

Autonomous Unmanned Vehicles for Disaster Response

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Introduction

In this work, we investigate solutions to problems that require multiple robotic platforms to act together, in a coordinated fashion, to make best use of their combined resources. To achieve this, we adopt a practical multidisciplinary approach, in which multiagent planning and coordination algorithms will be developed and deployed on real robotic platforms, including fixed-wing and quadrotor Unmanned Aerial Vehicles (UAVs). These platforms will operate under the principle of flexible autonomy, in which robotic platforms will operate in a fully autonomous manner when appropriate, while still being guided by human involvement when key operating decisions need to be made.

Active Sensing

- UAVs provide an invaluable mobile sensing platform for gathering information about the situation on the ground.

- Active Sensing attempts to maximise information gain, by deciding on-line what observations to make next given what we've already seen.

Example Scenario: find missing person using camera-equipped UAV

- Vision Accuracy Affected by
 - Person/UAV Pose
 - Clutter/Clothing
 - Correlated Observations
 - Images of overlapping positions

Solution:

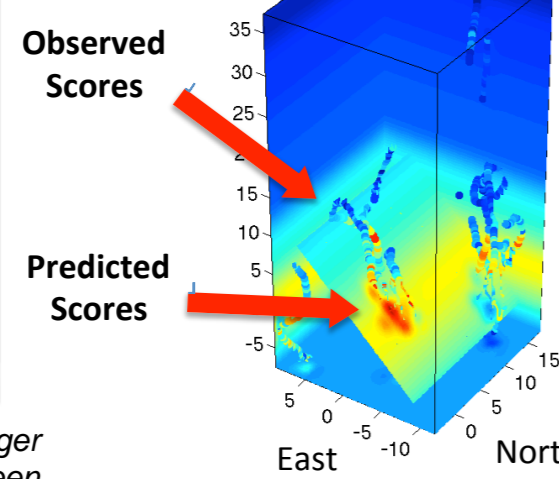
- Non-Parametric Bayesian Model of vision accuracy
- Model uncertainty based on vision classifier score, and correlations between scores over space/time.
- Choose where to look next to maximise information gain given previous observations
 - e.g. fly low to take closer look at possible target.



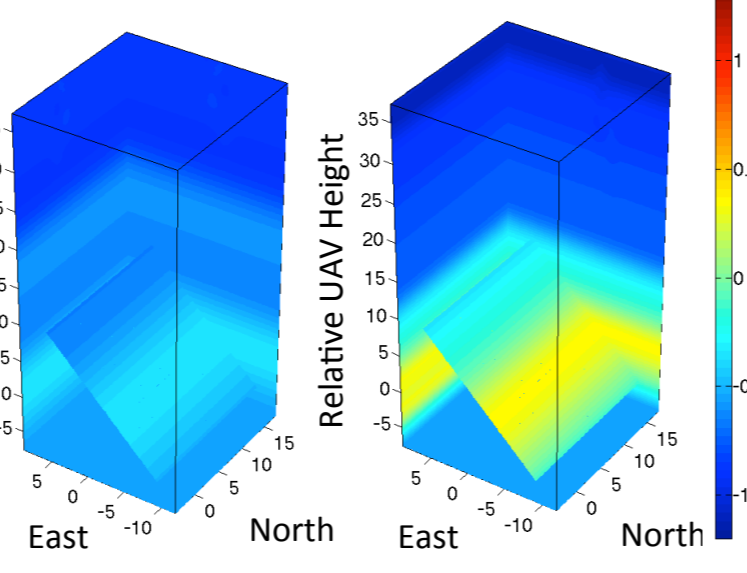
Observation Model



Possible targets viewed at altitude trigger closer inspection to discriminate between targets and clutter.



