# AI for Sustainability

## Deploying Intelligent Diagnostics and Optimal Control to Reduce the Climate Burden of Google Office Buildings

### Herrick Conferences 2024

Compressors | Refrigeration | Buildings

John Sipple
sipple@google.com

Google Research

# Effects of Climate Change

**Extreme climate events** comprising conditions beyond which many species are adapted are occurring on all continents, with severe impacts

Climate change is affecting ecosystem services connected to human health, livelihoods and well-being

Climate impacts on urban population health, livelihoods and well-being are felt disproportionately, with the most economically and socially marginalised being most affected

IPCC, 2022: Climate Change 2022: Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [H.-O. Pörtner, D.C. Roberts, M. Tignor, E.S. Poloczanska, K. Mintenbeck, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem, B. Rama (eds.)]. Cambridge University Press. Cambridge University Press, Cambridge, UK and New York, NY, USA, 3056 pp., doi:10.1017/9781009325844.

135 EJ

Global operational energy demand in buildings

+4%

Increase from 2020, and 3% previous peak in 2019

10 $GtCO_2$

Emissions exceed the pre-pandemic all-time high in 2019 by 2%

United Nations Environment Programme (2022). 2022 Global Status Report for Buildings and Construction: Towards a Zero-emission, Efficient and Resilient Buildings and Construction Sector. Nairobi.

Google Research

22.3

¢/kWh average Commercial Price for year ending April 2023 in California

86%

Commercial Electricity Price in California above average for the rest of the US

1

California's commercial electricity prices were the highest among the contiguous states and DC

California Energy Price Data for June 2023, California Center for Jobs and Economy
https://centerforjobs.org/ca/energy-reports/california-energy-price-data-for-june-2023

Google Research

"We are the first major company to make a commitment to operate on 24/7 carbon-free energy in all our data centers and campuses worldwide...by 2030."

**Sundar Pichai**

Our third decade of climate action: Realizing a carbon-free future, September 14, 2020, The Keyword

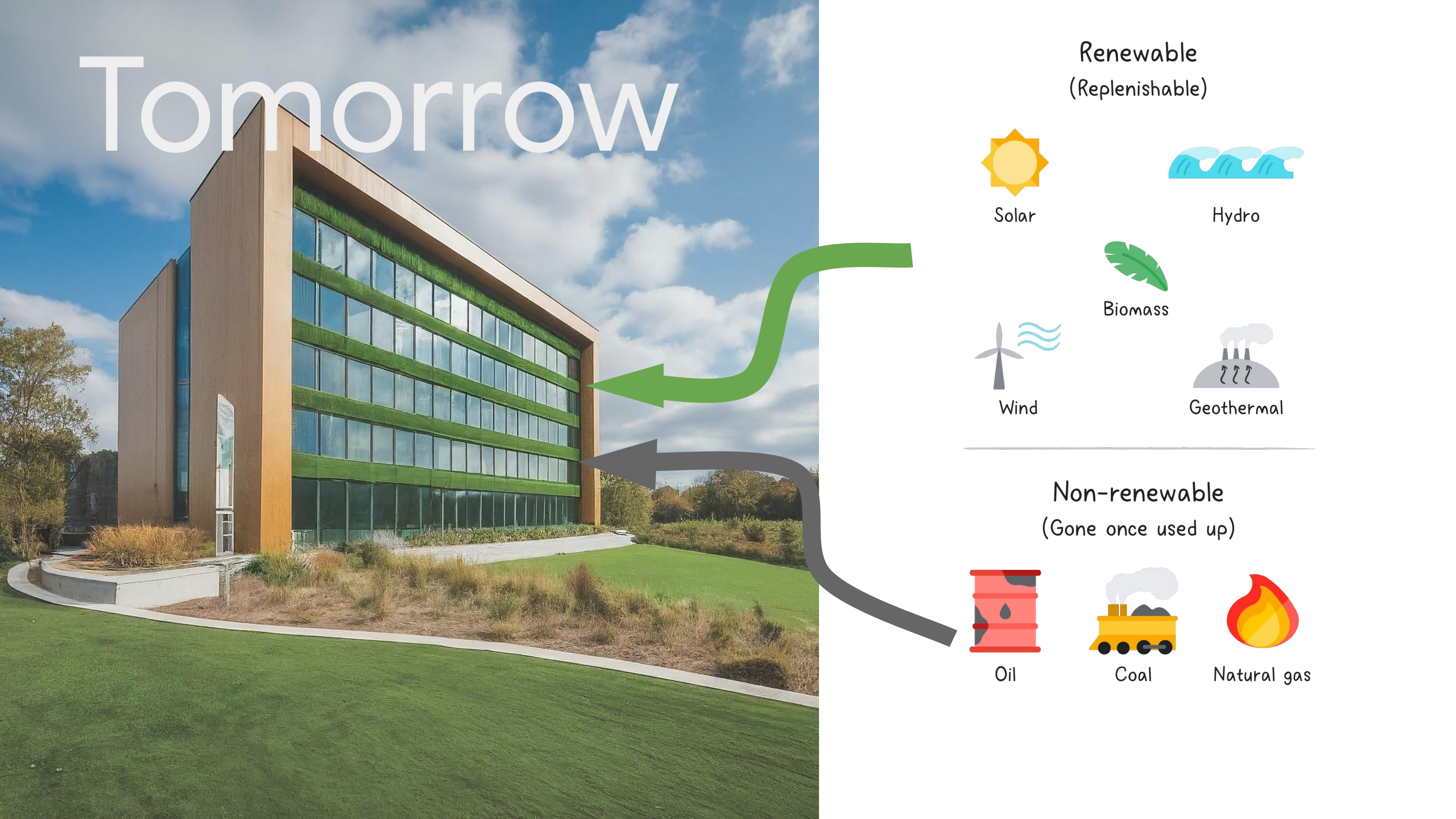
# Potential Applications of AI for Smart Buildings

- Monitoring and Fault Detection
  - Anomaly Detection
- Fault Explanation and Root-Cause Analysis
  - Explainable AI and Causal Reasoning
- Optimal Control to minimize Energy Use and Carbon Emission
  - Reinforcement Learning and Model Predictive Control
- Demand and Emission Forecasting
  - Sequence models and time-series regression
- Scenario Analysis and Simulation
  - World models and physics-enhanced ML

Google Research

# Challenges for AI in Smart Buildings

- Non-deterministic behavior
  - Infinitely many solutions lead to many possible behaviors
  - Not suitable for some safety-critical tasks
- Brittleness under seasonality
  - Assumption of stationarity leads to overconfidence
  - Requires periodic retraining and evaluation
- Local Minimum
  - Potentially learn suboptimal behavior
- Data Gremlins
  - Bias/Drift
  - Confounders/Uncontrolled Factors
  - Undersampling/Aliasing


Tomorrow
Renewable
(Replenishable)
Solar
Hydro
Biomass
Wind
Geothermal
Non-renewable
(Gone once used up)
Oil
Coal
Natural gas

We believe our near-term goals of reducing energy consumption and greenhouse gas emission at global scale can be achieved by applying AI for intelligent diagnostics and optimal control.

# AI-Based Solutions for Smart Buildings

## Optimal Control
Reduce energy use and $CO_2$ emission

## Explained Anomaly Detection
Explainable AI and Anomaly Detection to detect HVAC faults

## Project Freon
Detect leaky Air Conditioners

## Intelligent Diagnostics
Provide root-cause analysis and recommend fixes

# Optimal Control for Reducing Carbon Emission and Energy Consumption

# Research Hypothesis

## Objective:

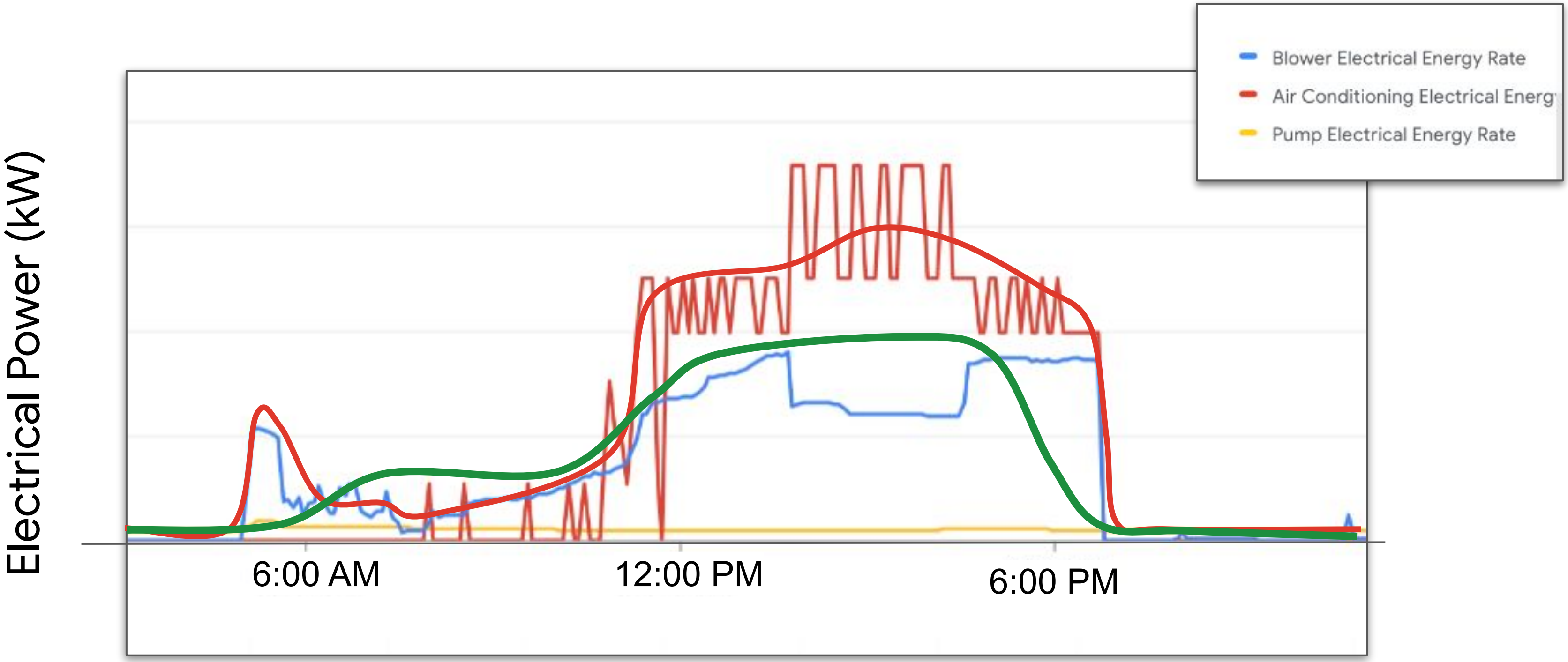
Adaptive control can reduce energy consumption and greenhouse gas emission from HVAC devices in commercial office buildings without compromising occupant comfort.

