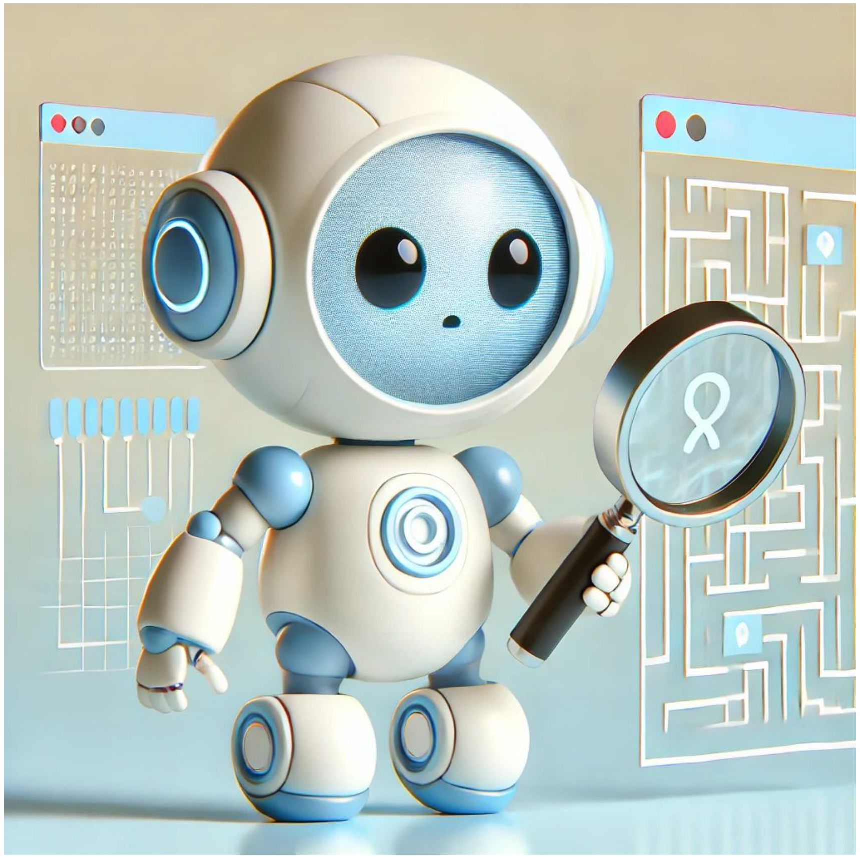
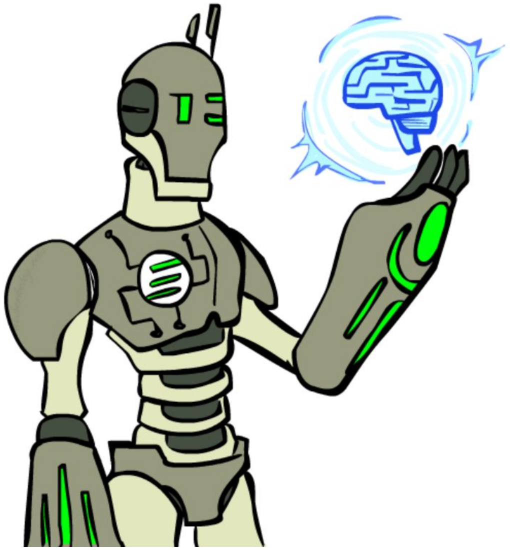
Introduction to AI

07/16/2025
Xiwang Guo



MAYFLOWER
A.S.T.E.M.
ACADEMY

Xiwang Guo: x.w.guo@163.com
 Google scholar
International Journal of Artificial Intelligence and Green Manufacturing



Summer project 1: AWS deeper racer

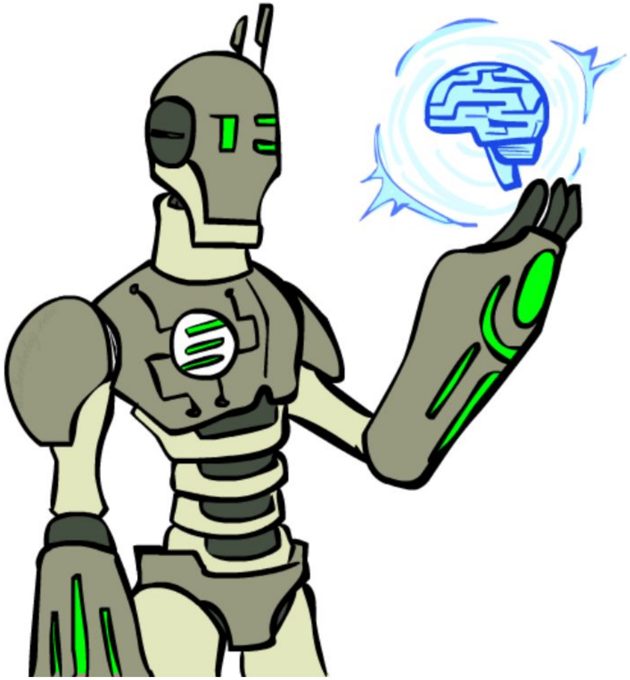
Summer project 2:
MIT APP Inventor 1
MIT APP Inventor 2
MIT APP Inventor 3

