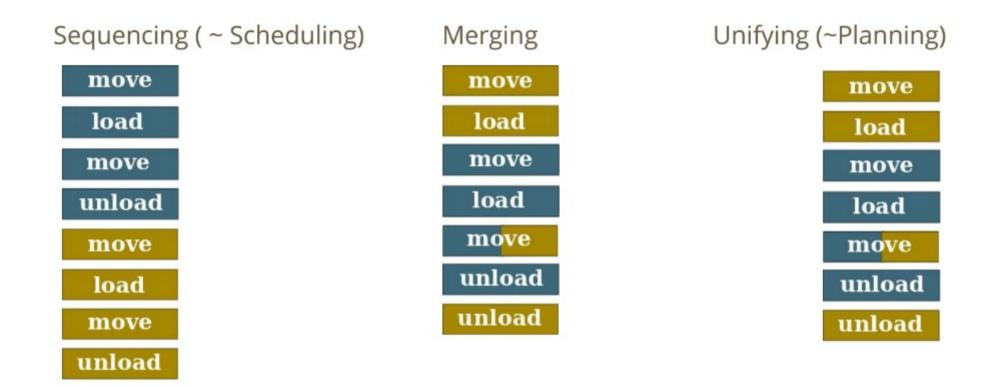


Dispatching Plans at the same time



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Plans can be merged in a more intelligent way. A single action can support the advancement towards multiple goals. [Mudrova et al. 2016]

Questions?

What is the glue in a Plan Execution framework that is *always* required?

How do we modify a domain model during execution?

Which parts of a domain model are transferable to other tasks?

Which parts of a domain model can be generated automatically

- From a description of the robot?
- From a source ontology?

How can we get rid of the planning expert?

- Can a description of a task be written by a non-expert, and a generic domain extended?