## Minimal Success Criteria:

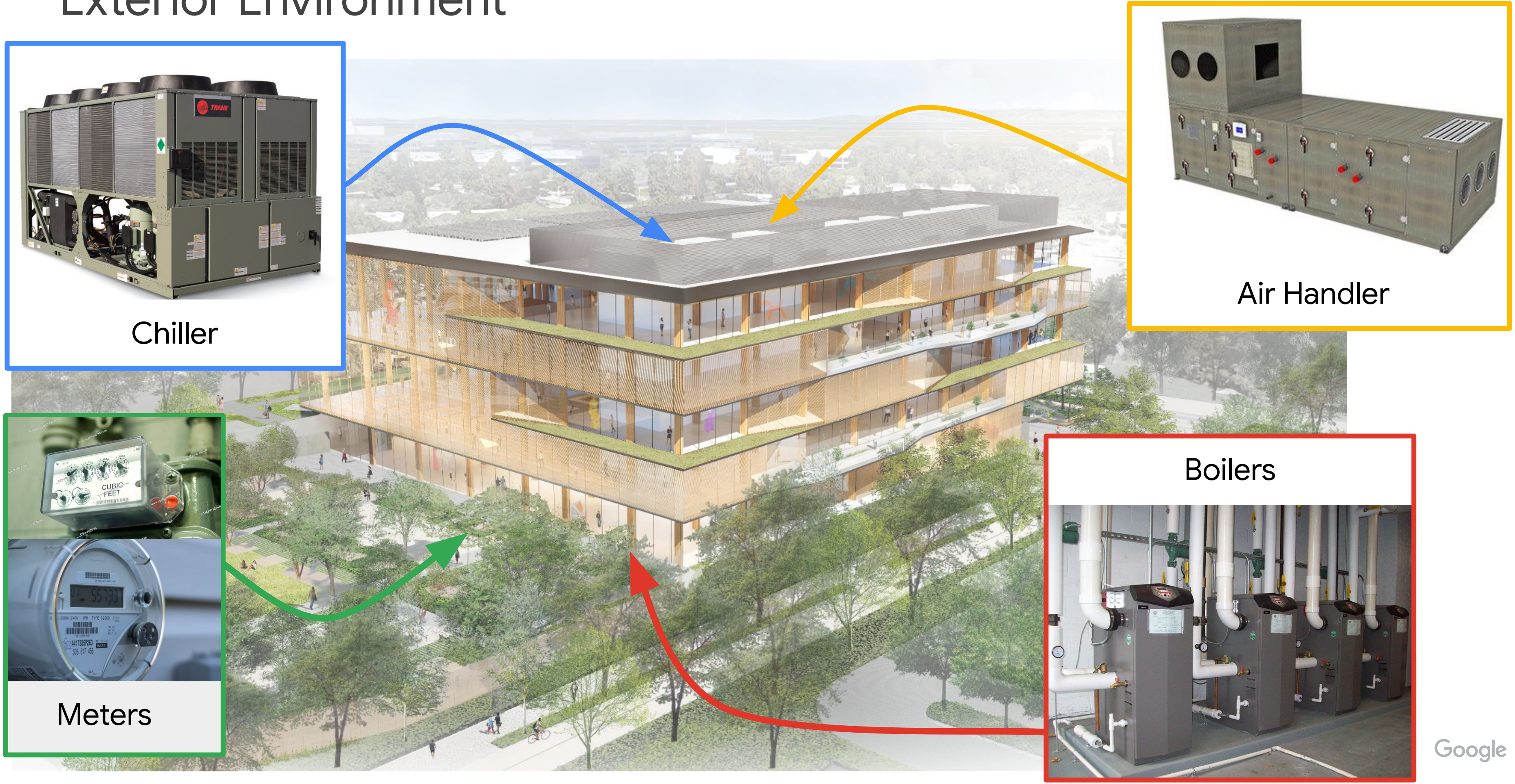
- 5%+ reduction in carbon emission,
- 5%+ reduction in energy consumption,
- maintain occupant comfort conditions

Google Research

# A typical workday



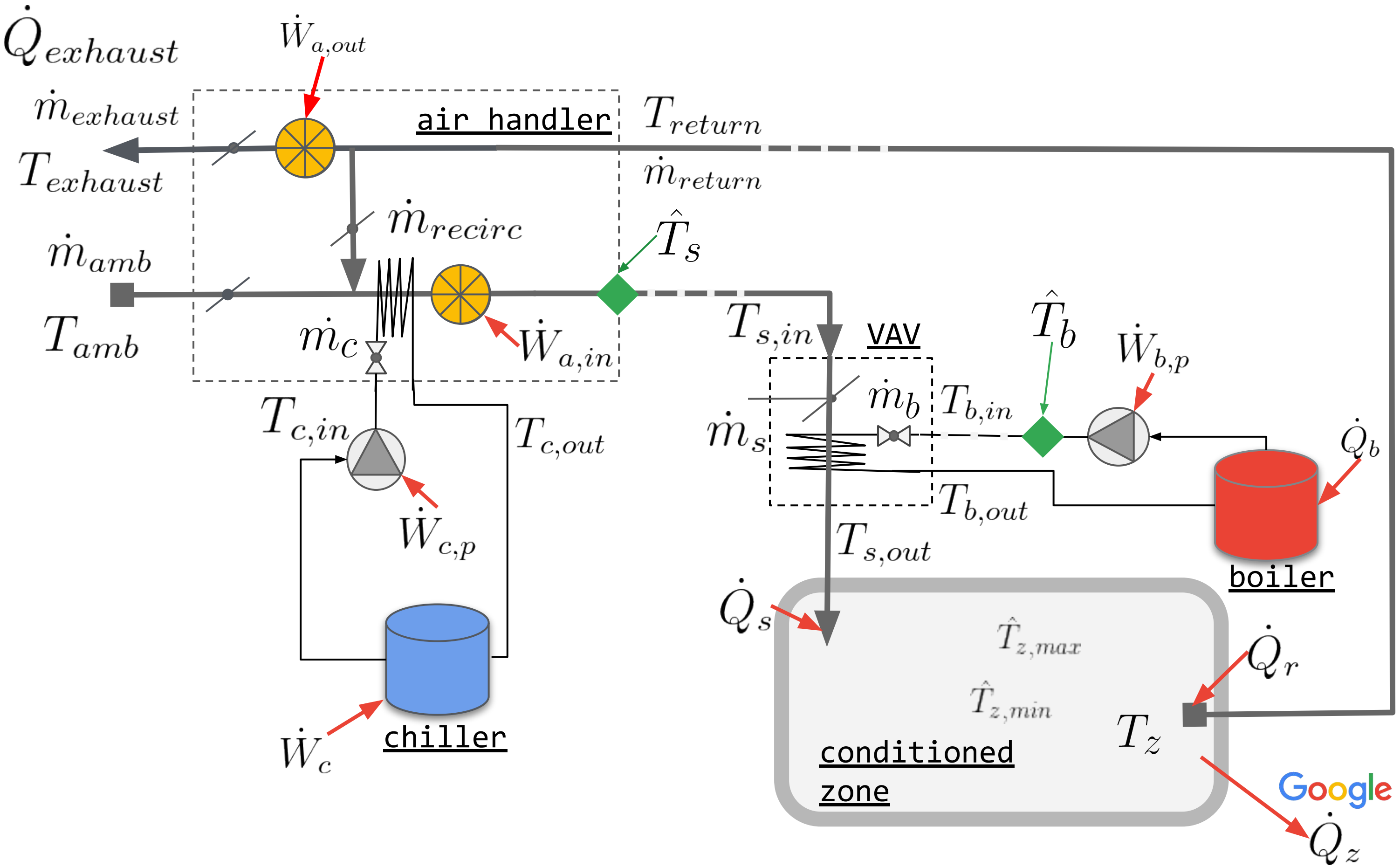
# Exterior Environment



# Interior Environment

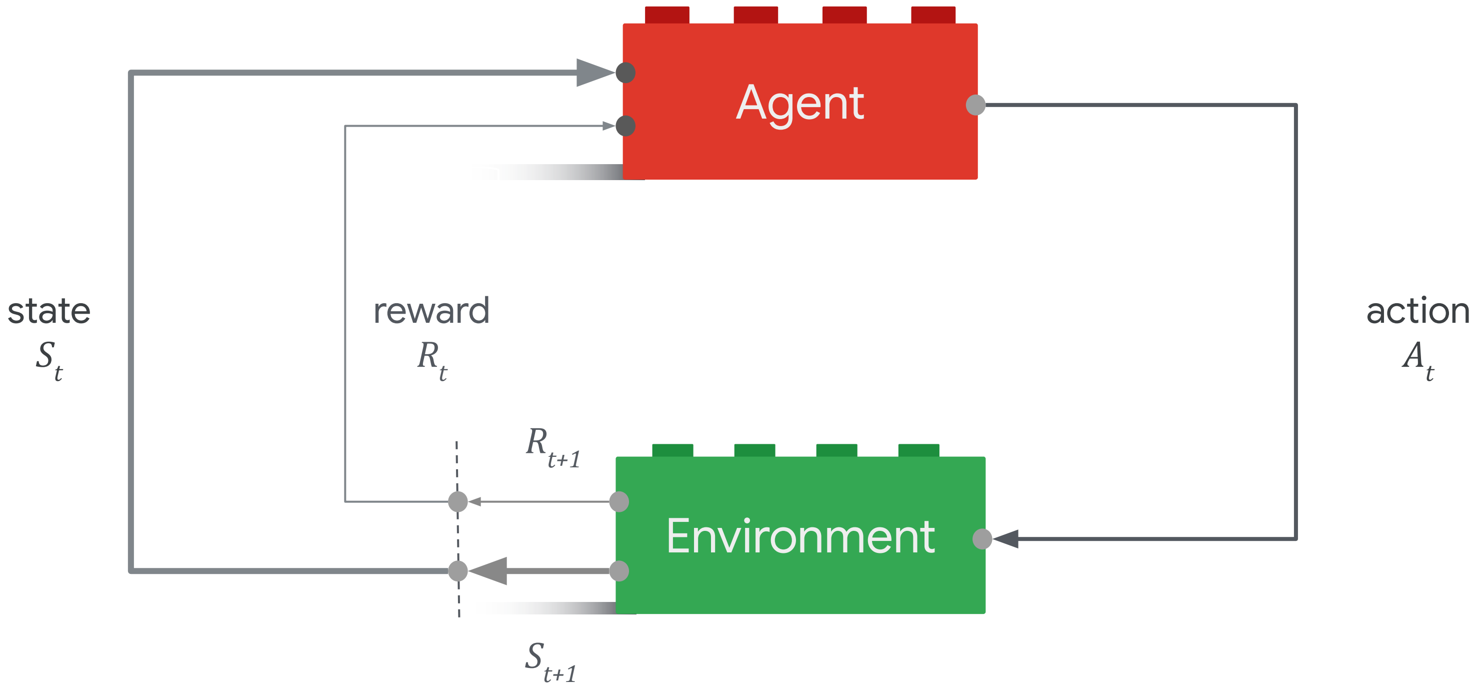

Google

# Environment Thermal Model



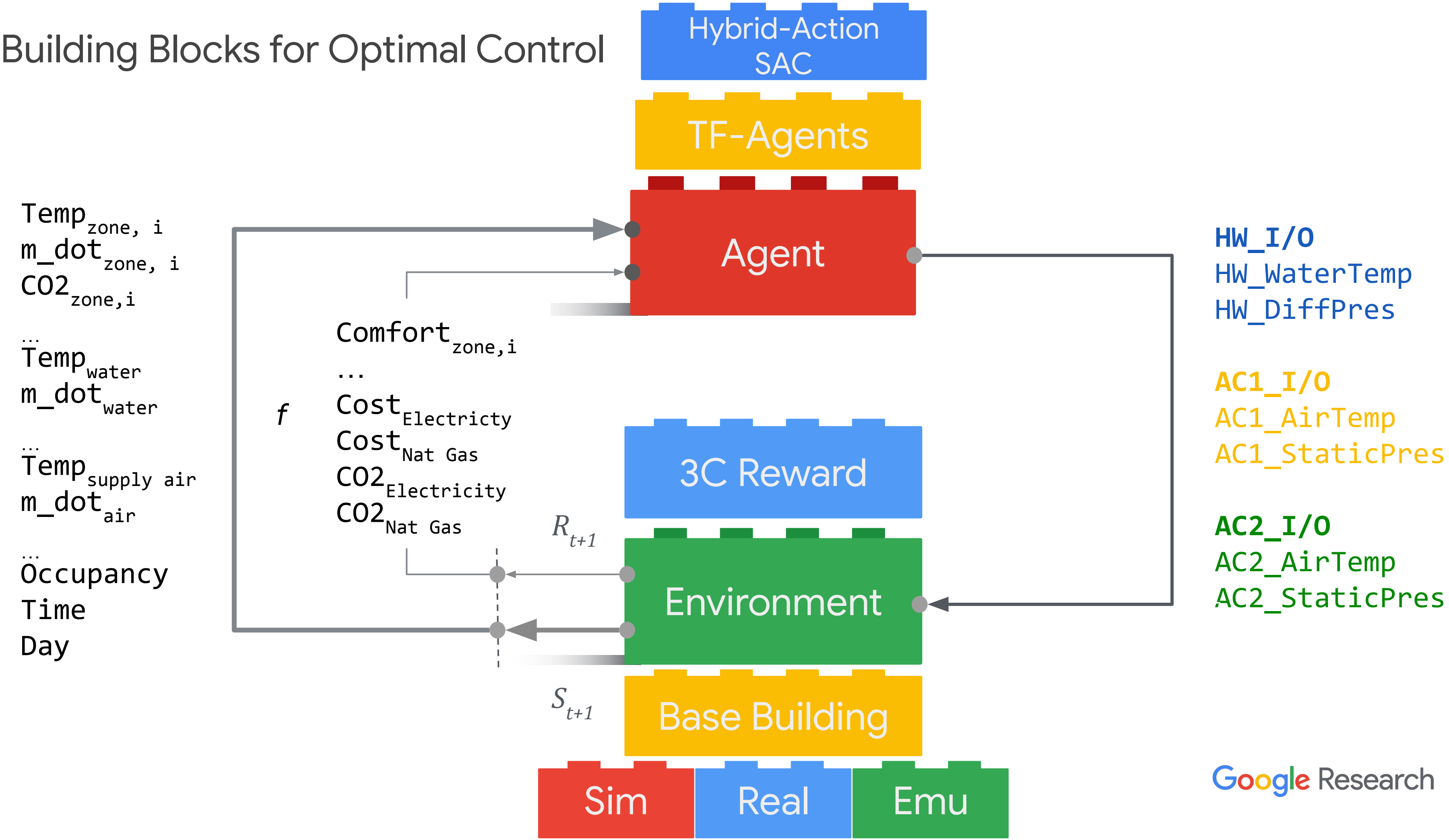

Google Research

# Optimal Control with Reinforcement Learning




Google Research

# Building Blocks for Optimal Control




Google Research

# Reward Function

# 3C Reward Function

## Comfort

Google exceeds standard comfort conditions for office buildings. Comfort conditions include room temperature and  ventilation/$CO_2$ levels. The agent must maintain these standards while minimizing cost.

