Designing Incentives to Maximize the Adoption of Rooftop Solar Technology

Extended Abstract

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ABSTRACT

Household level rooftop solar technology adoption is rising in many regions, driven by a multitude of factors, including falling prices and incentives such as tax breaks. It has also been shown in recent research that peer effects have an important role in the spread of solar adoption. This leads to a natural problem of how to design incentives to maximize adoption in such a model. While this is an instance of an "influence maximization" problem, prior results from the influence maximization literature cannot be used directly. In this work, we extend prior results from the literature on the use of submodularity to obtain a greedy approximation. We use this new result to do optimal "seed set" selection for a highly detailed, data-driven, agent-based model of household rooftop solar adoption.

KEYWORDS

solar adoption; agent based model; synthetic population

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1 INTRODUCTION

A recent model of the spread of rooftop solar technology has shown the existence of strong peer effects in the process. We refer to this model as the ZVLL model [6]. Here we study how to design incentives to maximize adoption in such a model—we refer to this as the MAX SOLAR ADOPTION (MAXSA) problem. This is an instance of the well studied "influence maximization" problems (e.g., [2, 3]), where the objective is to select a subset of initial adopters (who are given incentives), so that the expected size of the final set of adopters (as a result of peer effects) is maximized. In most diffusion models, the problem of selecting a seed set to maximize influence is NP-hard, and there has been a lot of work on finding near-optimal seed sets. Kempe et al. [3] showed that the influence objective is a submodular function of the seed set. Informally, this means the influence has a "diminishing marginal returns" property, and a result of [5] implies that a simple greedy algorithm gives an $(1-1/e)$-approximate solution. A powerful result of [4] shows that if the local activation function $f_v(\cdot)$ is submodular, then the influence function is submodular. However, there are several new aspects of MAXSA, so that it cannot be solved directly from earlier results on influence maximization. In particular, the result of [4] only holds for the so called "progressive" thresholds, and does not apply to the ZVLL model. Our contributions are summarized below.

(1) We design a $(1 - 1/e)$-approximation for the MAXSA problem. Our main contribution is an extension of the result of Mossel and Roch [4], and we show that even for non-progressive threshold models, submodularity of the local activation function implies submodularity of the influence function. The coupling argument of [4] does not work for our model, and we have to design a new coupling, which only has one stage (unlike three stages in [4]). As a result, a greedy algorithm gives a $(1 - 1/e)$-approximation.

(2) We propose a generalization of MAXSA, where the goal is to find a seed set that is "spread out". We formalize this as the MAX INDEPENDENT SOLAR ADOPTION (MAXINSA) problem, in which the pairwise distance between any two seed nodes is at least D, which is a parameter. This problem is also NP-hard, and we show that the greedy algorithm for influence maximization can be modified to give $1/8$-approximation for the MAXINSA problem.

(3) We adapt the ZVLL model to study MAXSA for a region in rural Virginia. We show how the adoption can be increased by choosing initial adopters using our algorithm. We find significant increase in adoption over other baselines.

2 METHODS

We consider a spatial diffusion model, which is motivated by models for solar adoption. Let V denote a set of households in a region, referred to as nodes in the rest of the paper. Each node has a spatial location, and we will consider the distance $d(u, v)$ between two nodes as the Euclidean distance. Let A_t denote the subset of all nodes which have adopted solar at time t. Then, A_0 denotes a seed set of initial adopters.

Let $B_v(S, r) = \{u \in V \cap S : d(u, v) \leq r\}$ denote the set of nodes in S which are in a ball of radius r centered at v. Let $n(S, v, r)$ be the number of infected neighbors of node v in the ball $B_v(S, r)$; this is a function of time, since the infected set changes over time. Let $I_v(S)$ denote the influence felt by a node v in set S from its infected neighbors, which we model as a linear equation of the form $I_v(S) = c_0 + \sum_{i=1} c_i n(S, v, r_i)$, where each c_i is a learned constant weight applied to radius r_i, and c_0 accounts for non-peer-based effects, such as economic constraints. Let $f_v(S) = \frac{L}{1+e^{-I_v(S)}}$ be a logistic model of the above influence function, which evaluates to the probability of infection for node v, where L is a constant. The ZVLL model shows that a spatial diffusion model in which

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each node v adopts with probability $f_v(A_t)$ at time t fits observed adoption dynamics of rooftop solar. The influence maximization problem can be formalized as follows. Let $\sigma_T(S_0) = \mathbb{E}[|A_T|]$ denote the expected total number of nodes which adopt solar after T steps of the diffusion process. Let w_v denote the cost for node v to adopt solar. Let $\mathrm{dist}(u, v)$ denote the distance between two nodes u, v.

Problem 1. *[Max Solar Adoption (MaxSA) problem] Given a certain budget B and time T, choose a seed set S_0 such that $\sum_{v \in S_0} w_v \le B$ and $\sigma_T(S_0)$ is maximized.*

MaxSA is NP-complete, even if we restrict the function to $T = 1$, i.e., the expected number of adopters in one time step.

Well separated seed set. For widespread solar adoption, potential grid instability is one of the concerns of power utilities. One way to address this is to ensure that rooftop solar generators are not clustered spatially. However, this cannot be captured using such a diffusion model. Instead, we take a step towards this problem by finding a seed set that is "well separated", i.e., the pairwise distance between any two nodes is larger than some parameter D.

