SENTRY

Soft Target Engineering to Neutralize the Threat Reality

U.S. Department of Homeland Security Center of Excellence

Decision Trees in Action: Evacuation and Fire Safety

A project where undergraduates study the LA wildfires, apply decision trees to model fire evacuation logic, simulate a crowded venue, track how civilians depart after an alarm, and develop plans to deploy first responders in case of natural or manmade threats

Figure 1: NASA evacuation simulation exercise[NASnd]

A SENTRY Undergraduate Teaching Module

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ACKNOWLEDGEMENT AND DISCLAIMER

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Summary of the Module:

The goal of this module is to introduce undergraduates across a variety of disciplines to the vital field of artificial intelligence and machine learning. This module introduces early undergraduates to an essential area of mathematics, the decision tree algorithm, which is the foundation of some of the most widely used classification algorithms (ham or spam? cat or dog? fire or no fire?) in machine learning today. In this module, students learn how to use basic logic to build elementary decision trees, essentially resembling a series of "yes/no" questions, that progressively split data into smaller subsets based on specific features, ultimately leading to a final prediction at the leaf nodes. For this reason, simple decision trees are easy to understand and interpret, making them accessible to students in elementary college mathematics courses. This module challenges students to simulate a crowded venue, track how civilians depart after an alarm, and develop plans to deploy first responders in case of natural or manmade threats. Specifically this module predicts which exit each civilian will use, so first responders could make triage plans. Overall this module will equip students to advance the safety and security of their communities.

Target Audience: First-year undergraduates.

Prerequisites: Algebra I, elementary descriptive statistics, elementary geometry.

Keywords: active learning, cooperative learning, decision trees, evacuation, hands-on learning, machine learning, modeling, tactile learning.

Anticipated Number of Class Periods: 3 classes, approximately 160 minutes

Of special note:

This module includes supplemental online materials freely available in the cloud at `https://github.com/rubripes11/exit-prediction`

Note to teachers: Teacher notes appear in red in the module, allowing faculty to pull these notes off the teacher version to create a student version of the module.

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Table 1 describes the class time used by the components of this module. Each component has some standalone value, and gains meaning when presented as part of the whole.

Topic	Class time (minutes)
Introduction	5
The LA Wildfires, Urban Fires, and Citizen Science	25
Decision Trees	60
Simulation Math Content	10
Simulate a Crowded Venue	60
Total	160

Table 1: Topic Class Time

Table 2 maps the exercises to Bloom's Taxonomy [And01]. The authors of this module use Active Verbs for Bloom's Revised Taxonomy [Cen25] as a quick reference.

Goal	Objective	Learning Outcome Students will be able to	Exercise	Bloom's Taxonomy
Los Angeles Wildfires	Learn from history	Describe a lesson LA can learn from history	2.1	1 Remember
Decision Trees	Decision Trees in emergency planning	State crowded place evacuation challenges	3.1.1	
		Describe potential safety hazards	3.1.2	2 Understand
		Design decision tree	3.1.3	5 Evaluate
		Describe sensor Combination	3.1.4	2 Understand
	Machine Learning for Public Safety	Design decision tree by selecting first split	3.2.1	5 Evaluate
Simulation math content	Probability	Generate uniform distribution via active learning	4.1.1	
Simulate a crowded venue	Gather meaningful data	Describe a familiar venue via numerical measurements	5.1.1	1 Remember
		Describe animation headline	5.4.1a	
		Discuss animation conclusion	5.4.1b	2 Understand

Table 2: Exercise Bloom's Taxonomy Levels

1 Introduction

This topic will take five (5) minutes of class time.
In recent months, the U.S. has witnessed a succession of catastrophic natural disasters. First Hurricanes Milton and Helene devastated communities in Florida, Georgia, and North Carolina; then California wildfires, fueled by the Santa Ana winds and drought, ravaged the Pacific Palisades and Altadena communities in Los Angeles.
What can we do to prepare for natural and man-made disasters and help protect the safety of our neighborhoods? As stated in a Rand Corporation report, "All disasters are local, and community groups form the backbone of response." [Cha21]