## Cost

Electrical energy cost varies by time of day and day of week. Natural gas costs fluctuate less, but also vary monthly. Typically, buildings are biased to comfort and tend to consume more energy than required to meet comfort conditions.

## Carbon

Both natural gas and electricity emit carbon dioxide into the atmosphere. The agent should minimize carbon emissions.

$$r = u \times r_{comfort} + v \times r_{cost} + w \times r_{carbon}$$

Google Research

# Offline Training

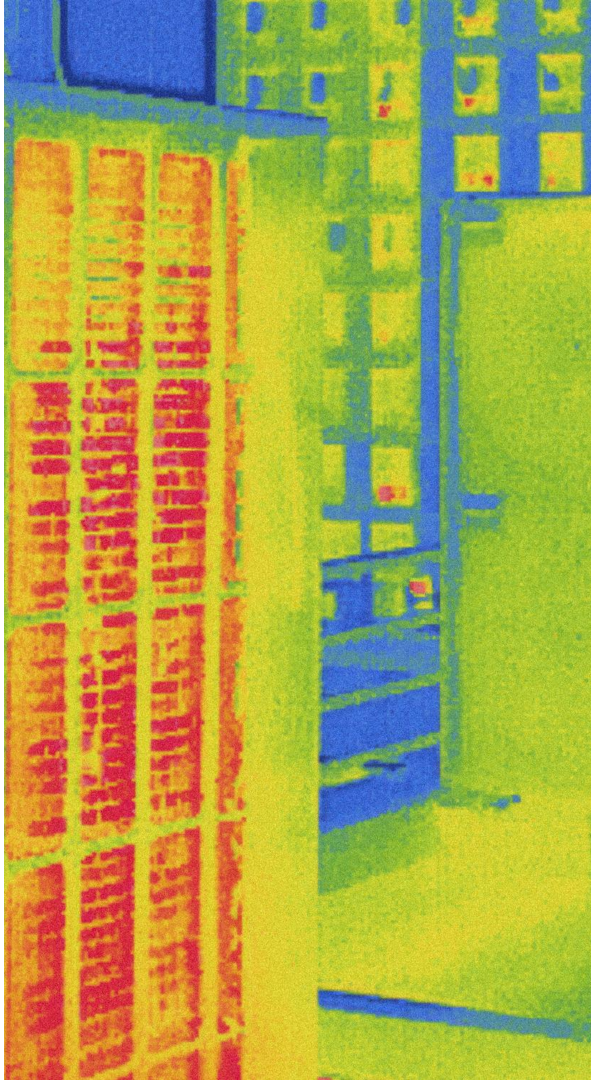
# Offline Training

Need to train a viable agent offline

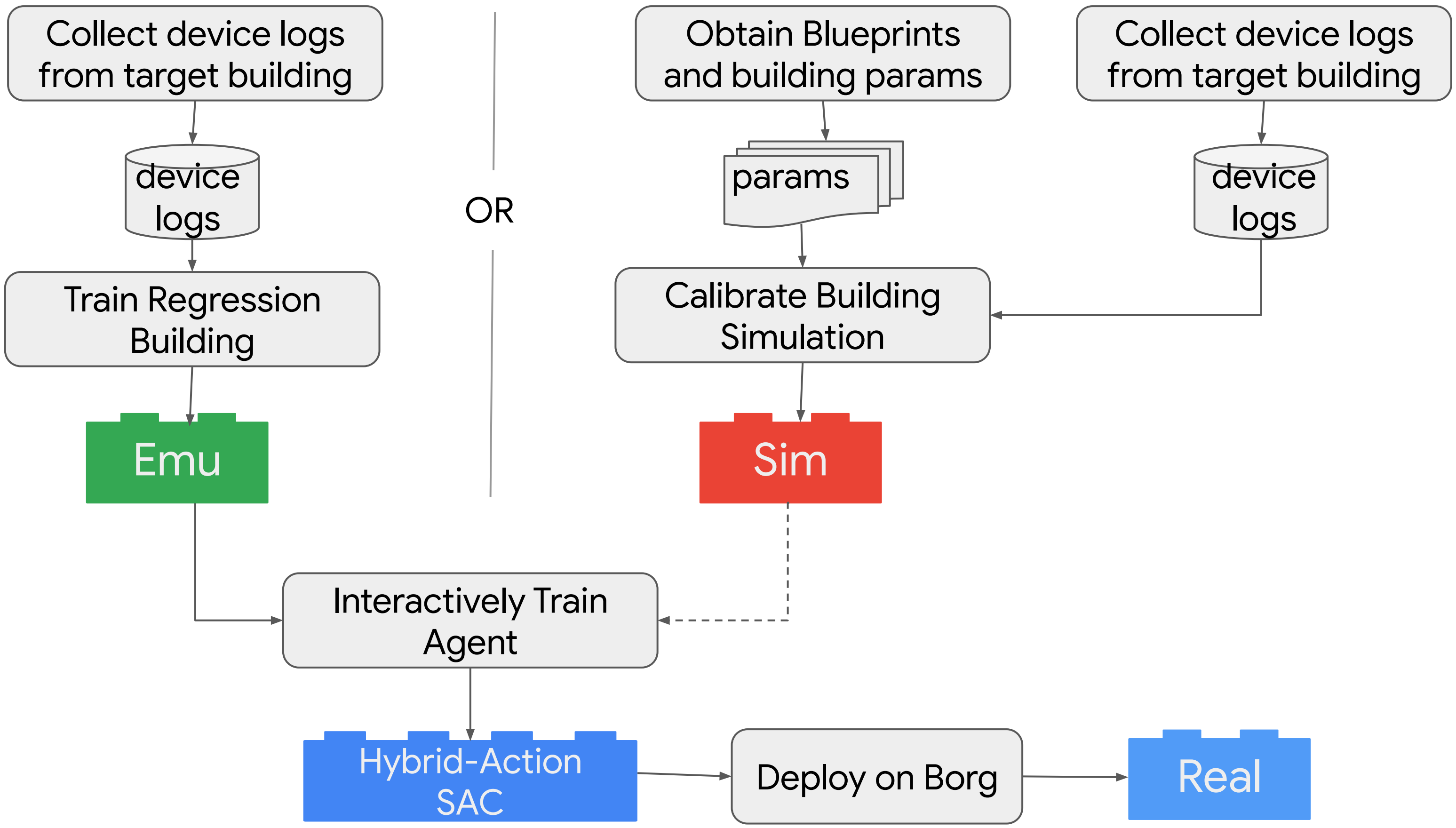
- Training requires many iterations
- Thermodynamics is slow

“***Digital twins***” for offline training

- **Sim**ulation: Model the thermodynamics
- **Emu**lation: Multivariate regression

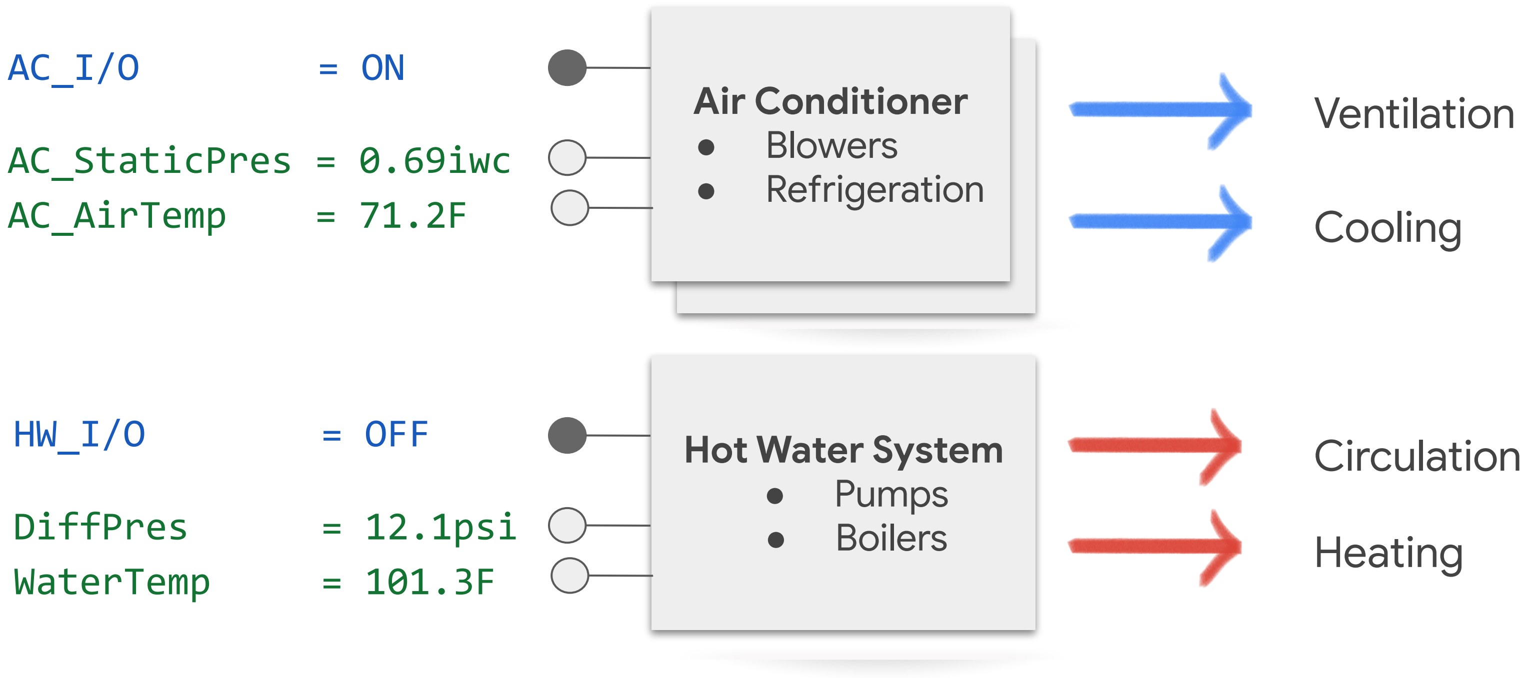


# Offline Training Approaches: **Emulation** vs. **Simulation**



# Agent Design

# Hybrid Action Spaces



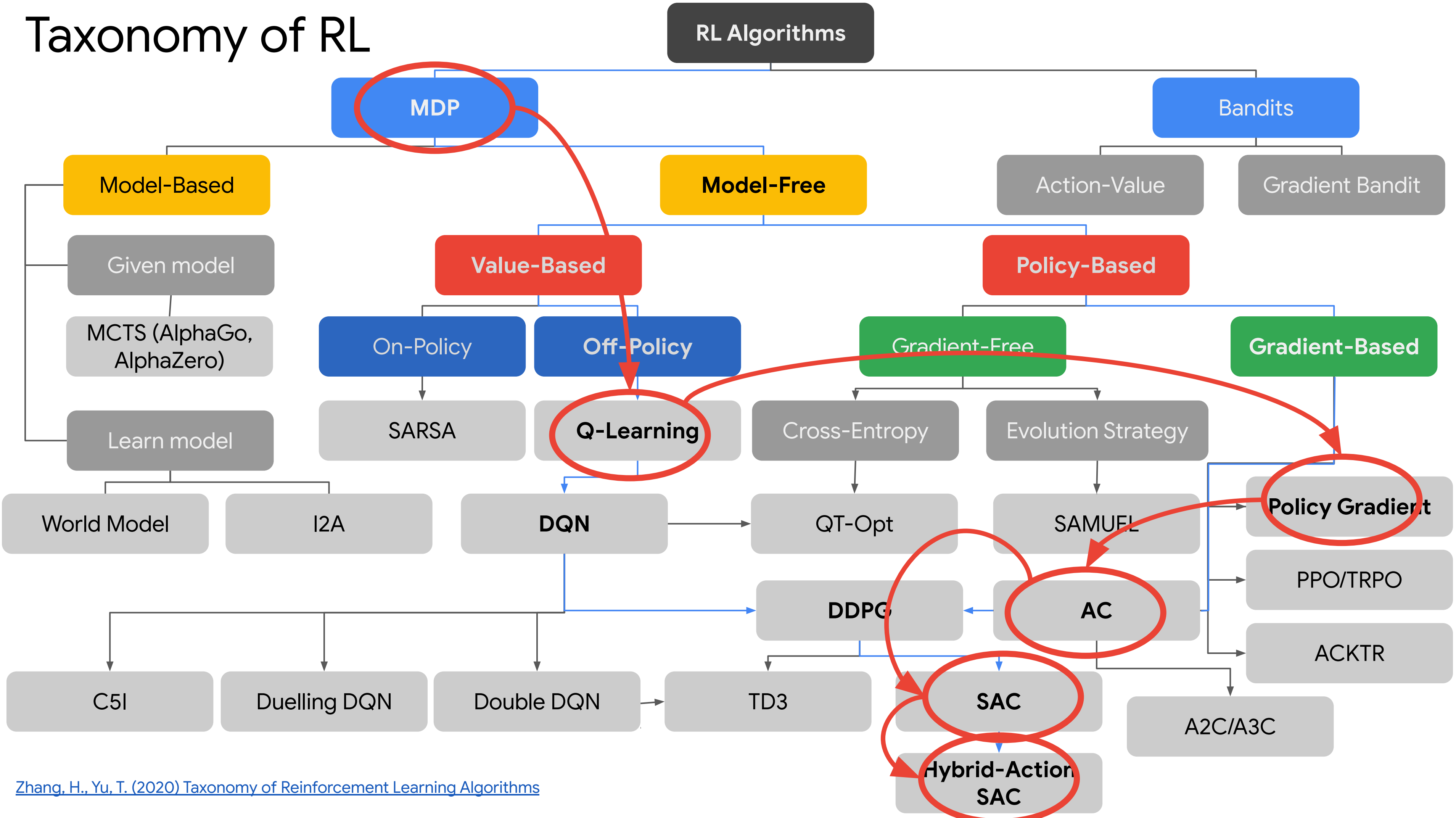

Actions are both continuous and discrete.