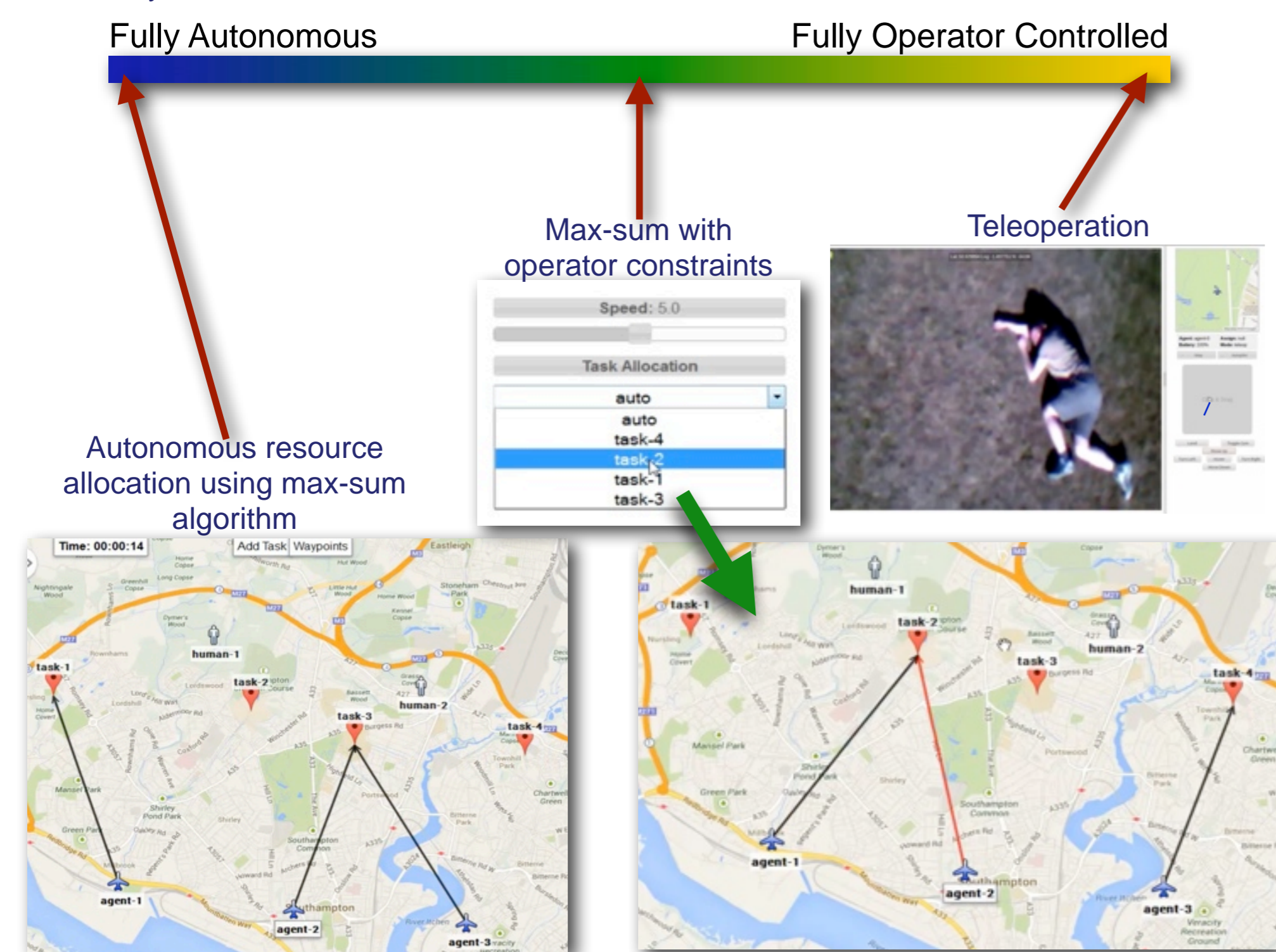
Mean Class Conditional Scores



Flexible Autonomy

To enable efficient use of resources, different levels of UAV autonomy may be appropriate at different times.

- In some circumstances, it may be appropriate for a first responder to focus on high-level goals and task definition, by delegating resource allocation decisions to the UAVs.
- However, ultimate control must remain with the first responders, by allowing them to view and modify plans proposed by the UAVs, and take full manual control (teleoperation) when appropriate.
- To support these different modes of operation, we have developed a GUI that enables first responders to both delegate control to UAVs, modify plans, and take full control when necessary.

