Home Service Scheduler

A technical AI/ML Approach

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Industry problem being solved

Home Service Scheduler ("HSS"), an automation and augmentation implementation of Machine Learning.

Problem

Remembering to schedule maintenance tasks for your home is difficult and time consuming.
Using the Machine Learning powered Home Service Scheduler, the homeowner has a personal assistant that assists in the classification of reports using **appliance serial numbers, home appliance warranties**, property tax information, and organization of inspection reports, in order to provide timely, relevant, and contextual notifications to maximize the value of a home.

For the sake of this ND, we will focus on appliance service notifications

Why use ML/AI in solving this task?

The HSS ML/AI model classifies homeowner documents and artifacts (e.g. previous service receipts and warranty information), in order to organize and generate then send automated recommendations and maintenance reminders for home inventory warranties, tax payments, and the owners preferred home service providers.

Why is this important, why now?

Homeownership for Millennials is on the rise yet roughly 1 in 3 under the age of 35 who own a home express frustration and remorse due to the hidden costs of maintenance after a home purchase.

As of 2020, there are **1 in 3 Americans** in this segment of homeowners who will need this service.

In 2021 as home prices rise, housing costs also rise for these new homeowners. Home Service Scheduler aims to relieve the pain and anxiety of managing these hidden costs.

Success means increases in homeowner satisfaction with the service.

Application of ML/AI

ML/AI Tasks

The primary task is to have our ML model understand from a given dataset and recommend to a homeowner the best time predicted to schedule home service due to a potential issue in a home.

Key Outcome

Timely, relevant, and contextual notification virtual assistant service with secure dashboard for a homeowner, renter, or property manager to have a pulse of their home and related expenses between buying and selling.

KPIs

Adoption

- # of total active users
- % sustained high CSAT user rating month over month

Retention

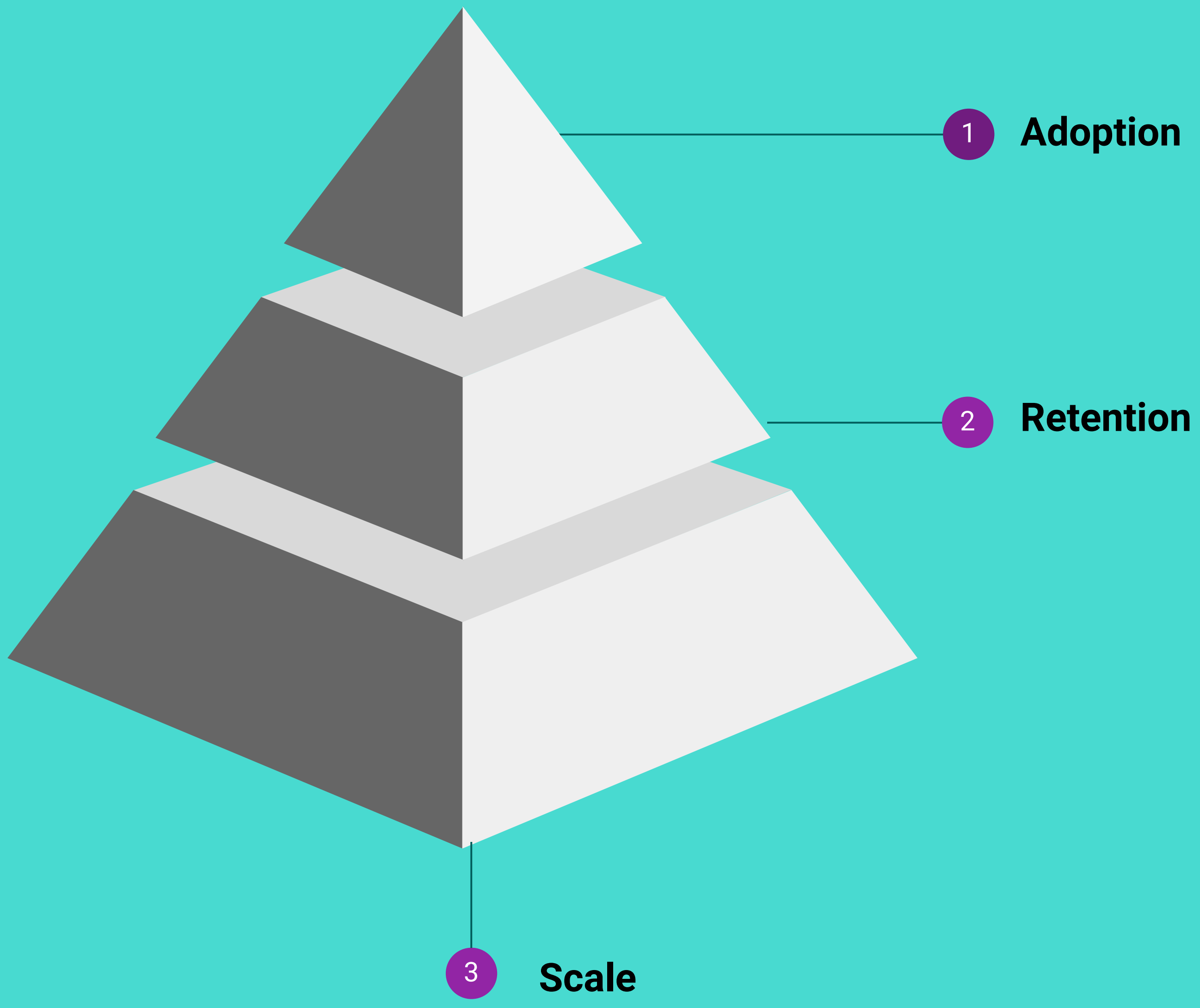
- # of quarterly active renters
- % rate of paying homeowners