2 The LA Wildfires, Urban Fires, and Citizen Science

This topic will take twenty-five (25) minutes of class time.
Prompted by occurrences of hurricanes, tornados, and public health crises, ordinary citizens are voluntarily monitoring and recording data (e.g., disease outbreaks and floods) and sending their data to scientists who analyze the data to detect unusual patterns or trends that could indicate emerging threats.
Public engagement in scientific research is called citizen science or street science. When the public uses scientific methods to help with disaster preparedness, response, and recovery, this is called disaster citizen science.
Today, Watch Duty is playing a critical role in monitoring wildfires. Founded in 2021, Watch Duty is "a nonprofit with a team of 200 volunteers and 15 full-time employees, including retired firefighters and dispatchers. That team listens to radio broadcasts from emergency responders and transmits live updates to the app, which maps the fires and delineates evacuation zones." Watch Duty, a Wildfire-Tracking App, Provides a Lifeline in Los Angeles [Tan25] Watch Duty Wildfire Maps (please see graphic below) is one of the most downloaded smartphone apps and is in widespread use in California for monitoring wildfires.

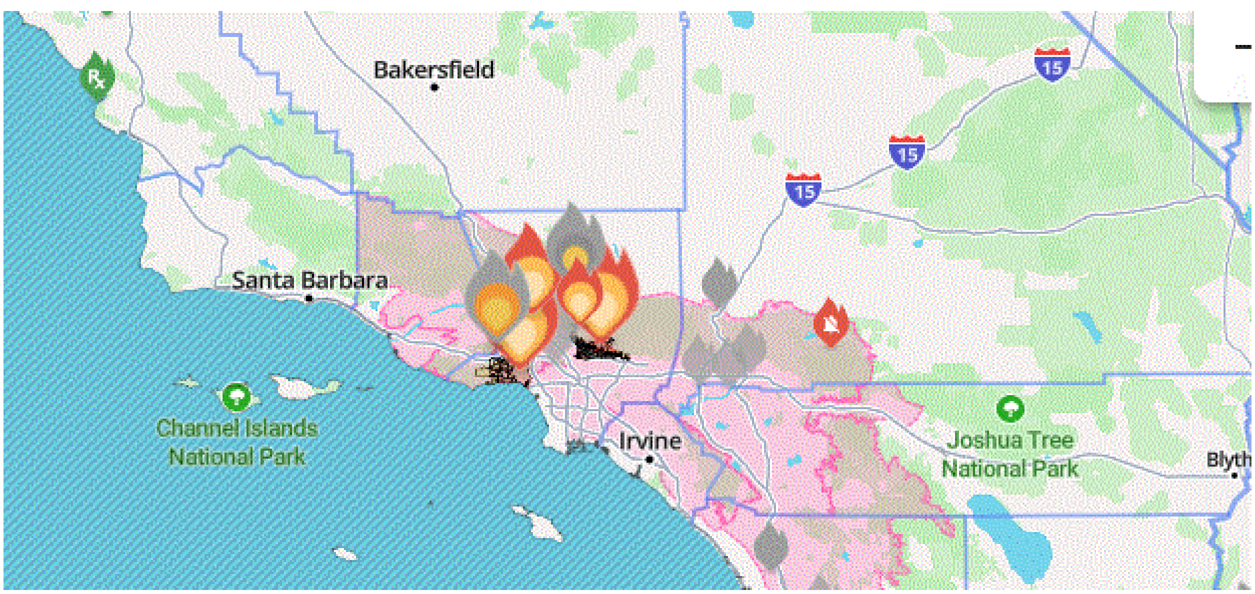

Figure 2: Watch Duty Wildfire Maps

2.1 Exercise Los Angeles learn from history

While the LA wildfires are far removed from the urban fires of the 1870's, there may be lessons for LA that can be learned from the Great Chicago Fire of 1871 and the Great Boston Fire of 1872. Read the NY Times article, What Los Angeles Could Learn From Great Fires of the Past: Rebuilding can be a chance to rethink things. [Bad25] From your reading, describe a lesson that the author says LA could learn from the Great Fires of the past.
"For years now, Los Angeles has been straining under a housing crisis, one that will be worsened by the wildfires. Facing thousands of destroyed homes and newly homeless residents, Gov. Gavin Newsom and Los Angeles's mayor, Karen Bass, acknowledged that the region's onerous obstacles to construction would impede recovery from disaster. Offering a measure of both certainty and compassion, they promised to waive environmental regulations, to speed up permitting, to create a "one-stop shop" for the bureaucracy of home building." Rebuilding [Bad25]
We now introduce decision trees and see how they may be used to protect soft targets and crowded venues through fire detection.

3 Decision Trees

This topic will take sixty (60) minutes of class time.

3.1 Decision trees in emergency planning