Today

What is artificial intelligence?

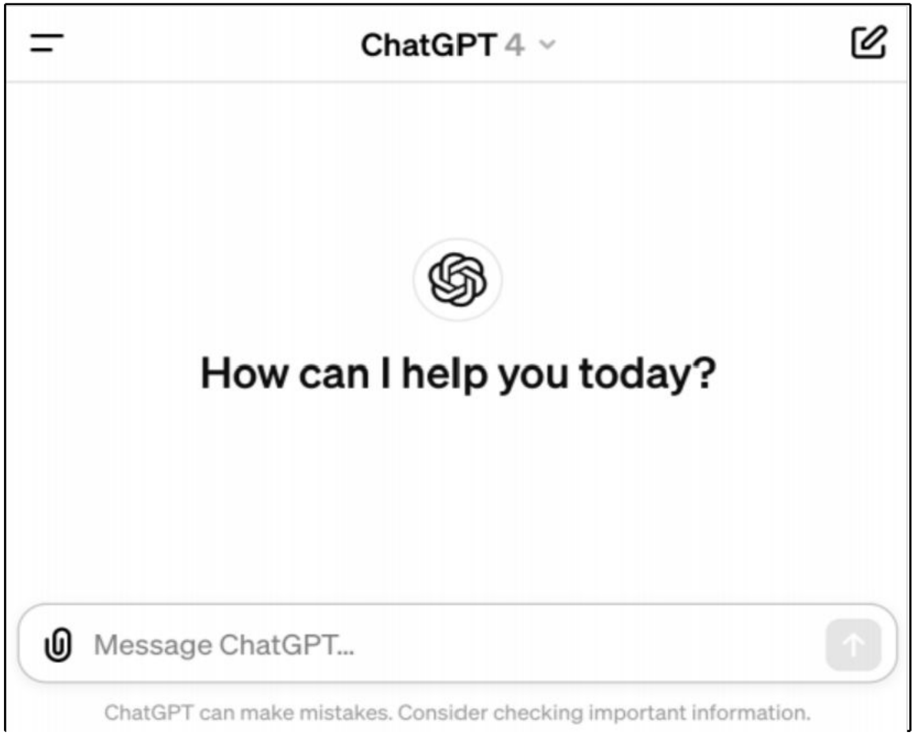
What can AI do?

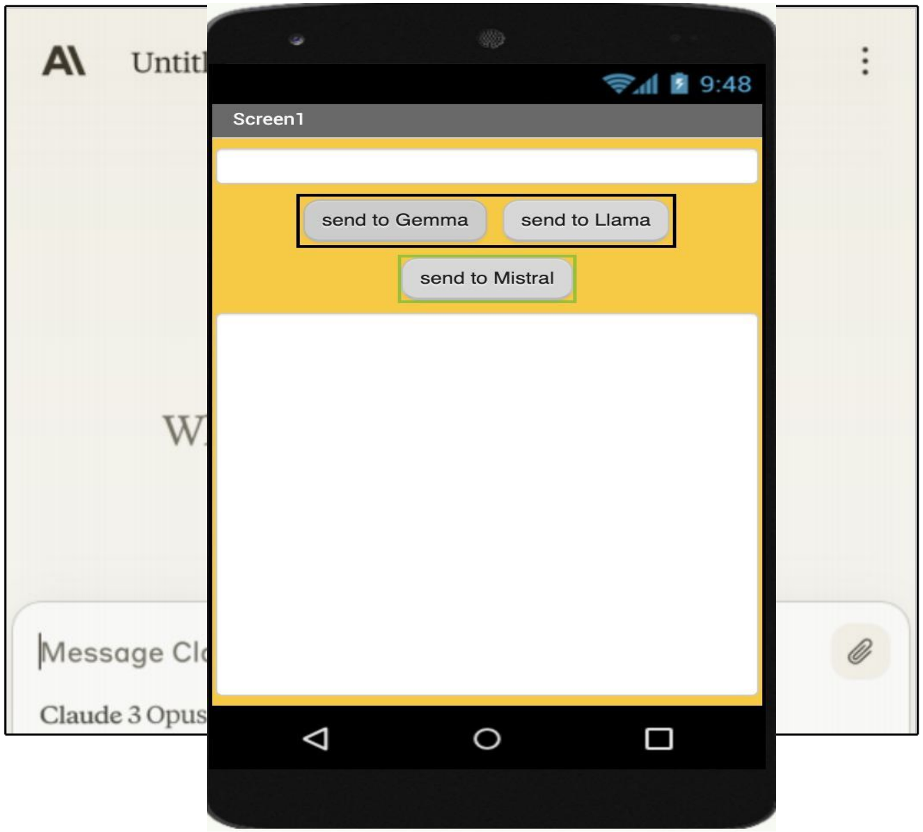
What is this course?



