

# Reward Maximization for Task allocation in Opportunistic crowdsensing networks

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**Abstract**—The abstract goes here.

**Index Terms**—Computer Society, IEEEtran, journal, L<sup>A</sup>T<sub>E</sub>X, paper, template.

## 1 Introduction

THIS demo file is intended to serve as a “starter file” for IEEE Computer Society journal papers produced under L<sup>A</sup>T<sub>E</sub>X using IEEEtran.cls version 1.8a and later. I wish you the best of success.

mds

September 17, 2014

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Michael Shell Biography text here.

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## 2 Conclusion

The conclusion goes here.

## Appendix A

### Proof of the First Zonklar Equation

Appendix one text goes here.

John Doe Biography text here.

## Appendix B

Appendix two text goes here.

## Acknowledgments

The authors would like to thank...

## References

- [1] H. Kopka and P. W. Daly, *A Guide to L<sup>A</sup>T<sub>E</sub>X*, 3rd ed. Harlow, England: Addison-Wesley, 1999.

Jane Doe Biography text here.

## Appendix C

### MAB algorithm

#### C.1 $\epsilon$ -greedy-TA

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**Algorithm 1**  $\epsilon$ -Greedy-TA

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**Input:**  $K$ : the number of arms;  
 $R$ : reward function;  
 $T$ : the round of times;  
 $\epsilon$ : probability

**Output:**  $r$ : the accumulate reward.

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1:  $r = 0$ ;
2:  $\forall i = 1, 2, \dots, K : Q(i) = 0, count(i) = 0$ ;
3: for  $t = 1, 2, \dots, T$  do
4:   if  $rand() < \epsilon$  then
5:     randomly choose one from  $1, 2, \dots, K$  and assignment
       to  $k$ 
6:   else
7:      $k = \arg \max_i Q(i)$ 
8:    $v = R(k)$ ;
9:    $r = r + v$ ;
10:   $Q(k) = \frac{Q(k) * count(k) + v}{count(k) + 1}$ ;
11:   $count(k) = count(k) + 1$ ;

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if the reward of the arm is very uncertainty, for example, its probability distributions contains too much value, then it will need more exploration, and then it need big  $\epsilon$  value. Vice versa.

**C.2 softmax-TA**

In softmax algorithm, it according to the known mean reward of the arms to decide to choose which arm. If the mean reward is bigger, and the probability of choose this arm is bigger.

And the probability distribution of choose a arm is Boltzmann distributions:

$$P(k) = \frac{e^{\frac{Q(k)}{\tau}}}{\sum_{i=1}^K e^{\frac{Q(i)}{\tau}}} \quad (1)$$

$Q(i)$  represent the mean reward upon now;  $\tau > 0$  is called "temperature", and when  $\tau$  is very small, the mean reward bigger one will have higher probability to be choose.

**Algorithm 2** softmax-TA

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**Input:**  $K$ : the number of arms;  
 $R$ : reward function;  
 $T$ : the round of times;  
 $\tau$ : temperature parameter

**Output:**  $r$ : the accumulate reward.

```

 $r = 0$ ;
2:  $\forall i = 1, 2, \dots, K : Q(i) = 0, count(i) = 0$ ;
for  $t = 1, 2, \dots, T$  do
4:  randomly choose an arm from  $1, 2, \dots, K$  according to
   equation (1);
    $v = R(k)$ ;
6:   $r = r + v$ ;
    $Q(k) = \frac{Q(k) * count(k) + v}{count(k) + 1}$ ;
8:   $count(k) = count(k) + 1$ ;

```

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