According to FEMA, "Soft targets and crowded places ... are typically defined as locations or environments that are easily accessible, attract large numbers of people on a predictable or semi-predictable basis, and may be vulnerable to attacks using simple tactics and readily available weapons." Security of Soft Targets and Crowded Places–Resource Guide [Cyb19] Shopping malls, sports stadiums, and houses of worship are examples of soft targets. These public venues are vulnerable not only to man-made threats, but they are also vulnerable to fire, floods, and tornados.

3.1.1 Exercise evacuation challenges

State three challenges in evacuating soft targets and crowded places.
Challenges in evacuating these venues include: Large and unpredictable crowd dynamics, complex layouts with multiple entry and exit points making it difficult to determine the closest exit, limited staff training and awareness.
Binary decision trees are based on if-then statements. They offer practical, rule-based models for decision-making in emergency planning. For example, a straightforward rule that is universally applied for public venues is the following: If there is a fire, then evacuate. A simple sketch, called a decision tree, helps to visualize this decision process. Please ponder the decision tree in Figure 3.

3.1.2 Exercise safety hazards

Give an example of a public venue and describe 3 potential safety hazards that need to be anticipated as part of its emergency planning.
For night clubs, potential safety hazards include fire hazards such as open flames used in pyrotechnics and improper storage of combustible materials. Other safety hazards include too few

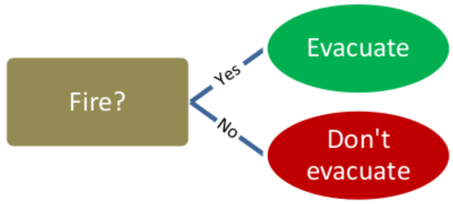

Figure 3: Binary decision tree

exits and overcrowding, which can lead to crowd crush, risks of slips and falls, and threats of violence.
Other features, besides the presence of fire, can lead to the decision to evacuate a public venue. For example, consider the following scenario: A theater has an automatic fire alarm system. When an alarm is triggered, the venue manager must decide whether to evacuate immediately or investigate first. The decision depends on two key factors: (1) Is there visible smoke? (Yes/No); (2) Is there heat detected? (Yes/No). Figure 4 shows a binary decision tree for this scenario. It shows the tree's root node (brown), yes/no branches, an internal decision node (blue), and leaf nodes (oval) that show final decision outcomes. Another feature of this tree is its depth. The depth of a decision tree is the number of splits that occur from the top of the tree down to its deepest decision. The tree in figure 4 has depth 2. Public venues today may be equipped with a

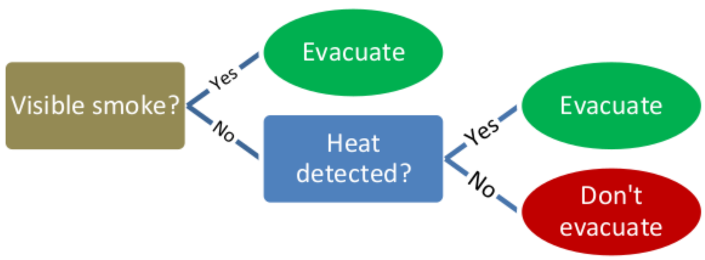

Figure 4: Evacuate or investigate?