Success Metrics

We begin by proving the value of the service in the market **using x** as a baseline for our success measures.

Baseline determined by market research on the Millennial segment of potential and new homeowners, and segments who have purchased a home in the last 5 years.

From this segment we need to validate with those who have expressed frustration in hidden costs of maintaining a home



Once we consistently meet the key performance indicators for adoption, we move to retention using y as our baseline.
We scale by measuring recurring revenue based on consistently meeting the first and second KPI's defined in this and the previous slide.

Data

Data Acquisition

Finding open datasets for home appliance serial numbers in order to map to warranty information is a difficult task due to licensing constraints. We would need to refresh this data every 36 months e.g. to account for newer home appliances.

Using AWS Data Exchange I will need purchase **$xxx.xx** worth of storage to house **xxxxGB** worth of data. This approach reduces the net cost of recurring costs.

Publicly sourced https://aws.amazon.com/data-exchange	**User provided** Crowdsourced

Data Acquisition

1 Appliance Serial Numbers

- User provided
- Google Dataset Search
- Statista
- Kaggle
- AWS Data Exchange
- Bestbuy & Amazon Reviews Dataset

2 Appliance warranties

- User provided
- AWS Data Exchange
- EU External Trade Dataset

3 Inspection Reports

- User provided
- Crowdsourced and anonymized

4 Property tax information

- User provided
- USA.gov hosted State and local property tax records

Publicly sourced

User provided

Protecting sensitive and personally identifiable information

Since appliance warranty and serial number information does not include PII and can be sourced through data exchanges as mentioned previously, the strategy would be to start there.

Inspection reports and property tax information, however, may “sweep up” PII. This is another area where Machine Learning and Differential Privacy (“DiffP”) can help.

Leveraging newly open sourced privacy technologies such as Tensorflow Privacy, Private Join and Compute and Google’s open differentially private algorithms, we can anonymize sensitive property inspection & tax information data before data is sent to the HSS application. Diff P would adds random data to the dataset prior to transmission.

Protecting PII, how to overcome

To afford our customers trust with this service, we will have to employ clear contextual information and visualized ML explainability about user submitted data, specifically, how the data will be used. We make it clear, for example, that this data will not be sold to third parties.

Next, we would provide clear choices and controls for the customer to understand what data they want to share with the service through an intuitive interface and only progressively ask permission for personal information when the service needs to provide value to the user.

Finally, routine security and privacy by design principles from the beginning including privacy impact assessments to govern consent, data minimisation and zero trust approaches to storing user information.

Data Tuning - Home Appliance Service Need Notification Example

I would need to refresh home appliance data every 36 months to account for newer home appliances. Where data was accessed via AWS Data Exchange, we'll subscribe to the Data Providers dataset for a fee.

In the case of a homeowner subscribed to HVAC Service notifications, the model will be classified by season, region, defect_trends, extreme_weather_info, make, model, last_serviced, warranty, and known_appliance_issues, eventually sensor data. The notification will include relevant labels recommending professional service a year from the previous maintenance date or earlier given it meets our model framework prediction.

Data Tuning - Home Appliance Service Need Notification Example

If Metric for AI Tool Δ Threshold do Action

Warmer than normal summer

If the region of the home has warmer than normal summer

HSS

Model weights probability of needing service earlier than a year for a standard central AC or a furnace

Predicts HVAC Performance Exceed X%

Model predicts true positive and or true negatives of a possible HVAC performance related wear

Δ Confidence

Send notification stating % confidence of recommendation of early maintenance check

Framework followed- Experfy

Data Source

Consider the size and source of your data; what biases are built into the data and how might the data be improved?