What is AI?

Today's AI


ChatGPT 4
How can I help you today?
Message ChatGPT...
ChatGPT can make mistakes. Consider checking important information.


9:48
Screen1
send to Gemma
send to Llama
send to Mistral
Claude 3 Opus

Rational Decisions

We'll use the term rational in a very specific, technical way:

Rational: maximally achieving pre-defined goals

Rationality only concerns what decisions are made

(not the thought process behind them)

Goals are expressed in terms of the utility of outcomes

Being rational means maximizing your expected utility

A better title for this course would be:
Computational Rationality

What About the Brain?

Brains (human minds) are very good at making rational decisions, but not perfect

Brains aren’t as modular as software, so hard to reverse engineer!

“Brains are to intelligence as wings are to flight”

Lessons learned from the brain: memory and simulation are key to decision making

A (Short) History of AI

1940-1950: Early days

1943: McCulloch & Pitts: Boolean circuit model of brain

1950: Turing's “Computing Machinery and Intelligence”

1950—70: Excitement: Look, Ma, no hands!

1950s: Early AI programs, including Samuel's checkers program, Newell & Simon's Logic Theorist, Gelernter's Geometry Engine

1956: Dartmouth meeting: “Artificial Intelligence” adopted

1965: Robinson's complete algorithm for logical reasoning

1970—90: Knowledge-based approaches

1969—79: Early development of knowledge-based systems

1980—88: Expert systems industry booms

1988—93: Expert systems industry busts: “AI Winter”

1990—: Statistical approaches

Resurgence of probability, focus on uncertainty

General increase in technical depth

Agents and learning systems… “AI Spring”?

2000—: Where are we now?

A (Short) History of AI

What Can AI Do?

Quiz: Which of the following can be done at present?

- Play a decent game of table tennis?
- Play a decent game of Jeopardy?
- Drive safely along a curving mountain road?
- Drive safely along Telegraph Avenue?
- Buy a week's worth of groceries on the web?
- Buy a week's worth of groceries at Berkeley Bowl?
- Discover and prove a new mathematical theorem?
- Converse successfully with another person for an hour?
- Perform a surgical operation?
- Put away the dishes and fold the laundry?
- Translate spoken Chinese into spoken English in real time?
- Write an intentionally funny story?

What Can AI Do?

Natural Language Processing

Speech technologies (e.g. Siri)

Automatic speech recognition (ASR)

Text-to-speech synthesis (TTS)

Dialog systems

Language processing technologies

Question answering

Machine translation

Natural Language Processing

Computer Vision (Perception)

Object and face recognition

Scene segmentation

Image classification


Tiny
Sorter

Robotics

Robotics

Part mech. eng.

Part AI

Reality much

harder than

simulations!

Technologies

Vehicles

Rescue

Soccer!