variety of sensors, e.g., sensors that track temperature, smoke, toxic gases, and crowd density. These sensors operate on if-then logic: if a measurement exceeds a predetermined threshold, then an evacuation is initiated. Heat sensors, for example, activate if the Temp exceeds 135 °F, smoke sensors activate if the smoke density exceeds 0.1% obscuration per foot (obs/ft), CO sensors activate if the CO level exceeds 50 parts per million (50 ppm) for prolonged exposure or 150 ppm for immediate danger, and crowd sensors activate if the crowd density level exceeds 4 people per square meter (ppl/m^2).

3.1.3 Exercise design decision tree

Design a decision tree for whether or not to evacuate a public venue based on the following three features: (1) Is there visible smoke? (Yes/No); (2) Does the crowd density (CD) exceed 4 ppl/m^2; (3) Does the CO level exceed 50 ppm? (Yes/No).
The decision tree in figure 5 meets the specifications stated in this exercise. Its depth is 3.
Combinations of different levels of features can also prompt a venue's evacuation.

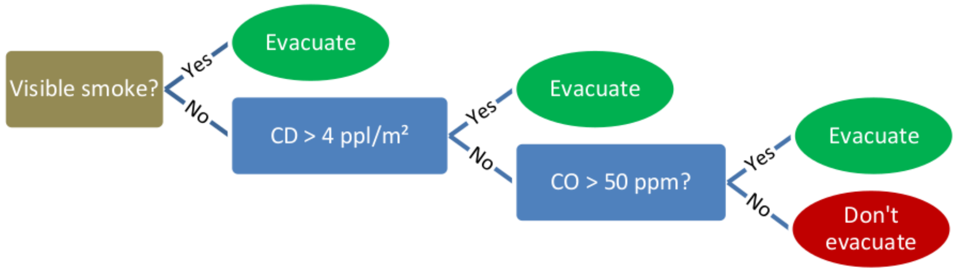

Figure 5: Evacuate public venue?

3.1.4 Exercise describe sensor combinations

For the evacuation decision tree shown in figure 6, how many possible combinations of sensor readings and their levels lead to the decision to evacuate? Describe those combinations.

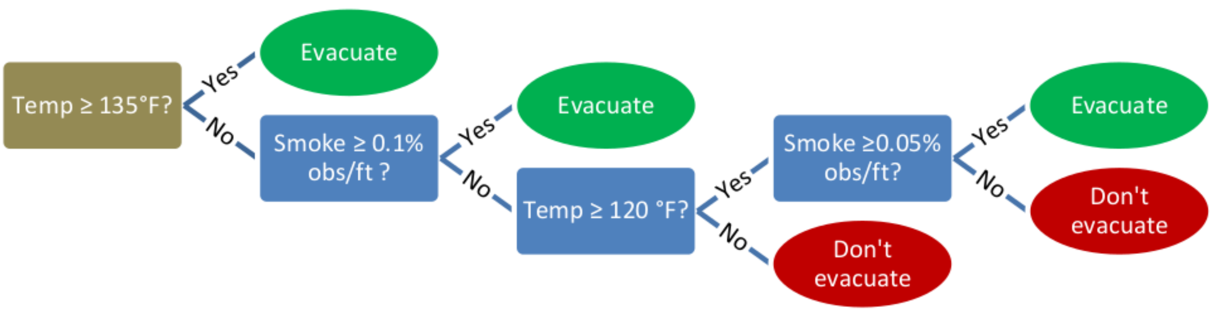

Figure 6: Sensor reading combinations

There are three combinations of features that lead to the decision to evacuate: (1) Temp is at least 135° F, or (2) Temp is less than 135° F and Smoke is at least 0.1% obs/ft, or (3) Temp is least 120° F but less than 135° F and Smoke is at least 0.05% obs/ft but less than 0.1% obs/ft. This binary decision tree has depth 4.