Data Labels

User need	AI output	Data needed	Labels
When is should I plan to to have my HVAC maintained next?	HVAC make and model reliability trend (current)	Season, Region, Extreme weather data	season, region, extreme_weather_info
	HVAC make and model maintenance prediction based on region/weather (future)	Make, Model, Warranty,	defect_trends, make, model, warranty,
		Known Issues/Trends, Previous service date	known_appliance_issues, last_serviced

Data Model

Model Building

I will start small with resourcing for our prototype. I will build models vs outsourcing model training from the onset.

I will host using Google Auto ML, and leverage performance modeling and tuning tools available or the portfolio of GCP’s AI Platform tools, and once I’m consistently achieving desired results, through continuous research activities with real homeowners, will look to more advanced tools such as TensorFlow with an in-house team.

Evaluating Results: Roof Maintenance Prediction

Our dataset is divided into training and test, training primarily for training and test for predictions. To measure the success of our models performance I will rely on the following:

Confusion Matrix	Accuracy	Recall	Precision	F1 score

Taking confusion matrix as our example for a Roof repair prediction. I aim to train two classifications per the first model i.e. **extreme_weather_info** and **region** classifications to train our model in a logistical regression format. The second model with three labels to map **materials**, **build_style**, **roof_installation_date**, **roof_type**, **known_defects**.

Humidity and heat for example are detrimental to the typical 25-30 year life of a roof, we will want to notify the user with a high level of accuracy when the model predicts an early maintenance check for a roof. Accuracy as measured by (TP+TN)/(TP+FP+FN+TN) from our confusion matrix to determine the models ability to correctly predict class labels. For our example *Accuracy = (TP+TN)/Age of roof*

This approach gives us insights into which roof type is likely to have defects earlier than normal. Blending the two models gives us a level of confidence that if extreme weather for a specific region, given the roof build configuration and installation date, send a notification for a calculated date our model predicts for roof issues.

Minimum Viable Product

Design

Design

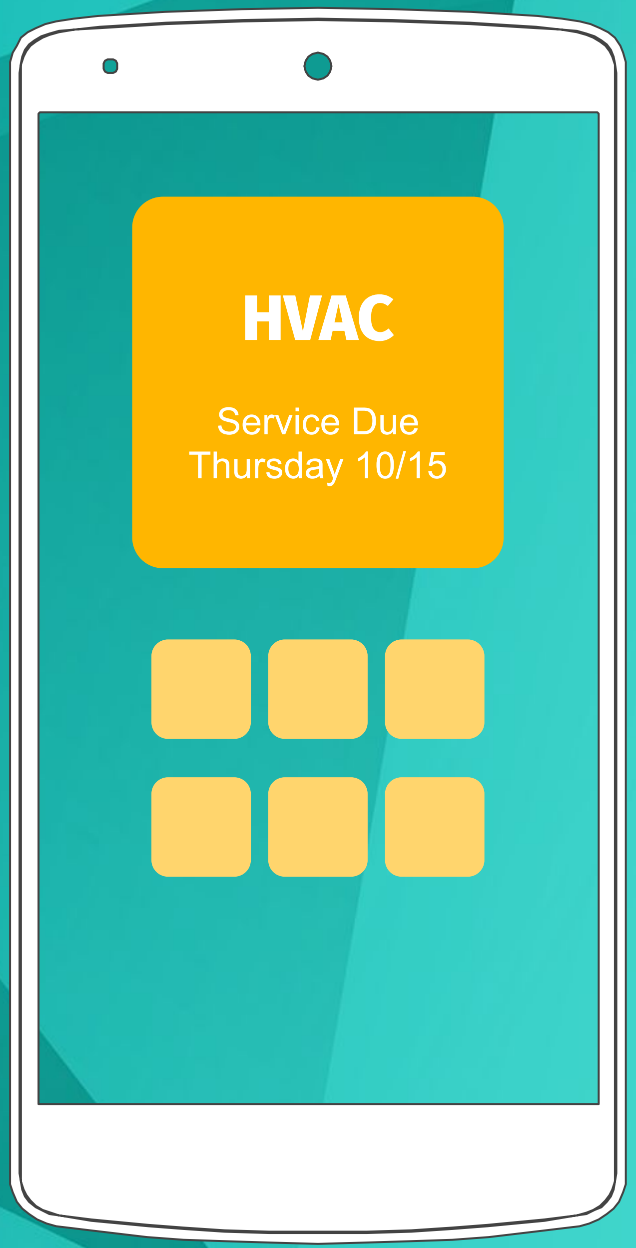
To generate a measure of our AI system's confidence, we would need to test which notifications meet our goal of relevance and contextual notifications.