Google Research

Standard RL algorithms are generally discrete or continuous, but few are both

Very few benchmark RL environments that expose hybrid actions

# Taxonomy of RL




[Zhang, H., Yu, T. (2020) Taxonomy of Reinforcement Learning Algorithms]

# Hybrid-Action Soft Actor-Critic

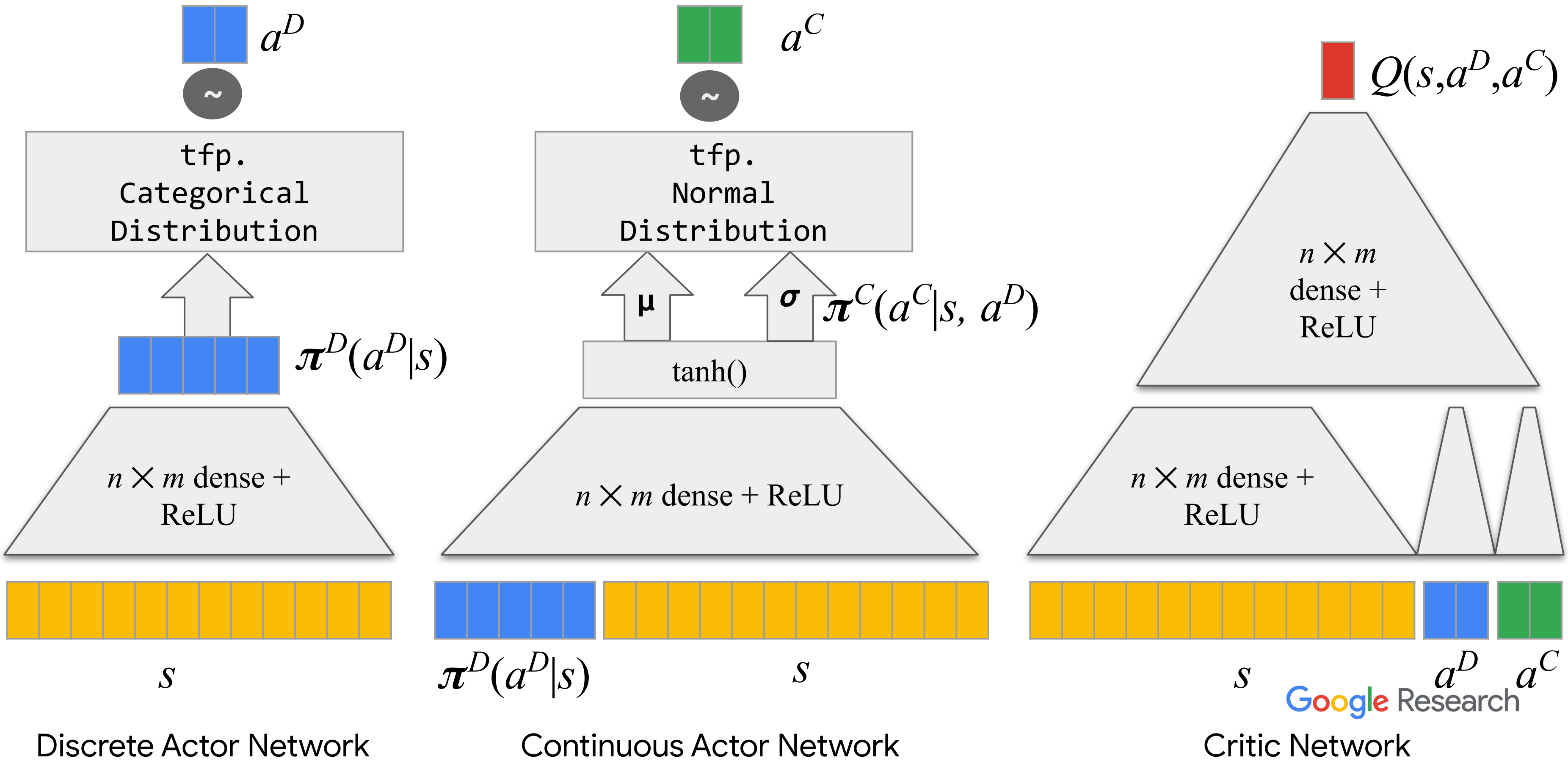
Applies existing “best practices”

- Policy Gradient
- Actor-Critic
- Experience Replay Buffers
- Target actor and dual critic networks
- Maximum Entropy RL
- Continuous Action Spaces

Introduces two new concepts:

- Action Pretraining
- Hybrid Action Spaces

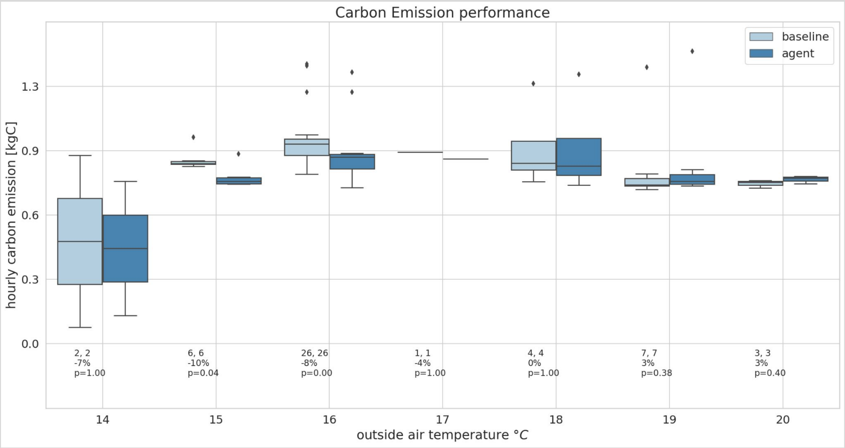
# Hybrid-Action SAC Networks

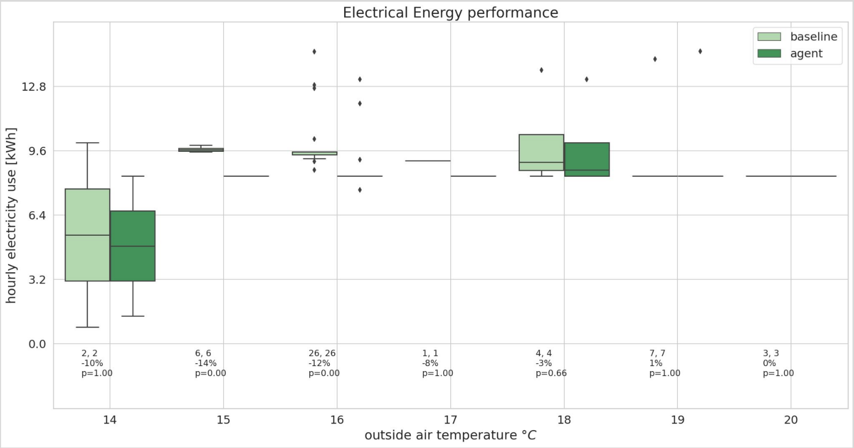


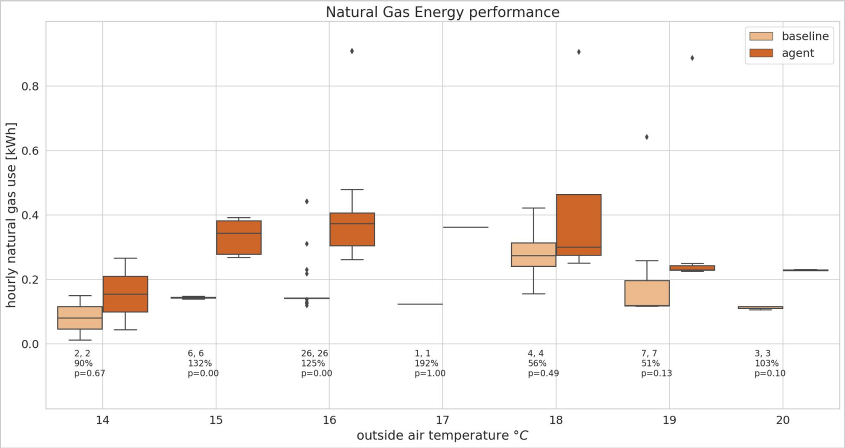

Google Research

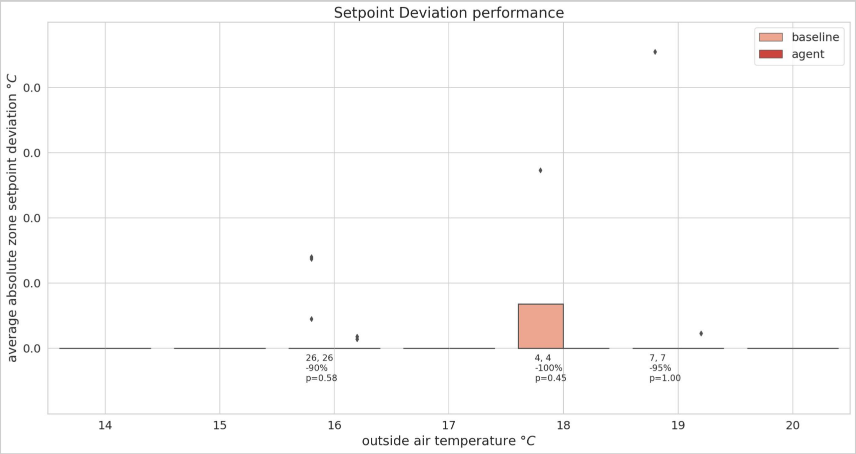
# Validation

# Validation Metrics



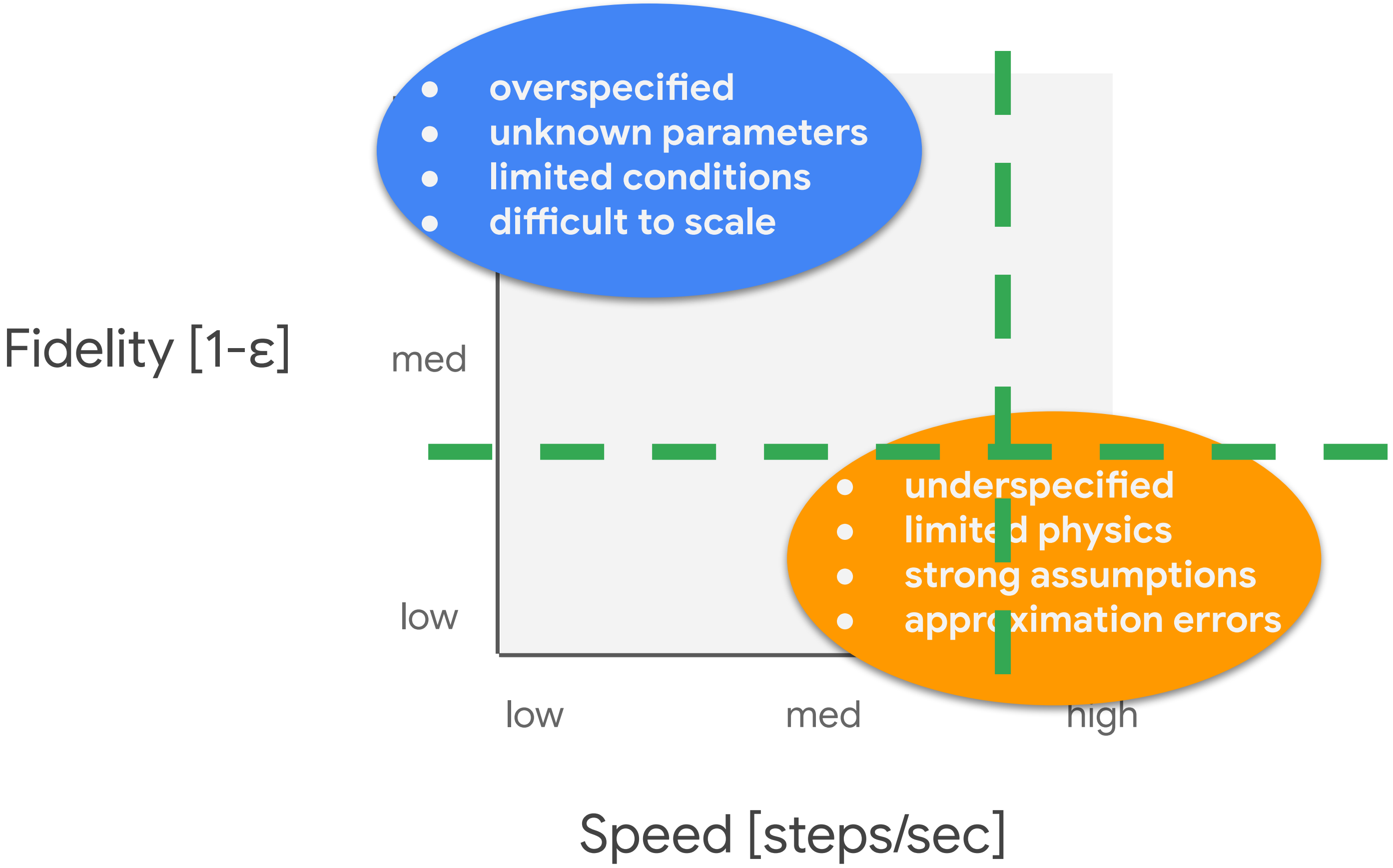




Google
1055 JOAQUIN RD

# Calibrated Building Simulation to estimate building energy consumption and carbon emission enabling offline agent training

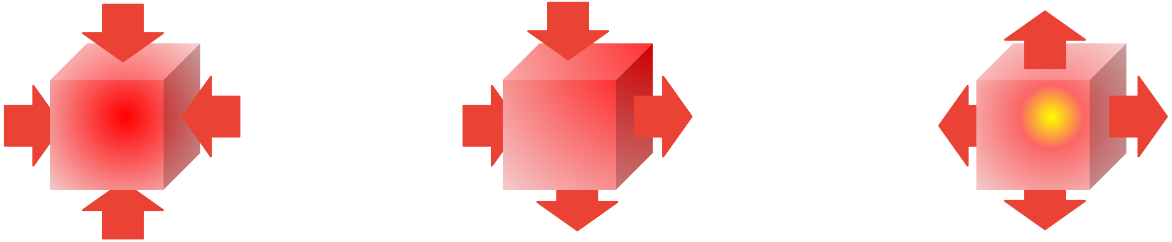
# Sim Fidelity vs. Efficiency




Google Research

# Energy Balance for unsteady thermal diffusion

**Thermal Absorption** + **Thermal Flux** = **Thermal Source**

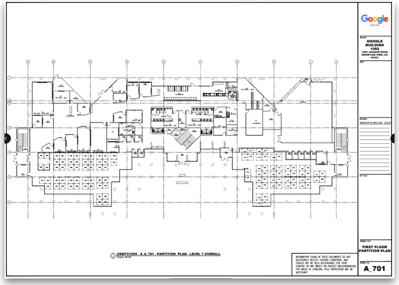


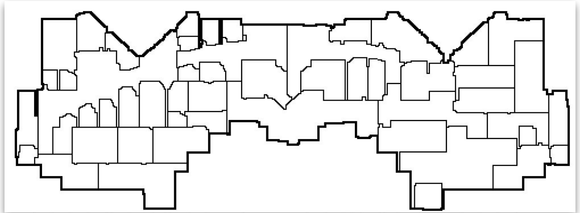
$$\frac{d}{dt}\int_{V(t)} Q\,dV + \oint_{S(t)} \mathbf{n}\cdot\mathbf{F}\,dS = \int_{V(t)} P\,dV$$

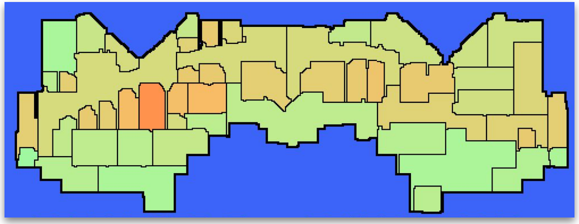
$t$ - time
V - volume
$Q$ - energy absorption by volume
$S$ - surface area

$\boldsymbol{F}$ - Flux, energy per surface area
$\boldsymbol{n}$ - Surface normal vector
$\boldsymbol{P}$ - Energy source per volume

# Customizing the Simulation for Other Buildings







**Extract Floorplan**

Ingest an image of a floorplan, and using OpenCV extract a floorplan grid.

**Pre-process**

Preprocess floorplan grid to make sure it is uniform. Add device parameters.

**Label Devices**

Interface that allows a human to quickly assign devices to zones

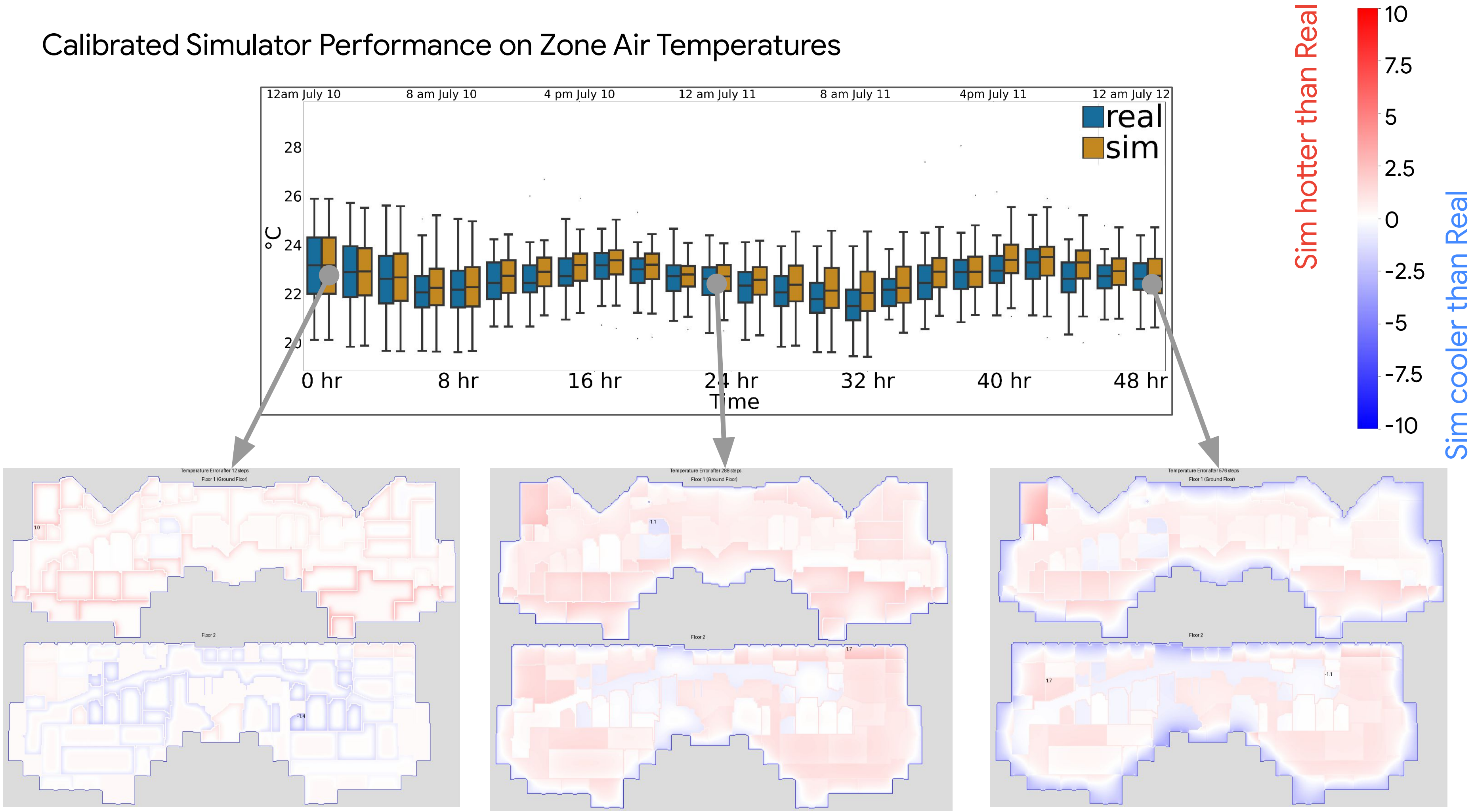
**Generate Simulator**

Generate a simulated RL environment that matches the real building in physical layout, device layout, and HVAC structure.

**Calibrate w/ Real World**

Use real world data to hyperparameter tune the simulator, to aid in sim-to-real transfer.

# Calibrated Simulator Performance on Zone Air Temperatures



Mean and Median Absolute Error on $N$ = 72 prediction window

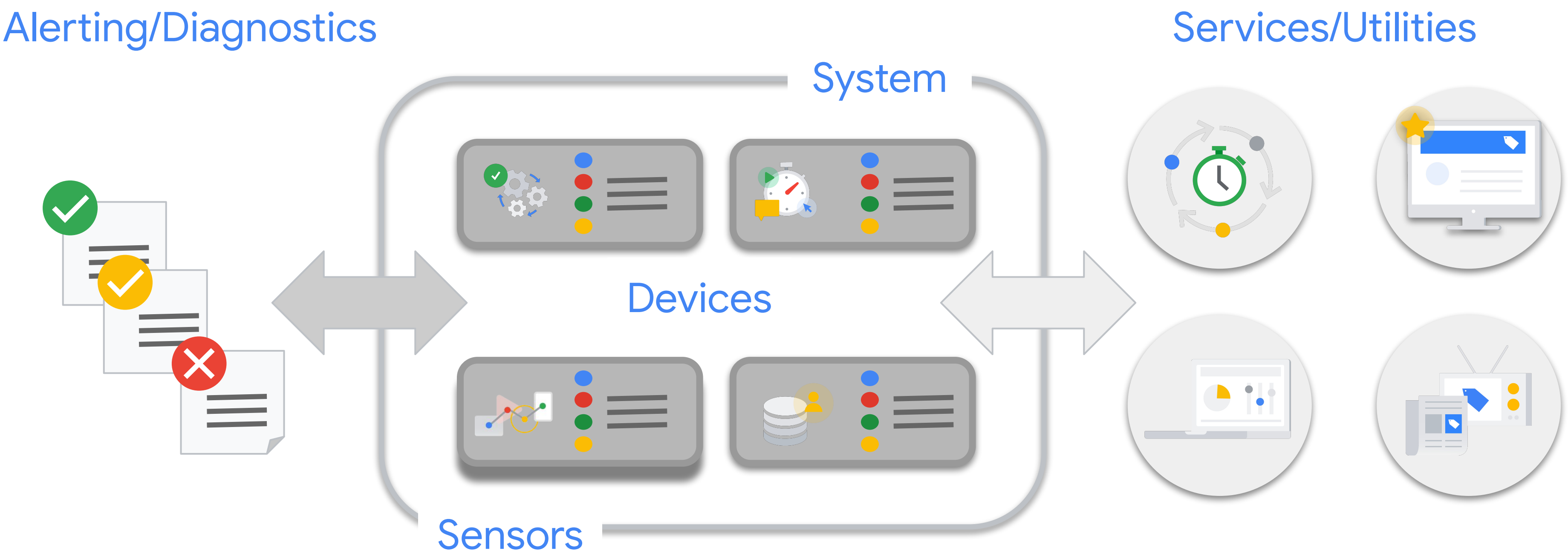
| Metric | Tuning Data (a) | Validation (b) | Validation (c) |
|---|---|---|---|
| MAE | $0.64\ ^{\circ}C$ | $0.63\ ^{\circ}C$ | $1.18\ ^{\circ}C$ |
| Median | $0.01\ ^{\circ}C$ | $0.18\ ^{\circ}C$ | $0.98\ ^{\circ}C$ |