3.2 Machine Learning with Decision Trees for Public Safety

Machine learning consists of algorithms that learn patterns from data to make predictions or decisions. When making decisions about whether to evacuate a building, the algorithm relies on historical data where each situation is labeled as either "Evacuate" or "Don't evacuate." This approach, which uses labeled data for training, is called supervised learning. Decision tree models make evacuation decisions by analyzing factors such as temperature, smoke levels, and crowd density, systematically splitting the data to reach the most accurate outcome.

3.2.1 Exercise select first split

Consider the fictitious dataset in table 3 for a set of five buildings.

Building	Smoke Level (0-10)	Temp (° F)	Crowd Density (0-10)	Decision
A	2	160	3	Evacuate
B	9	155	8	Evacuate
C	3	140	7	Don't evacuate
D	8	135	2	Don't evacuate
E	10	165	9	Evacuate

Table 3: Fictitious buildings

If you could make just one decision to start sorting buildings into "Evacuate" or "Don't Evacuate," which feature would be the most useful to split on first? Explain your reasoning and draw the first split decision tree.

Temperature provides a perfect separation of the buildings between the two classes using this rule: If temperature is greater than 145° F, evacuate; otherwise, don't evacuate. Buildings A, B, and E have temperatures above 145° F and are classified as "Evacuate." Buildings C and D, with temperatures at or below 145° F, are classified as "Don't evacuate." By contrast, smoke level does not provide a clear separation. Some buildings with high smoke levels require evacuation, while others do not, meaning no single threshold can reliably divide all five buildings into the two classes. Crowd density faces the same issue - it does not consistently predict evacuation status on the first split. Please find the first split binary decision tree for table 3 in figure 7.

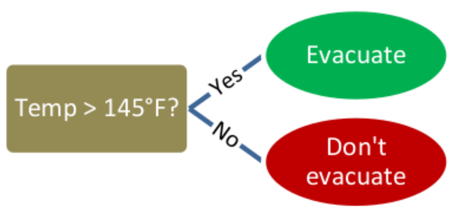

Figure 7: Solution select first split

When decision tree machine learning is used to classify an email as ham or spam or, in the case of public safety, to determine whether to evacuate a building, the goal is to make the correct decision as efficiently as possible. This means asking the fewest number of questions about features (or making the fewest splits) necessary to reach a confident decision. When multiple features are involved - such as smoke, temperature, and crowd density - are involved, the algorithm prioritizes features that create the purest splits, meaning the groups are as homogeneous as possible. This process uses metrics called entropy and Gini index we suggest as topics for further exploration. For a glimpse into how this process works, let's look at another dataset of five buildings in table 4, and consider the question: If you were to build a binary decision tree to decide whether to evacuate a building, which feature would you use for your first split and why?

Building	Smoke Level (0-10)	Temp (° F)	Crowd Density (0-10)	Decision
A	7	148	6	Evacuate
B	4	161	3	Evacuate
C	3	127	4	Don't evacuate
D	5	138	7	Evacuate
E	6	134	5	Don't evacuate

Table 4: Select first split

For this dataset, there is no single feature that perfectly separates the classes initially. This is because some buildings with low temperatures evacuate, some do not. For smoke level, some buildings with moderate smoke level evacuate, some do not. The same is true for the crowd density feature. So, how do we judge the "best" first split in this scenario?