Problem 2. *[Max Independent Solar Adoption (MaxInSA) problem] Given a budget B, time T, and a bound d, choose a seed set S_0 such that (1) $\sum_{v \in S_0} w_v \le B$, (2) $\min_{u,v \in S_0} dist(u, v) \ge D$, and (3) $\sigma_T(S_0)$ is maximized.*

MaxInSA generalizes MaxSA, and is therefore also NP-hard.

2.1 Submodularity of influence for non-progressive functions

The diffusion process defined above is referred to as "non-progressive" in [4], since the random threshold $\theta_v(t)$ is chosen randomly at each time. For a progressive threshold model (in which θ_v is only selected once), Mossel and Roch [4] show that if the functions $f_v(\cdot)$ are submodular, then the influence function $\sigma(S)$ is submodular. Their proof involves a careful coupling, which does not extend to the non-progressive setting. We design a different proof to extend the result of [4] to non-progressive functions.

Theorem 2.1. *If the functions $f_v(\cdot)$ are all monotone and submodular, then $\sigma(S)$ is submodular.*

3 EXPERIMENTS & RESULTS

We ran experiments for the 24401 zip code in Virginia, USA. We build a model of the population of the region by drawing from a "synthetic population" of Virginia [1].

3.1 Local function

The submodularity result requires that the local function be submodular as well. A logistic function, $f_v = \frac{1}{1+e^{b+cx}}$, is submodular for $x \ge 0$ if $b = 0$. However, in the logistic regression used in the ZVLL model, there is a non-zero intercept of ~ -10.19. In order to apply our method, we modify the logistic function as follows to make it submodular.

$$f_v(x) = \begin{cases} \frac{\epsilon}{1+e^{10.91-x}}, & \text{if } x \ge 14 \\ \epsilon \cdot 0.0683x, & \text{otherwise} \end{cases}$$

We do a binary search over ϵ until the adopter curve for the composite function above matches that of the ZVLL model. We found that, for $\epsilon = 0.0012$, we obtained a very good match with the ZVLL model's results. We have used the ZVLL model on Virginia data for zip code 24401 to evaluate our methods. We compare four different seeding approaches:

Random: Seed nodes are chosen uniformly randomly among all the nodes in the network. The number of nodes chosen is given by the budget. We used values of the budget from 1 through 10.

ZVLL model: In this case also, the seed nodes are chosen randomly, but the diffusion model is the original ZVLL model, without the modifications to the logistic function described above.

Naïve greedy: In this approach, we run the diffusion model, with the modified function at each node, 30 times for each possible seed node independently. We rank the seed nodes in descending order of the mean number of adopters. Then we choose our seed set to be the top B nodes, where B is the budget.

Adaptive greedy: In this approach, we start by setting the seed set to ϕ. Then we run 30 simulations with each node as the single seed node. We rank the nodes by descending order of total number of adopters and add the top one to the seed set. In the next round, the seed set has this node in it. We run 30 simulations with each node paired with the already chosen seed node and then rank these $n - 1$ pairs in descending order. The node that pairs best with the previous node is added to the seed set, and so on.

Figure 1 shows a comparison of the four approaches. We see that the adaptive greedy approach outperforms the other approaches at all budget levels.

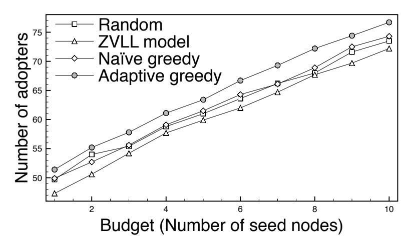

Figure 1: A comparison of four seedings strategies. See text above.

4 CONCLUSIONS

We demonstrate that a data-driven, high resolution simulation platform can be combined with a diffusion model and an optimizer such as our greedy optimizer to address questions of optimality, which is a new frontier in the use of big simulations. This holds the promise of moving the conversation from hypothetical and counter-factual simulations to notions of optimal behavior and optimal action in large scale settings.

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REFERENCES

[1] Abhijin Adiga, Aditya Agashe, Shaikh Arifuzzaman, Christopher L. Barrett, Richard J. Beckman, Keith R. Bisset, Jiangzhuo Chen, Youngyun Chungbaek, Stephen G. Eubank, Sandeep Gupta, Maleq Khan, Christopher J. Kuhlman, Eric Lofgren, Bryan L. Lewis, Achla Marathe, Madhav V. Marathe, Henning S. Mortveit, Eric Nordberg, Caitlin Rivers, Paula Stretz, Samarth Swarup, Amanda Wilson, and Dawen Xie. 2015. *Generating a Synthetic Population of the United States.* Technical Report NDSSL 15-009. Network Dynamics and Simulation Science Laboratory.

[2] D. Easley and J. Kleinberg. 2010. *Networks, Crowds, and Markets: Reasoning About a Highly Connected World.* Cambridge University Press.

[3] David Kempe, Jon Kleinberg, and Eva Tardos. 2015. Maximizing the Spread of Influence through a Social Network. *Theory of Computing* 11(4) (2015), 105–147.

[4] E. Mossel and S. Roch. 2010. Submodularity of Infuence in Social Networks: From Local to Global. *SIAM Journal of Computing* (2010).

[5] G. L. Nemhauser, L. A. Wolsey, and M. L. Fisher. 1973. An analysis of approximations for maximizing submodular set functions. *MATHEMATICAL PROGRAMMING* 1 (1973), 265–294.

[6] Haifeng Zhang, Yevgeniy Vorobeychik, Joshua Letchford, and Kiran Lakkaraju. 2015. Data-Driven Agent-Based Modeling, with Application to Rooftop Solar Adoption. In *Proc. AAMAS.*