To do so we'd need to algorithmically optimize and classify the types of notifications homeowners receive by:

Critical	**Important**	**Informational**	**Reminder**

Design

N-best recommendations in notifications of our models best predictor for example when the HVAC system should be next serviced would help us measure user trust of the models results and retention of the service.



Use Cases

	Activate	Learn	Use/Goal
User need	Activate	Learn	Use/Goal
Epics	Signup Connect/Upload docs Test notification First Notification	Privacy features Alert & reminder tuning Service subscription categories	Notification deep-links to dashboard Embedded Usefulness Feedback Form ML Generated Service Recommendations Engine Subscriptions & Unsubscriptions

How will this be adopted? Go-to-market plan

Channels

- ❑ Direct to consumer marketing
- ❑ Homeowners associations
- ❑ Home services providers
- ❑ Insurance partnerships

Adoption Framework

- ❑ Millennial segment of potential and new homeowners, and segments who have purchased a home in the last 5 years
- ❑ Expressed frustration in hidden costs of maintaining a home

Go-to-market

Product roadmap and go-to-market follows business strategy. We focus on one metric at a time by optimizing the product for adoption. Once we consistently achieve the goals we nurture the first cohort and optimize for retention, then growth.

- ❑ Adoption
- ❑ Retention
- ❑ Growth

Scale
Post Deployment

Monitoring and Evaluation

Designing for Longevity

I’m starting with home appliances like HVAC’s and roofs given research of what homeowners need help with the most.
For typical home appliances would need to validate our assumption that each class of home appliance datasets need refreshing every 36 months e.g. to account for newer home appliances. Through employing research tactics like A/B tests, we’ll be able to validate the consistency and accuracy of predictions per model per appliance.

Additional research and testing of other models will allow our product to learn which of the following other datasets to create value for our users.

- Roof/Foundation
- Appliances/HVAC
- Windows/Doors
- Plumbing/Winterization
- Electrical

Monitor Bias

Homes in poorer areas in society tend to be less maintained than affluent regions. Typically homeowners in less affluent communities may have a higher rate of home or appliance repair predictions per period.

This could possibly lead to higher costs if the models aren't calibrated to consider higher costs of maintaining our home.

This further leads to a breakdown of our value proposition of keeping homeowners engaged with keeping up with the value of their home if they are constantly pinged about home expense items.

I will have to mitigate this by providing cost efficient options for homeowners in less affluent communities.

Appendix

Home Service Scheduler - Design Canvas

Product View | Market View

Problem

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Solution

Timely, relevant, and contextual notification virtual assistant service with secure dashboard for a homeowner, renter, or property manager to have a pulse of their home and related expenses between buying and selling.

Key Metrics/KPIs

- # of quarterly active renters
- % rate of paying homeowners
- # of total active users
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Unique Value Proposition

For homeowners, looking for a simplified home maintenance, HSS is a simple digital assistant tuned to the home/homeowner's logged property information and provides timely, contextual, and relevant notifications so that the home appreciates in value at the time of sale, or for a lessee/renter, a seamless transition at the end of a term.

Unlike homebinder.com, Poppins is less about checklists, but rather simplifies driving value and cost savings on the home by focusing on timely, contextual, and relevant information to the homeowner.

Unfair Advantage

- Team experience
- Exclusive partnerships
- Speed
- Trade secrets
- Market Timing

Channels

- Homeowners associations
- Home services providers
- Insurance partnerships
- Direct to consumer

Target Customer

- Home owners*
- Renters†
- Agents/Brokers
- Property managers
- Insurance companies
- Homeowners associations
- Home services + pros providers
    - Roof/Foundation
    - Windows/Doors
    - Plumbing/Winterization
    - Electrical
    - Appliances/HVAC

Elevator Pitch

As a vehicle owner, you get signals and alerts whenever you need an oil change, a visual reminder when the inspection is due with a sticker, or a check engine light when the engine needs servicing. Unfortunately for homeowners, there are no such notifications aimed at increasing the value, reliability, and safety of your home.
Homeownership is broken after purchase and before sale.
The Home Service Scheduler is free AI/ML driven service **for homeowners** looking for the piece of mind with about **maintenance and home improvement responsibilities**.
By leveraging previous home improvement and maintenance documents, Home Service Scheduler **securely, sends timely, relevant, and contextual notifications to the homeowner** connecting them with service providers and recommendations.