Goldfeder, J., Sipple, J. (2023) A Lightweight Calibrated Simulation Enabling Efficient Offline Learning for Optimal Control of Real Buildings

Google Research

# Fault Detection and Diagnosis (FDD) to find and explain HVAC faults

# Telemetry Environment



# Heating, Ventilation, Air Conditioning (HVAC)

**Problem**: ACs, Hot Water Systems, VAVs fail, resulting in uncomfortable conditions and wasted energy and $CO_2$ emission

**Stakeholder**: REWS, FORT

**Fleet**: 35k+ devices in 200 buildings (200+ types)

**Datastream**: Unlabeled numeric multivariate, temps, pressure, etc., 5 min interval

**Anomaly Detector**: MADI

# Anomaly Detection

**Device** generates a sequence of $D$-dimensional **observations** $x$

$x = [\text{zone air temp} = 18.0\ ℃, \text{static pressure} = 128\ \text{pa}, \ldots]$

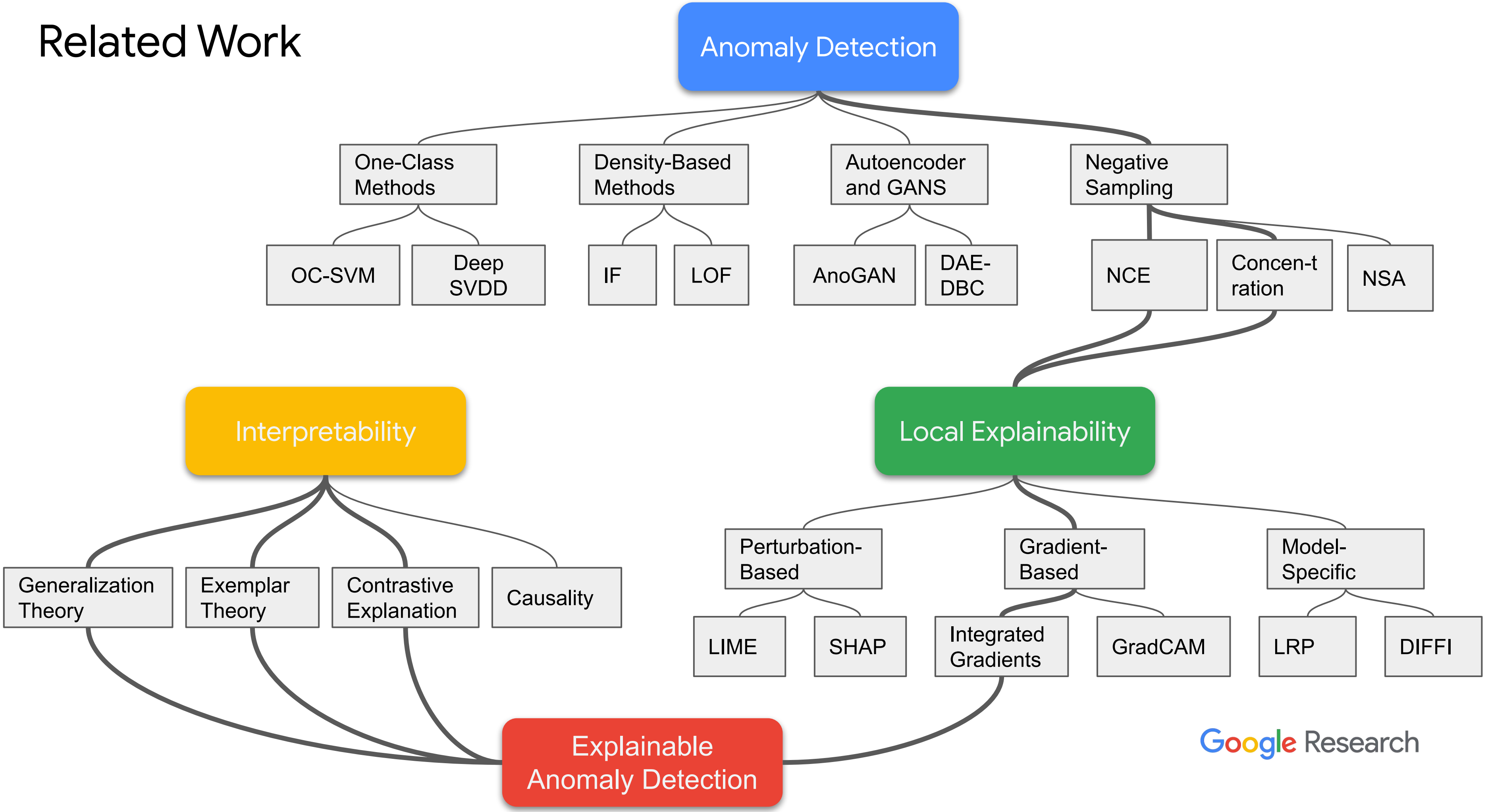
What is "normal"?

**Anomaly Detection** is the task of determining whether $x$ is $\text{Normal}$

How do we test?

**Anomaly Detector** is a differentiable function
$F: \mathbb{R}^D \rightarrow [\mathit{Anomalous} \approx 0 \text{ to } \mathit{Normal} \approx 1]$

# Related Work



# Anomaly Detection with MADI

Multivariate Anomaly Detection with Interpretability (MADI)

- Sipple J., (2020) Interpretable, Multidimensional, Multimodal Anomaly Detection with Negative Sampling for Detection of Device Failure, ICML 2020

- Sipple J., Youssef, A., (2022) A General-Purpose Method for Applying Explainable AI for Anomaly Detection, ISMIS 2022

**Anomaly Detection based on Noise-Contrastive Estimation and Neural Nets**

**Anomaly Explanations using Integrated Gradients**

# Anomaly Detection Results

| ROC-AUC % | OC-SVM | Deep SVDD | Iso Forest | Extended Iso Forest | **NegSampleRnd Forest** | **NegSample Neural Net** |
|---|---|---|---|---|---|---|
| Forest Cover* | 53 ±20 | 69 ±7 | 85 ±4 | **93 ±1** | 80 ±2 | 86 ±4 |
| Shuttle* | 93 ±0 | 88 ±9 | **96 ±1** | 91 ±1 | **93 ±7** | **96 ±5** |
| Mammography* | 71 ±7 | 78 ±6 | 77 ±2 | **86 ±2** | **85 ±4** | 84 ±2 |
| Mulcross* | 90 ±0 | 54 ±4 | 88 ±0 | 66 ±4 | 94 ±1 | **99 ±1** |
| Satellite* | 51 ±1 | 62 ±3 | 67 ±2 | **71 ±3** | 65 ±4 | **73 ±3** |
| Smart Buildings | 76 ±1 | 60 ±7 | 71 ±7 | 80 ±4 | **95 ±1** | 93 ±1 |

* Courtesy of ODDS Library [http://odds.cs.stonybrook.edu].
Stony Brook, NY: Stony Brook University, Department of Computer Science

Google Research

# Anomaly Explanation

Given $F(\boldsymbol{x}) \approx 0$, what make $\boldsymbol{x}$ anomalous?

- *Describe the Symptoms*
- Map $\boldsymbol{x}$ to an **attribution**
- May also use a **contrastive normal point** $x$'

Why is it "anomalous"?

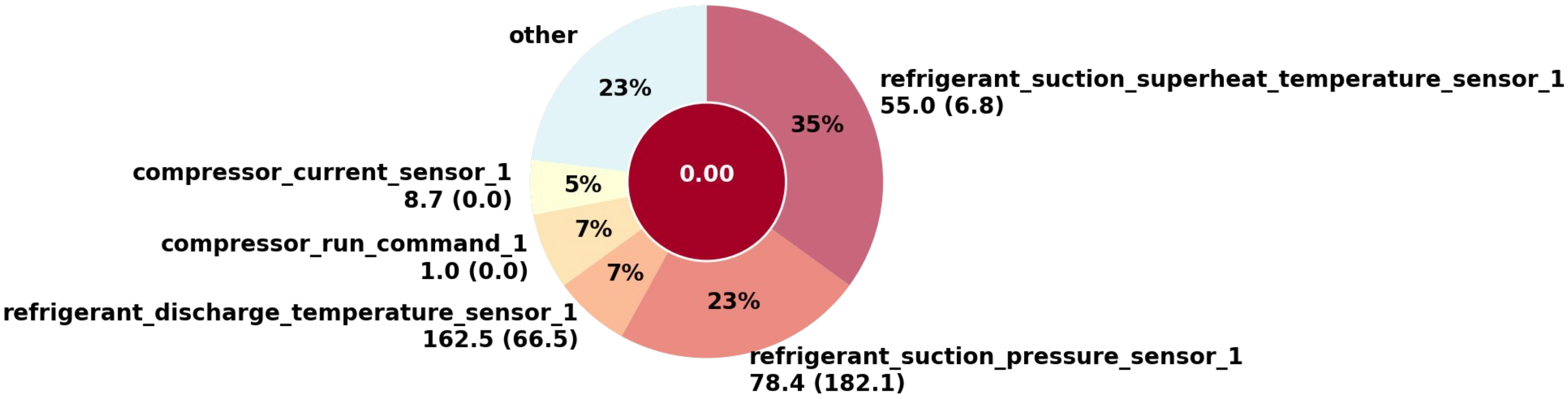
Enables an expert's **interpretation** that maps Symptoms to Diagnosis

# Comparing AI Explainability Methods

| | Contrastive | Complete | Sensitive | Proportional |
|---|---|---|---|---|
| **LIME** Ribiero2016 | − | + | − | − |
| **SHAP** Lundberg2017 | − | + | + | + |
| **OC-DTD** Kaufmann2020 | − | + | − | − |
| **LRP** Bach2015 | − | + | − | − |
| **IG** Sundararajan2017 | + | + | + | + |

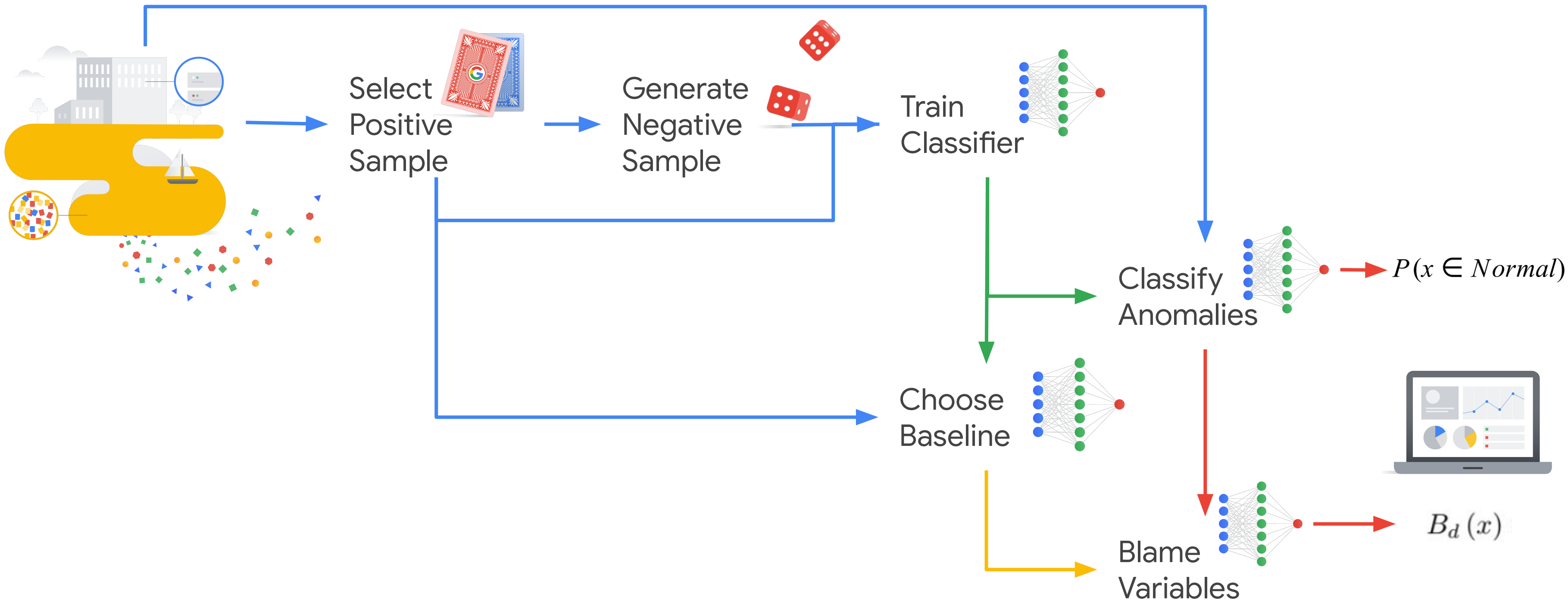
Google Research

# Anomaly Detection with Explanation



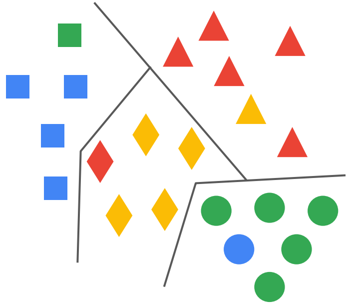

Sipple, J., (2020). [Interpretable, Multidimensional, Multimodal Anomaly Detection with Negative Sampling for Detection of Device Failure]

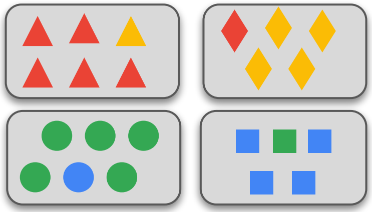
# Anomaly Detection Pipeline with Interpretability

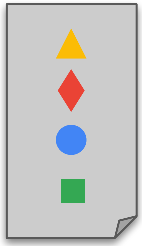



Google Research

# Distributed Anomaly Detection Framework







Segment the population into homogeneous cohorts.