Lots of automation…

In this class:

We ignore mechanical aspects

Methods for planning

Methods for control

Robotics

Course Topics

Part I: Machine learning

Clustering

Classification

Regression

Supervised learning

Unsupervised learning

Reinforcement learning

Part II: Deep learning hardware and software

Hardware

software

Part III: Project

Lab1: Teachable machine

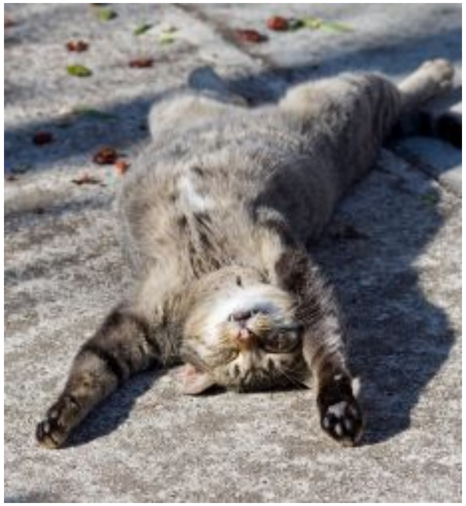
Lab2: MIT APP Inventor

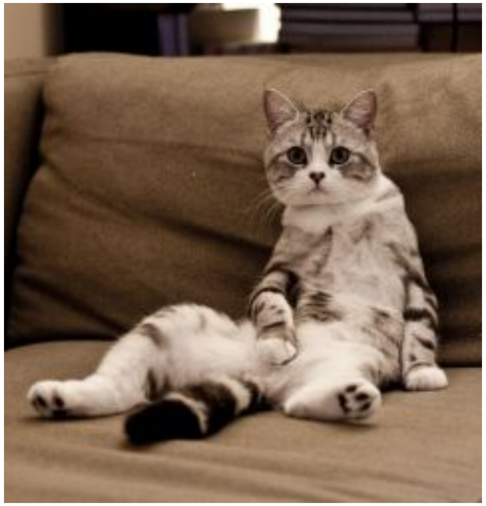
With the right data and the right model, machine learning can solve many problems.

But finding the right data and training the right model
can be difficult.

Challenges: Illumination

Challenges: Deformation





Challenges: Occlusion

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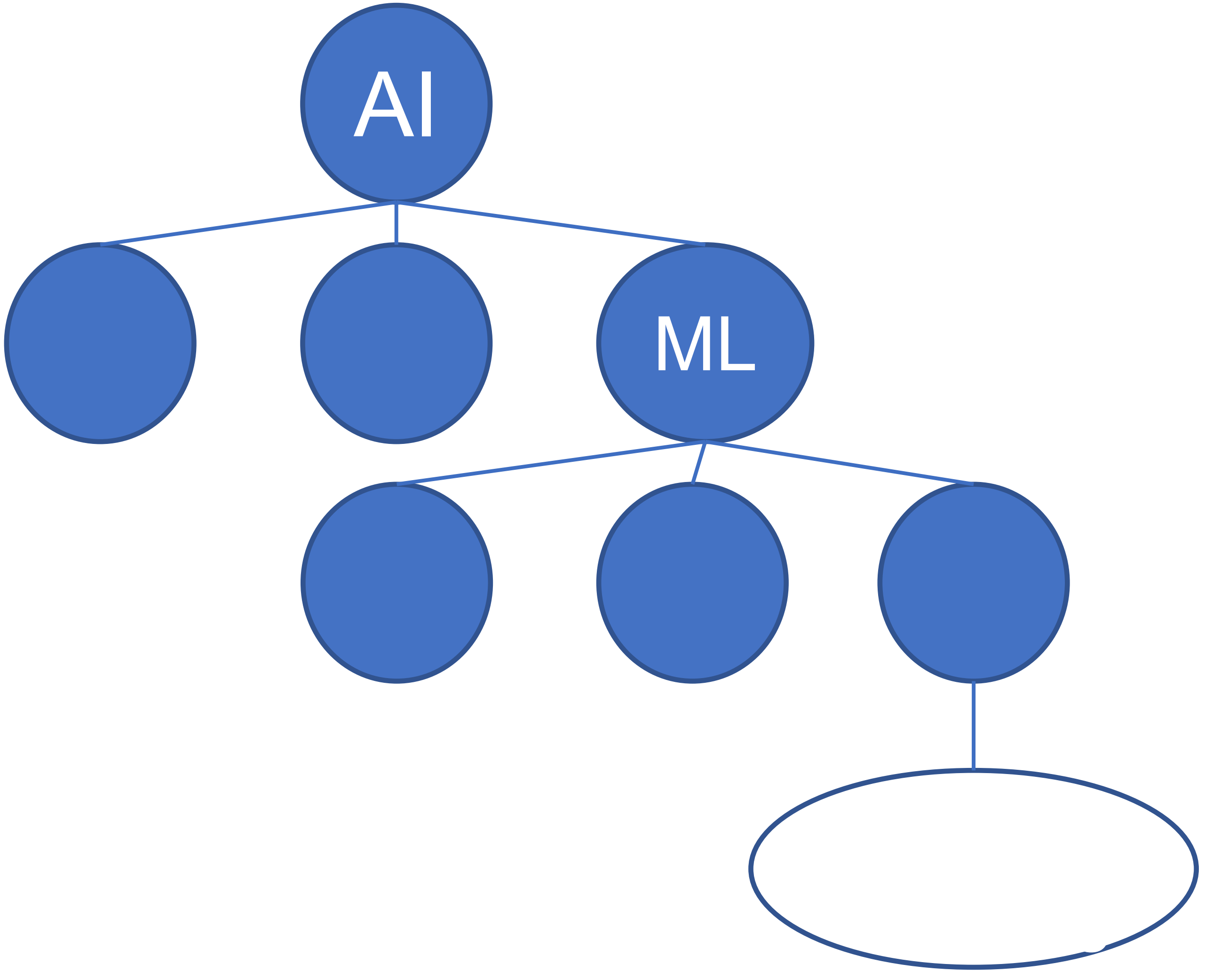
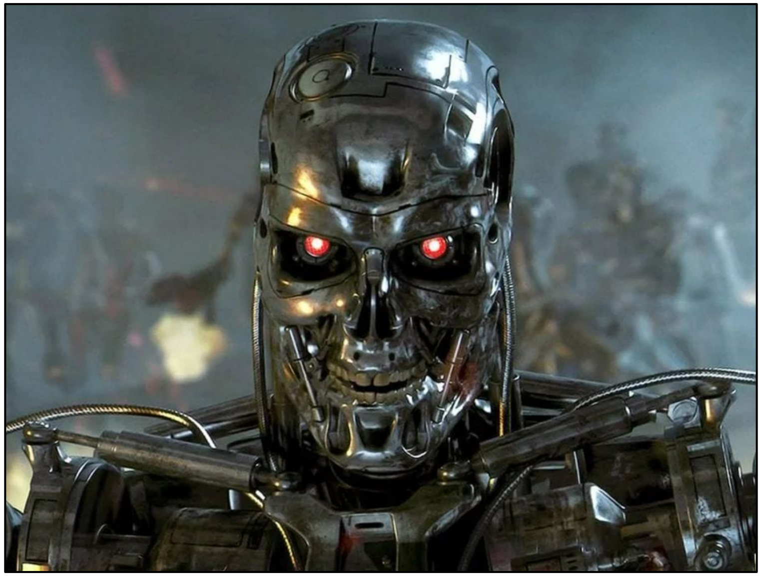
Challenges: Background Clutter

