# On Learning Planning Goals for Traffic Control

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4th Workshop on Goal Reasoning. IJCAI'16

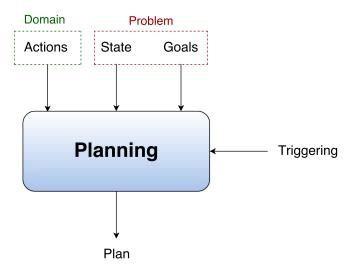




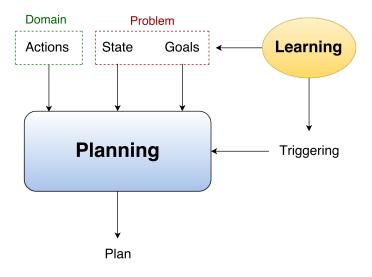
### Goal reasoning

- Goal directed behavior is a hallmark of intelligence
- Most of the times goals do not remain static
- In some domains, predicting goal's appearance can increase system's autonomy and performance

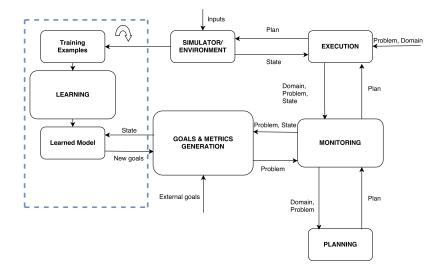
### **Automated Planning**



### **Motivation**



### Architecture



### **Traffic Control**

### **Automated Planning**

- $\blacktriangleright$  State  $\rightarrow$  static and dynamic state of the city
- $\blacktriangleright$  Goals  $\rightarrow$  achieve low density in streets with high density
- $\blacktriangleright$  Actions  $\rightarrow$  set traffic lights to green or red
- Triggering  $\rightarrow$  when a street has high density [Gulić et al., 2015]

### **Relational Learning**

- ► Predict the density → given previous N time steps densities, predict when the density is going to be high
- $\blacktriangleright$  Triggering  $\rightarrow$  if a high density is predicted in any street, then a goal for decreasing its density is raised

### Learning task

- Algorithm: TILDE, generates relational decision trees
- Time series prediction approach
- Subset of the planning domain predicates
- Target concept: density(street, level)
- Background knowledge:
  - connection(street, street)
  - green-Step(traffic-light, street)
  - density-Level-Step(street)

### **Predicting goals**



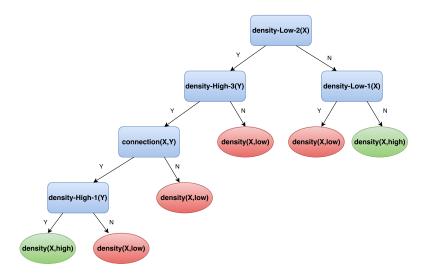
#### 2 density levels - Accuracy

Training/Test			С	D	E
A	0.99	0.94	0.99	0.97	0.99
В	0.99	0.95	0.99	0.98	0.99
С	0.96	0.93	0.99	0.97	0.99
D	0.96	0.93	0.99	0.98	0.99
E	0.96	0.93	0.99	0.97 0.98 0.97 0.98 0.97	0.99

#### Houston downtown

Predicting goals

### **Predictive model**



#### **Traffic management** *Experimental setting*

### Systems to compare

	AP	Reactive goals	Predicted goals
Static			
Planning	$\checkmark$	$\checkmark$	
Learning	$\checkmark$		$\checkmark$

### Metrics

- ► *CO*<sub>2</sub>
- Number of steps all the cars reach their destination
- Average waiting time (AWT)
- Average travel time (ATT)
- Planner executions (PE)

#### **Traffic management** *Results*

### Uncongested city - 5300 cars in one hour

	Steps	$C0_{2}$	AWT	ATT	ΡE
Static				172	
Planning	4070	1117	95	175	22
Learning				167	15

Alberto Pozanco *et al.* 

#### **Traffic management** *Results*

### Uncongested city - 5300 cars in one hour

	Steps	$C0_{2}$	AWT	ATT	ΡE
Static	3969	1103	93	172	
Planning	4070	1117	95	175	22
Learning	3881	1090	88	167	15

### Congested city - 6000 cars in one hour

	Steps	$C0_{2}$	AWT	ATT	ΡE
Static	-	2553	582	638	
Planning	-	2187	435	506	48
Learning	4070	1265	121	204	46

## Conclusions

- Autonomous system that generates its own goals, predicting their appearance
- Relational Learning works well with Automated Planning
- Promising results in the traffic domain

### Current and Future work

- Integrate Anticipatory Planning
- Carry out online learning
- Apply multi-agent approach



### "Urban Traffic Control Assisted by AI Planning and Relational Learning"

Workshop on Agents in Traffic and Transportation

July, 10 @ Madison Room

### **Planning domain**

```
(:action hm-green-to-all-ways
:parameters (?t - traffic-light ?c - crossing ?sin - street
            ?sout1 - street ?sout2 - street ?sout3 - street)
:precondition (and (goes-into ?sin ?c)
                 (goes-out ?sout1 ?c)
                 (traffic-lights-from-street ?t ?c ?sin)
                     (not (opposite-direction ?sin ?sout1))
                     (densityLevel ?sout1 moderate)...)
:effect (and (not (state-to-street ?t ?sout1 red))
                     (densityLevel ?sin low)...)
```