Resegment periodically.

Launch independent Anomaly Detection instances on borg for each cohort.

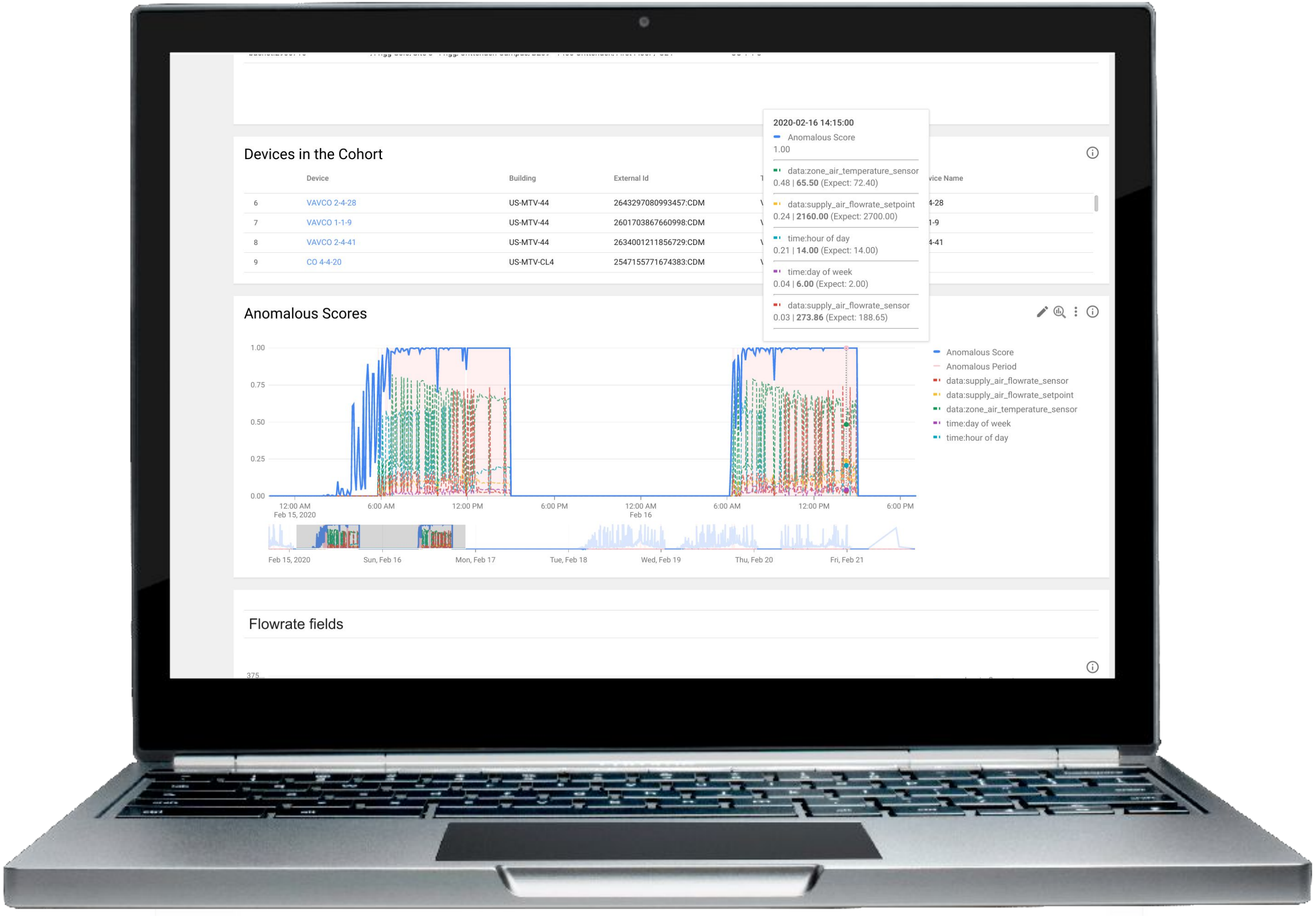
Update the cohort membership when population changes.

Aggregate the results from all the instances.

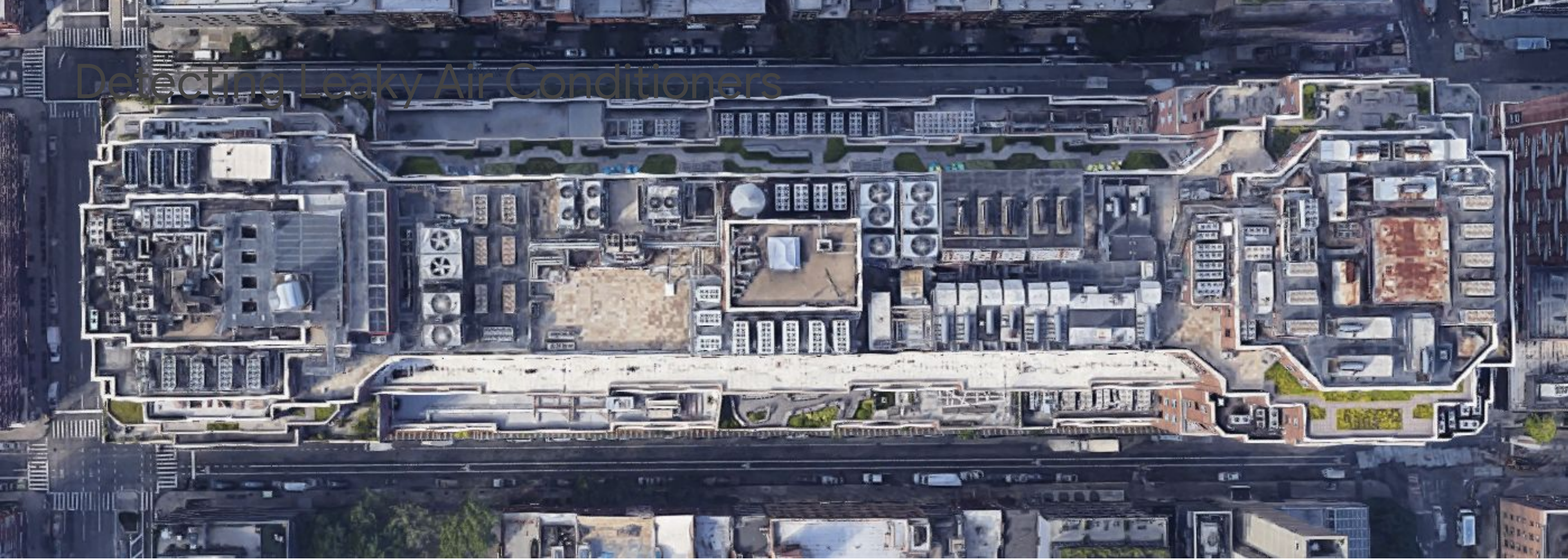
Rank order the anomalous members by severity.

Publish top N most anomalous devices via PubSub topic to consumers.

Google Research


Devices in the Cohort
Device
Building
External Id
6 VAVCO 2-4-28 US-MTV-44 2643297080993457:CDM
7 VAVCO 1-1-9 US-MTV-44 2601703867660998:CDM
8 VAVCO 2-4-41 US-MTV-44 2634001211856729:CDM
9 CO 4-4-20 US-MTV-CL4 2547155771674383:CDM
2020-02-16 14:15:00
Anomalous Score
1.00
data:zone_air_temperature_sensor
0.48 | 65.50 (Expect: 72.40)
data:supply_air_flowrate_setpoint
0.24 | 2160.00 (Expect: 2700.00)
time:hour of day
0.21 | 14.00 (Expect: 14.00)
time:day of week
0.04 | 6.00 (Expect: 2.00)
data:supply_air_flowrate_sensor
0.03 | 273.86 (Expect: 188.65)
Anomalous Scores
Anomalous Score
Anomalous Period
data:supply_air_flowrate_sensor
data:supply_air_flowrate_setpoint
data:zone_air_temperature_sensor
time:day of week
time:hour of day
12:00 AM Feb 15, 2020
6:00 AM
12:00 PM
6:00 PM
12:00 AM Feb 16
6:00 AM
12:00 PM
6:00 PM
Feb 15, 2020
Sun, Feb 16
Mon, Feb 17
Tue, Feb 18
Wed, Feb 19
Thu, Feb 20
Fri, Feb 21
Flowrate fields

# Project Freon to detect leaky Air Conditioners




# Refrigerants

- 1,000s times more potent contributor to global warming than $CO_2$
- Fastest growing GHG emission, at 4.6% per year in the last decade
- Reducing emission starts with early leak detection

Google Research

United Nations Environment Programme (2019). Emissions Gap Report 2019. UNEP,Nairobi.

# Sensors

**Temperature (F)**

1. Suspension Temperature
2. Discharge Temperature
3. Liquid Temperature
4. Liquid Saturation Temperature
5. Vapor Saturation Temperature
6. Subcooling Temperature
7. Superheat Temperature
8. Discharge Air Temperature
9. Return Air Temperature
10. Mixed Air Temperature
11. Zone Air Temperature
12. Outside Air Temperature

**Pressure (psig)**

1. Suction Pressure
2. Discharge Pressure
3. Liquid Pressure

**Current (A)**

1. Discharge Fan Current
2. Compressor Current
3. Condensing Fan Current

**Relative Humidity (%)**

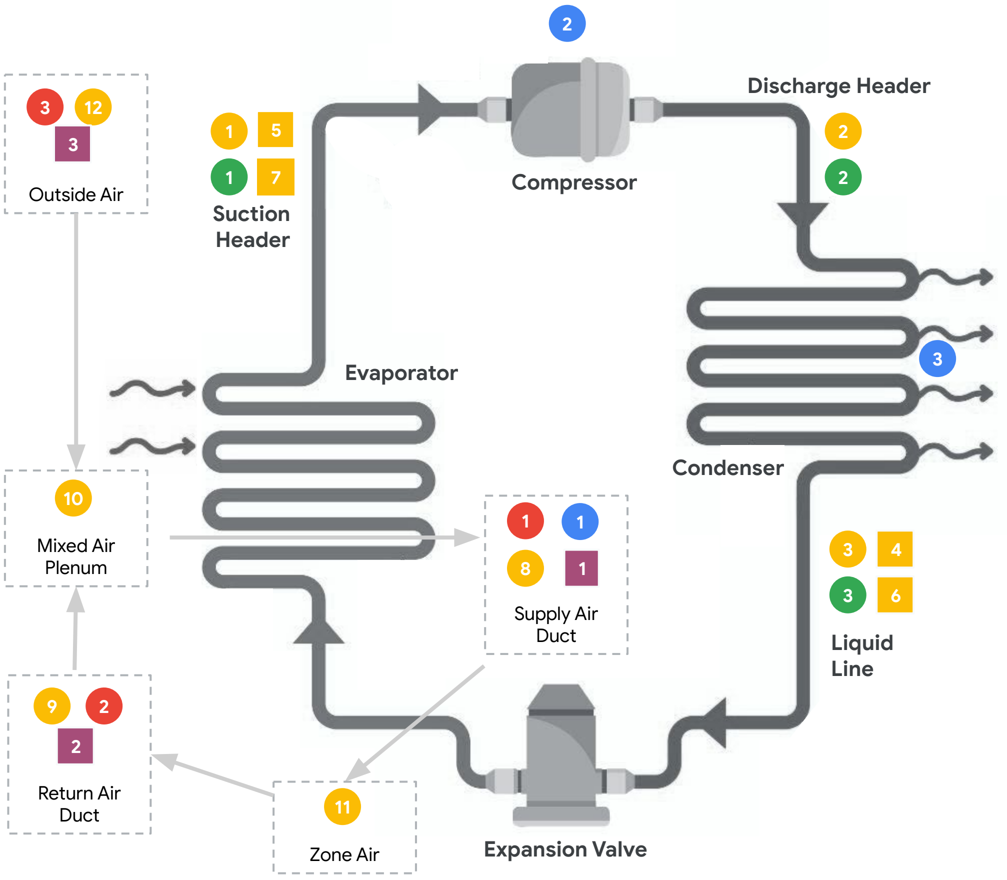
1. Discharge Air Relative Humidity
2. Return Air Relative Humidity
3. Outside Air Relative Humidity

