The Solar Influencer Next Door: Predicting Low-Income Solar Referrals and Leads

Benjamin Sigrin, Ashok Sekar, Emma Tome, and Madeline Geocaris

National Renewable Energy Laboratory
December 22, 2021

Percent

- ≥ 60
- 55 – 60
- 50 – 55
- 45 – 50
- < 45
SEEDS II Overview
Solar Energy Evolution and Diffusion Studies, Solar Energy Technologies Office

Project Goal:
Identify strategies to scale up solar adoption among low-and-moderate income (LMI) communities across the U.S.

Use historic data to develop predictive models for adoption and referrals

Determine technical potential of LMI market and opportunities for new deployment models

https://maps.nrel.gov/solar-for-all

- Survey LMI adopters
- Comparative city case studies
- Pilot test referral elicitation strategies
Why is Solar Adoption in Underserved Communities Important?

- Growing divide in adoption rates by income groups
- A large, unaddressed market: 100s of GW of potential

Extending solar to more communities could:
- Reduce energy burden
- Support energy equity
- Accelerate decarbonization
- Meet policy goals
Some Families Face More Barriers to Adopting Solar

• Affordability
• Homeownership
• Financial: ability to secure financing or monetize tax-based incentives
• Structural: Unsuitable roof, electric code compliance
• Information and distrust

=> This analysis studies low-income owner-occupied potential
California’s Low-Income Solar Programs

Our study uses anonymized household-level data from these programs:

- Largest source of low-income program data in the U.S.
- Single provider means that all leads and referrals are captured in the database
Why do referrals matter?
RESULT: Program Outcomes

Eligibility criteria:
• Own and live in home
• Income below 80% AMI
• Live in an eligible geography:
  • Qualified census tract
  • Enterprise Zone
  • Targeted Economic Area
  • Opportunity Zone
  • Disadvantaged Community

Over 85% of leads contacted do not receive solar. Of these, geographic ineligibility is the largest barrier.
The Biggest Source of Solar Leads Is Right Next Door

- Referrals are the largest sources of leads and clients
- Referrals had nearly highest success rate
- Many other successful methods of lead generation
Predictive Modeling Approach

**Tract-level**
Within eligible geographies, where do LMI installations occur?

**Adoption**
Will a qualified lead become lost or disinterested?

**Referrals**
Will a former client provide a referral?
Predictive estimates of solar uptake and socio-demographic predictor variables (Yu et al. 2018)

Rooftop technical potential estimates by building, income, tenure. (Sigrin and Mooney 2018)

Environmental and socioeconomic vulnerability indicators (OEHHA 2017)

Installed base Distance measures (Graziano, Bollinger, Gillingham 2019) (LBNL Tracking the Sun)

Demographics Lead source Electricity consumption PV system specs

Tract data (Public)

Client data (Private)
Modeling approach

1. **Training:**
   Fitting the model to a subset of data

2. **Validate**
   Evaluate hyperparameter fit

   "Crossfold" data 5 times to avoid overfitting

3. **Test**
   Evaluate model fit on out-of-sample data

4. **Analyze**
   Feature importance, variable influence

**Predictive models** can be evaluated in many ways, but ultimately:

- How well does the model predict out-of-sample?
- Does the performance on the Test approximate that of the Training?

Balanced Accuracy used to assess performance due to imbalanced data, i.e. more non-referrals than referrals
Decision tree

- Partition features according to the outcome of interest

Random forest

- Creates many decision trees from a random subset of available variables
- Averages the predictions from the trees
Extreme Gradient Boosting (XGBoost)

Hyperparameters:
- n trees
- max depth
- min samples
- learning rate
- subsampling rows/columns
- scoring

Uses several “weak learners”, trained sequentially on the residual error of the previous model.

The contribution of each tree is weighted by the learning rate. Early stopping reduces overfitting.
Lost Lead and Referral Models
Example: When are predictive models useful?

Predictive models always imply some households are not pursued. Used well they reduce time spent for a positive outcome.