Table 5 compares three possible features for the first split

Feature for first split	Pure Groups After Split	Mixed Groups Left
Temperature > 145	Group 1 Temp > 145 2 buildings (A, B) pure node: (evacuate)	Group 2 Temp ≤ 145 3 buildings (C, D, E) mixed; needs further splitting
Smoke > 3	Group 1 Smoke > 3 4 buildings (A, B, D, E) mixed	Group 2 Smoke ≤ 3 1 building (C) pure node (don't evacuate)
Crowd density > 3	Group 1 Crowd density > 3 4 buildings (A, C, D, E) mixed	Group 2 Crowd density ≤ 3 1 building (B) pure node (evacuate)

Table 5: Possible first split features

From table 5, we can conclude that while it is not perfect, Temperature $> 145\ ^\circ$ F is the best first split. It immediately classifies two buildings, leaving only three to resolve. In contrast, splits based on Smoke > 3 or Crowd Density > 3 do separate some cases, but they result in a larger, more mixed group, requiring additional steps to reach a final classification. This example illustrates how a decision tree is built in stages—starting with a feature that provides a strong initial split and then refining the decision with additional features, ultimately progressing from a simple rule to a more nuanced model.

3.3 For further exploration

To understand how decision trees are used in machine learning classification algorithms, you will need to learn about Gini index and entropy, which use probability to measure the quality and efficiency of the splits in a decision tree. "Whether to Play Tennis" is a classic case used to illustrate decision trees and the Gini index; it checks Outlook (i.e., weather outlook), Humidity, and Wind to decide whether to play tennis on a given day. A detailed explanation of this example can be found in the article Decision Tree intuitive explanation [Sri19].

Binary decision trees check, sequentially, different features of a public venue to decide whether to evacuate. They are easy to interpret. In reality, fire alarms in buildings today work like a parallel process, applying machine learning algorithms like Random Forests and Boosted Trees to analyze sensor data from multiple monitoring devices. These are "ensemble" methods that combine multiple decision trees to make predictions, which often leads to better accuracy and robustness compared to single decision trees. To learn about these methods, read Random Forests Algorithm explained with a real-life example and some Python code [Ben21] and A Gentle Introduction to Ensemble Learning Algorithms [Bro21].

Before we can use decision trees in a simulation, we should understand some of the math used to construct the model.

4 Simulation Math Content

This topic will take ten (10) minutes of class time.

4.1 Probability

The simulation uses random numbers to model the movement of each individual before the alarm sounds.

Computation The Python script calls `numpy.random.rand`, which returns "... random samples from a uniform distribution over [0, 1)." numpy.random.rand [Num24]

4.1.1 Exercise uniform distribution active learning

The goal is to generate a set of random numbers between 0 and 1, where each number has an equal chance of being selected, as discussed in Section 5.2 of Introductory Statistics 2e [Ill23]. Here are several different methods of generating a uniform distribution.

1. Dice: Roll a die 10 times and record the results. Then, divide each result by the number of sides on the die (e.g., if you roll a 5 on a six-sided die, you would record 5/6). This will give a sample of 10 numbers between 0 and 1.

2. Poker Cards: Shuffle a deck of cards and draw 10 cards without replacement. For each card, assign a numerical value between 0 and 1 based on its rank (e.g., Ace = 0, 2 = 1/13, 3 = 2/13, ..., King = 12/13). For each suit, assign a numerical value between 0 and 1/13 (e.g., clubs = 0, diamonds = 1/52, hearts = 2/52 = 1/26, spades = 3/52.) Then the resulting value for each card is the sum of its rank and its suit (e.g. Ace of clubs = 0 + 0, 2 of diamonds = 1/13 + 1/52, 3 of hearts = 2/13 + 1/26, King of spades = 12/13 + 3/52). This will supply a sample of 10 numbers between 0 and 1.

3. small candies: Take a handful of small candies and count the number of each color. Then, divide the number of each color by the total number of small candies in their handful. This will yield a sample of numbers between 0 and 1.

The authors have not yet found a specific reference using active learning to illustrate the uniform distribution. Please find general ideas in Tactile Learning Activities in Mathematics: A Recipe Book for the Undergraduate Classroom [Bar18] and [Hag95].