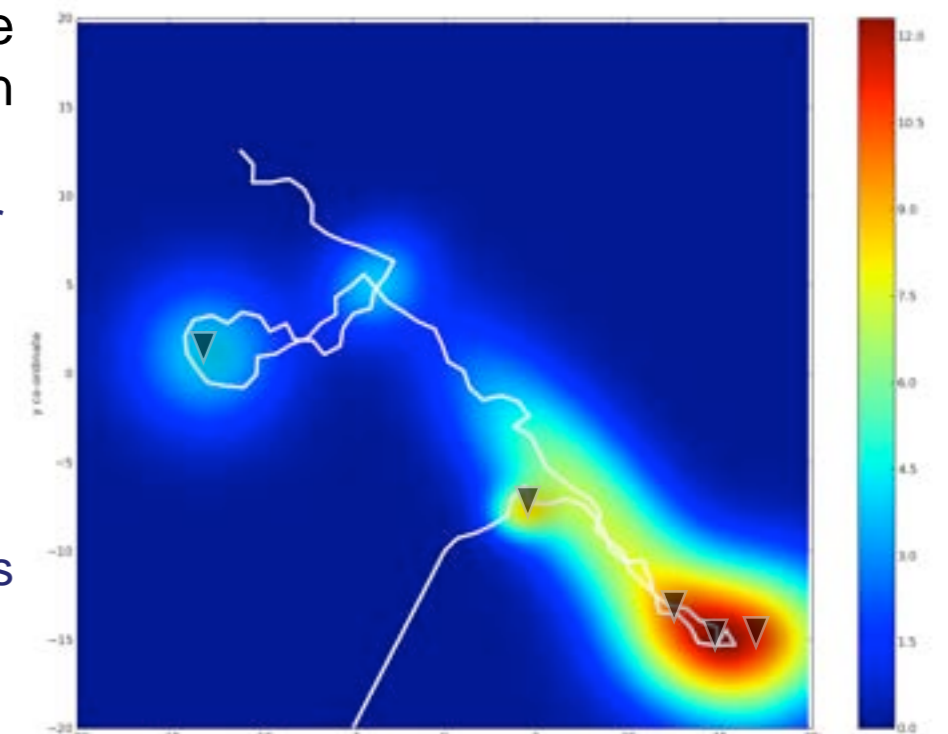


Co-ordination

Currently, there are no existing complete systems that combine detailed exploration and examination of a disaster area by UAVs.

Gathering information about incidents in a disaster area requires:

- Exploration** to discover incidents or locations that require further investigation
 - Requires fast, high-altitude UAV
- Location attendance** to provide detailed information (i.e. imagery) about possible incidents or locations of interest
 - Requires UAV capable of hovering over positions at low-altitude

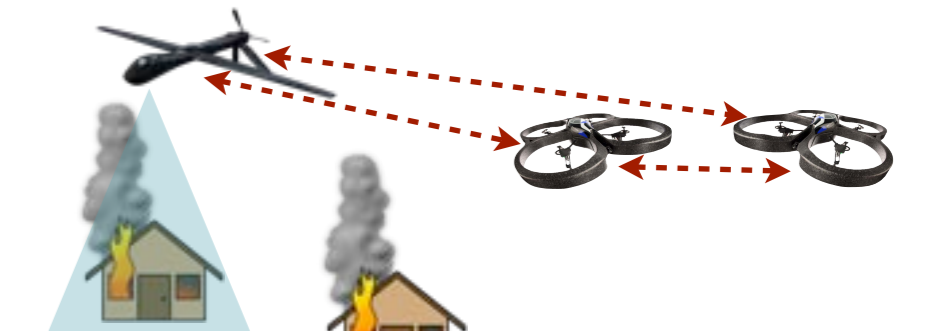


Example belief map (red for more likely belief) with exploratory path in white, and predictive positioning for low-level UAVs shown as black triangles.

Assume availability of a belief map based on ground reports of possible incidents.

Our first approach:

- Calculates goal positions for low-altitude UAVs (via simulated annealing) using belief map to place them near likely incident locations
- Uses a modified Rapidly-exploring Random Tree (RRT) to plan informative exploratory paths for a high-altitude UAV to traverse the disaster area and confirm the presence of incidents



Tasks created by high-level explorer. Task allocation is decentralised.

- Uses a max-sum task allocation algorithm to assign low-altitude UAVs to confirmed incidents.

Our second approach:

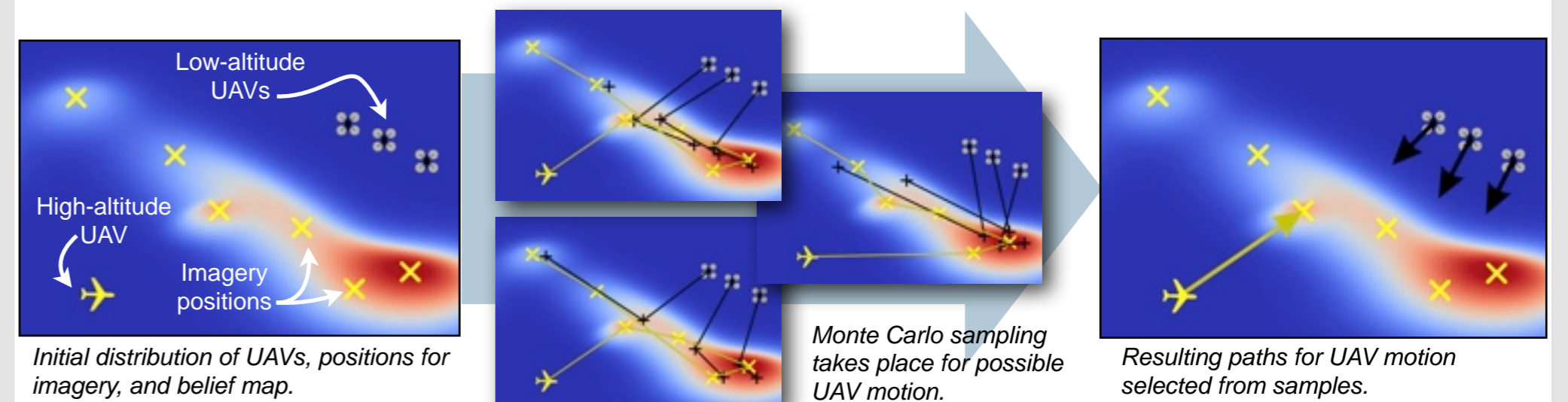
Principle: Monte Carlo sampling of possible UAV motion and imagery

Initially, we know:

- The position of the UAVs
- Locations to collect aerial imagery, based on the belief map

- A solution is calculated for each sample using max-sum.
- For each UAV, we assign a task or determine the direction of movement. This is done in a decentralised manner.
- The process is restarted with the new position of the UAVs.

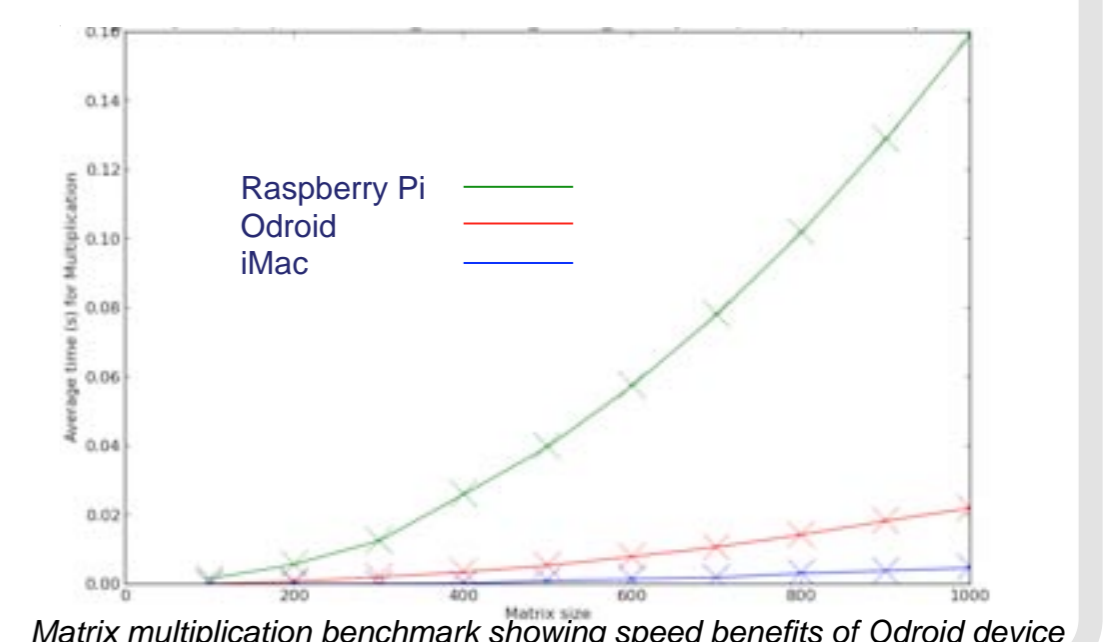
We use Monte Carlo sampling to determine different possible outcomes.



Hardware

We will deploy our algorithms on two main types of camera-equipped UAV:

- AR Drone 2.0**
 - Quadrotor UAV available commercially
 - Easy to integrate control with existing software frameworks
 - Compatible with GPS unit for waypoint following
 - Typical flight time 15mins
- Gliders**
 - Power-assisted gliders, purpose built by University of Southampton Faculty of Engineering and Environment
 - Can be launched by hand, or by attachment to helium balloon
 - Long flight time (depending on launch altitude)
 - Will be outfitted with Odroid U2 single-board computer



Matrix multiplication benchmark showing speed benefits of Odroid device

References

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