<table>
<thead>
<tr>
<th>Predicted</th>
<th>Actual</th>
<th>1000 Clients</th>
</tr>
</thead>
<tbody>
<tr>
<td>No</td>
<td>No</td>
<td>90%</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>5%</td>
</tr>
<tr>
<td>Yes</td>
<td>No</td>
<td>10%</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>95%</td>
</tr>
</tbody>
</table>

1. Model sensitivity and specificity influence predicted outcomes given actuals
2. For 1,000 clients apply the prevalence of providing a referral
3. Yielding 202 clients predicted to be referrers, of whom 114 are referrers. Clients not predicted to refer (798) are not pursued further though 6 are true referrers
Accuracy Improves with Additional Data and Random Forest Model

- **Prediction**
- **Referral**
- **Lost Lead**
- **Model Type**
  - XGB
  - Naïve Bayes

---

**Balanced Accuracy**

- **Public**
- **Private**
- **Public + Private**

- **XGB**
- **Naïve Bayes**
# Lost Lead Model Performance

<table>
<thead>
<tr>
<th>Model Type</th>
<th>Data Type</th>
<th>Prevalence</th>
<th>Sensitivity</th>
<th>Specificity</th>
<th>Precision</th>
<th>F1</th>
<th>Balanced Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>XGB</td>
<td>Public</td>
<td>0.20</td>
<td>0.51</td>
<td>0.71</td>
<td>0.31</td>
<td>0.38</td>
<td>0.61</td>
</tr>
<tr>
<td></td>
<td>All</td>
<td>0.87</td>
<td>0.87</td>
<td>0.87</td>
<td>0.63</td>
<td>0.73</td>
<td>0.87</td>
</tr>
<tr>
<td>Naïve Bayes</td>
<td>Public</td>
<td>0.55</td>
<td>0.55</td>
<td>0.56</td>
<td>0.24</td>
<td>0.33</td>
<td>0.55</td>
</tr>
<tr>
<td></td>
<td>All</td>
<td>0.90</td>
<td>0.90</td>
<td>0.50</td>
<td>0.32</td>
<td>0.47</td>
<td>0.70</td>
</tr>
</tbody>
</table>

Balanced accuracy is 87%.
Feature importance plots show the most relevant features for the prediction and the magnitude.

Number of referrers within 1.5 miles was the most important feature.

Several other proxies for peer effects were relevant as well as measures of environmental effects.
Conditional dependence plots, based on SHAP analysis, demonstrate the direction and magnitude of influence. For example, more referrers nearby decreases the chance of a prospective solar adopter becoming disinterested.
<table>
<thead>
<tr>
<th>Model Type</th>
<th>Data Type</th>
<th>Prevalence</th>
<th>Sensitivity</th>
<th>Specificity</th>
<th>Precision</th>
<th>F1</th>
<th>Balanced Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>XGB</td>
<td>Public</td>
<td>0.12</td>
<td>0.55</td>
<td>0.65</td>
<td>0.18</td>
<td>0.27</td>
<td>0.59</td>
</tr>
<tr>
<td>All</td>
<td></td>
<td></td>
<td>0.61</td>
<td>0.61</td>
<td>0.19</td>
<td>0.29</td>
<td>0.63</td>
</tr>
<tr>
<td>Naïve Bayes</td>
<td>Public</td>
<td>0.12</td>
<td>0.55</td>
<td>0.62</td>
<td>0.17</td>
<td>0.26</td>
<td>0.59</td>
</tr>
<tr>
<td>All</td>
<td></td>
<td></td>
<td>0.51</td>
<td>0.70</td>
<td>0.19</td>
<td>0.28</td>
<td>0.60</td>
</tr>
</tbody>
</table>

Balanced accuracy is 63%, lower than the lost lead model.
Compared to lose lead model, individual features have lower impact on prediction due to lower accuracy.

Distance from referrer is again the most impactful variable, as incentivizing referrals, internet access, expected solar bill savings.
Like lost leads, proximity to referrers and having been referred increases the chance of an adopter making a referral.

However, *unlike* lost leads, knowing the number of installations nearby did not have a large impact.
Program Implications

- **LMI adoption models** could support affordable solar program uptake and estimate policy outcomes.
  - Applying the lost lead model could save 20% of staff time to acquire leads.
  - Applying the referral model could save 56% of staff time to acquire referrers.
Program Implications

• **Referral incentives** should be built into program design.

• **More flexible eligibility requirements** could extend solar to more communities and reduce administrative burden.
Thank you

www.nrel.gov
NREL/PR-7A40-81771

Contacts: bsigrin@nrel.gov / ashok.sekar@nrel.gov
Read the Energy Research & Social Science article.
Subscribe to NREL SEEDS news.