4.2 Human Behavior

Now that we have introduced decision trees and the math used in the simulation, we can run the simulation.
Human behavior in emergencies can sometimes defy expectations, leading to rescue teams searching in the wrong place. For example, during the 2018 Thailand Cave Rescue, some rescuers waited at the cave mouth, and other rescuers searched for cracks in the cave system, but those were inappropriate places to look. The missing civilians traveled to relatively high ground inside the cave, instead of trying to egress from the cave, because the departure routes were all underwater, as described in The full story of Thailand's extraordinary cave rescue [BBC18].
In our simulation we use decision trees to predict which exit the civilians will use to evacuate a venue.

5 Simulate a Crowded Venue

This topic will take sixty (60) minutes of class time.
The accompanying Python script simulates a crowded venue.

5.1 Gather Meaningful Data

The simulation models a rectangular room having two exits, randomly placed.

5.1.1 Exercise measure room

Please find a real-world rectangular room and measure its length and width, in order to work with meaningful data. Please fill in the following table. Please specify the units for the length and width measurements.

Attribute	Value
Venue Name	
Venue Address	
Room Name	
Room Location	
Room Length	
Room Width	

Table 6: Exercise measure room

The teacher could expand this data gathering activity in to a citizen science project, as discussed in Neighborhood Walk [Bee24]

5.2 Download the Simulation

Access the web page `https://github.com/rubripes11/exit-prediction`
Download the files `evacuate.csv` and `predict-exit.py`
Edit the file `evacuate.csv` to enter the dimensions of your rectangular room. Please note that `evacuate.csv` needs the dimensions in feet, you might need to perform a unit conversion.

5.3 Run the Simulation

In order to run the simulation, you need a Python environment. You can install Python on a local computer or use a cloud service. As of this writing, several cloud services offer free or low-cost Python.
At run-time, the file `predict-exit.py` needs to find the file `evacuate.csv` and input parameter values from it. The details of this setup depend on your Python environment.
We tested the simulation on a free cloud service. On that service the parameters present in the file `evacuate.csv` consumed under 2 minutes of connect time for a single experiment.

5.4 Discuss the Results

The simulation produces both individual output files and a zip archive containing the individual output files.

These are the individual output files:

Name	Type	Description
ep$n$.mp4	Trial n	evacuation animation video file
ep$n$bar.png	Trial n	decision tree dual bar chart
ep$n$box.png	Trial n	evacuation time box and whisker plots
ep$n$.txt	Trial n	evacuation time summary statistics decision tree exit prediction summary statistics
ep$n$.xlsx	Trial n	evacuation time raw data
ep-bar.png	Experiment	decision tree dual bar chart
ep-box.png	Experiment	evacuation time box and whisker plots
ep.txt	Experiment	evacuation time summary statistics decision tree exit prediction summary statistics
ep.xlsx	Experiment	evacuation time raw data
train$n$.mp4	Train n	evacuation animation video file
train$n$box.png	Train n	evacuation time box and whisker plots
train$n$.txt	Train n	evacuation time summary statistics
train$n$.xlsx	Train n	evacuation time raw data

Table 7: Individual output files

5.4.1 Exercise ep$n$.mp4

(a) View at least one of the ep$n$.mp4 video files, the animation of evacuation trial n. At the end of the simulation, count how many of each person type remain in the venue and fill in the following table:

Genre	Color	Shape	Type	Remaining
Civilian	navy blue	hexagon	Fast Velocity	
Civilian	lightskyblue	hexagon	speed challenged	
Responder	crimson	asterisk	fireman	
Responder	lightcoral	plus-sign	medical	

Table 8: Exercise people remaining

Due to randomization, answers will vary, especially because this file reports on a single trial. The following results are common:

1. total venue occupancy at the end of the simulation will be less than 20% of the initial civilian occupancy
2. speed-challenged civilian occupancy at the end of the simulation should be zero or small

(b) Discuss the meaning present in the numerical results entered in part (a).
These phrases apply to the points stated in part(a) above.

1. everyone is trying to exit the venue
2. the responders search for and rescue the challenged civilians

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