**Enthalpy (BTU/lbm)**

1. Discharge Air Enthalpy
2. Return Air Enthalpy
3. Outside Air Enthalpy

Sensor (captures data not typically measured )

Calculated data



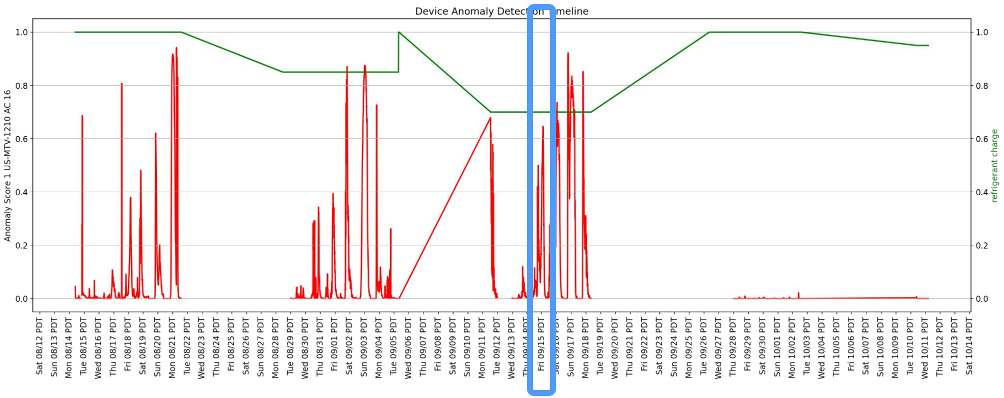

Google Research

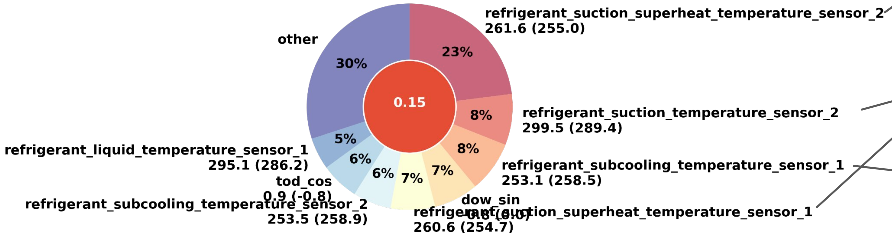
# Project Freon Test Sites

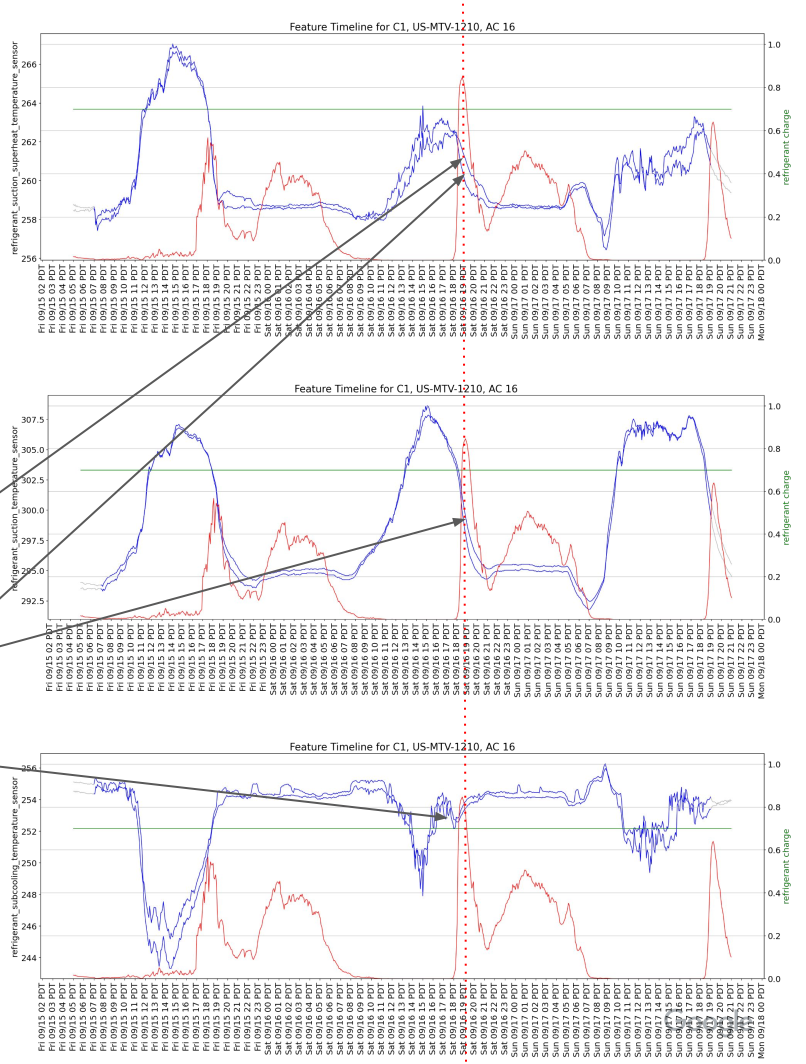

WERNER
AC-1
FEED FROM MSB
DANGER
ON
OFF


522B
CL550
Range:0~500psi
S/N:2305315043

# Explainability Analysis Example (1)




High refrigerant suction superheat temperature in circuits 1, 2; high refrigerant suction temperature circuit 2; low refrigerant subcooling temperature circuit 1, (on the descending edge of the duty cycle).

# Qualitative Assessment of Detection Performance

**Weather Conditions**
Cooling Degree Days

| | | | |
|---|---|---|---|
| **Hot** >8 | Detectable | Detectable | Detectable |
| **Mild** 4 - 8 | Detectable | Marginal | Marginal |
| **Cool** 0-3 | Marginal | Marginal | Undetectable |
| | **Severe** < 75% | **Significant** 75% - 85% | **Initial** > 85% |

**Leakage**
Charge Level

Google Research

# Intelligent Diagnostics provide root-cause analysis and recommend fixes

# Diagnosis and Causal Reasoning

Diagnosis: An investigation or analysis of the **cause** or nature of a condition, situation, or problem
Merriam-Webster Dictionary

Diagnose: identify the nature of (an illness or other problem) by examination of the symptoms.
Oxford Languages

Actual Causal Reasoning is a fundamental step in forming a diagnosis

Google Research

# LLMs and Actual Causal Reasoning

## LLMs outperform Structural Causal Models on the CRASS Counterfactual Reasoning benchmark and **6% lower than human annotators**

| CRASS Counterfactual reasoning benchmark example | | |
|---|---|---|
| Premise | Counterfactual Question | Multiple-choice Answers |
| A bird lands in a forest. | What would have happened if a plane had landed in a forest? | (a) The plane would have crashed.<br>(b) Everything would have been fine.<br>(c) The plane would have landed safe and sound.<br>(d) In a forest, you will find lots of planes. |

Google Research

Kiciman, E., Ness, R., Sharma, A, Chenhao, T., (2023) [Causal Reasoning and Large Language Models:](#) Opening a New Frontier for Causality

# LLMs and Reasoning about Normality

| BIG-Bench Hard Causal Judgements Task (example) | | |
|---|---|---|
| Passage and Question | Correct Answer | LLM rationale |
| Lauren and Jane work for the same company. They each need to use a computer for work sometimes. Unfortunately, the computer isn't very powerful. If two people are logged on at the same time, it usually crashes. So the company decided to institute an official policy.<br>It declared that Lauren would be the only one permitted to use the computer in the mornings and that Jane would be the only one permitted to use the computer in the afternoons.<br>As expected, Lauren logged on the computer the next day at 9:00 am.  But Jane decided to disobey the official policy. She also logged on at 9:00 am. The computer crashed immediately.<br>Did Jane cause the computer to crash? | Jane logging in at 9:00 am is an abnormal event because she followed policy | Jane's decision to log onto the computer at 9:00 am despite the official policy is abnormal, as it intentionally violates the company's policy put in place to prevent computer crashes. This action is unexpected and goes against the established social and workplace rules. **(correct)** |

Large Language Models achieve nearly 70% accuracy scores on generative causal reasoning tasks.

Google Research

Kiciman, E., Ness, R., Sharma, A, Chenhao, T., (2023) Causal Reasoning and Large Language Models: Opening a New Frontier for Causality

# Intelligent Diagnostics

## Detection

## Explanation

## Interpretation

**Continuous Monitoring** of device telemetry, a stream of multidimensional time-stamped observations from a fleet of devices.

**Anomaly Detection** trains anomaly detection models on unlabeled telemetry, and scores each observation with an anomaly score.

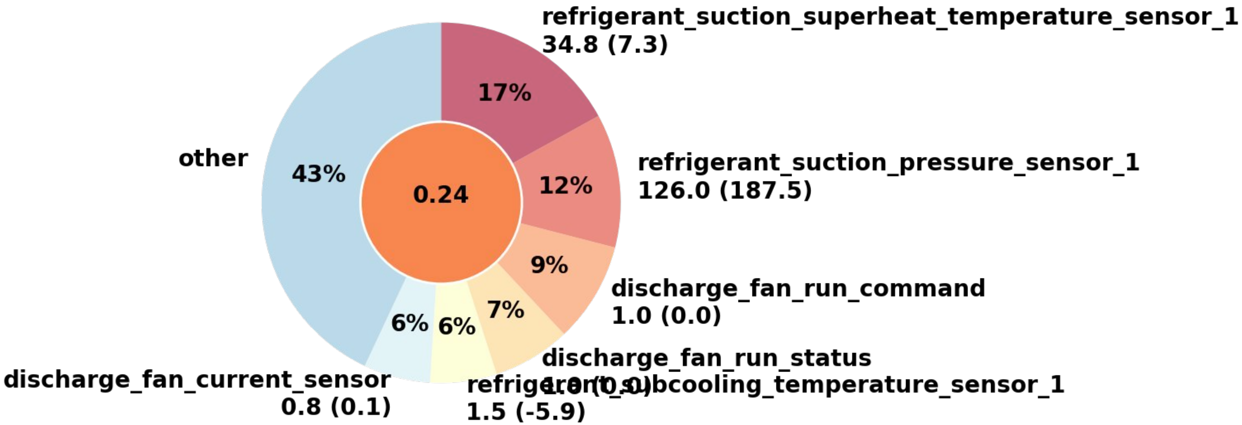
**Explainable AI** provides rich explanations of each anomaly, including

- Attributions
- Contrastive Normal

**Large Language Models** combine the explained anomaly with knowledge base to provide a diagnosis and suggested treatments.

Google Research

# From Explanation to Prompt




Consider an anomalous air conditioner. The refrigerant superheat temperature has 17% importance, observed is 34.8 degrees celsius, but expected to be 7.1 degrees celsius. The refrigerant suction pressure has 12% importance and  is observed 126.0 psi, but expected 187.5 psi. Provide a diagnosis of the problem with justification.

Google Research

# Gemini-based Diagnosis (Problem Understanding)

## The problem

The air conditioner is low on refrigerant.

## Justification

The superheat temperature is a measure of how much heat is left in the refrigerant after it has passed through the evaporator coil. The higher the superheat temperature, the less heat is being removed from the air. In this case, the superheat temperature is 34.8 degrees Fahrenheit which is much higher than the expected value of 7.1 degrees Fahrenheit. This indicates that there is not enough refrigerant in the system to remove the heat from the air.

The suction pressure is also a measure of the amount of refrigerant in the system. The lower the suction pressure, the less refrigerant is in the system. In this case, the suction pressure is 126.0 psi, which is much lower than the expected value of 187.5 psi. This further confirms that there is not enough refrigerant in the system.

# Gemini-based Diagnosis (Treatment Suggestion)

## The solution

The solution to this problem is to recharge the air conditioner with refrigerant. This can be done by a qualified HVAC technician.

## Other possible causes

There are a few other possible causes of the problem, but they are less likely. These include:

- A dirty evaporator coil.
- A malfunctioning expansion valve.
- A restriction in the refrigerant line.

If the superheat temperature and suction pressure are still abnormal after the air conditioner has been recharged, then one of these other causes may be the problem. A qualified HVAC technician will be able to diagnose the problem and make the necessary repairs.

# Parting Thoughts

AI has an enormous potential to offset the climate burden from buildings

We must work collaboratively to leverage the potential of AI

Google is willing to partner as you unlock the opportunity of AI to increase efficiency and reduce emission