Challenges: Intraclass variation

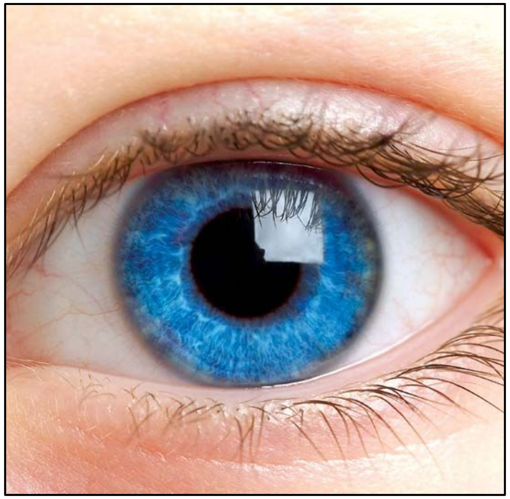

AI
ML

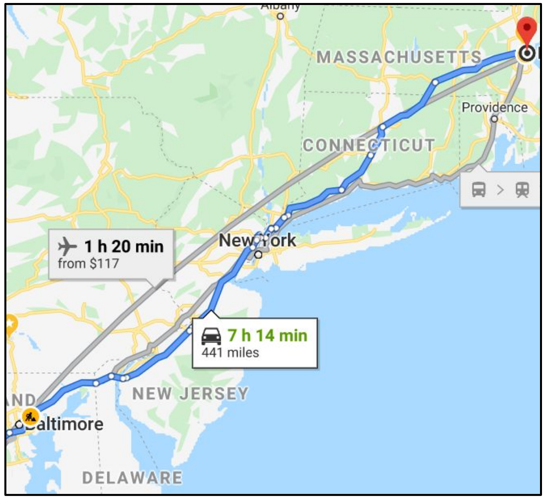
AI can be general or narrow.



AI can be **general** or narrow.

Typical “narrow” tasks include vision, language processing, and planning.





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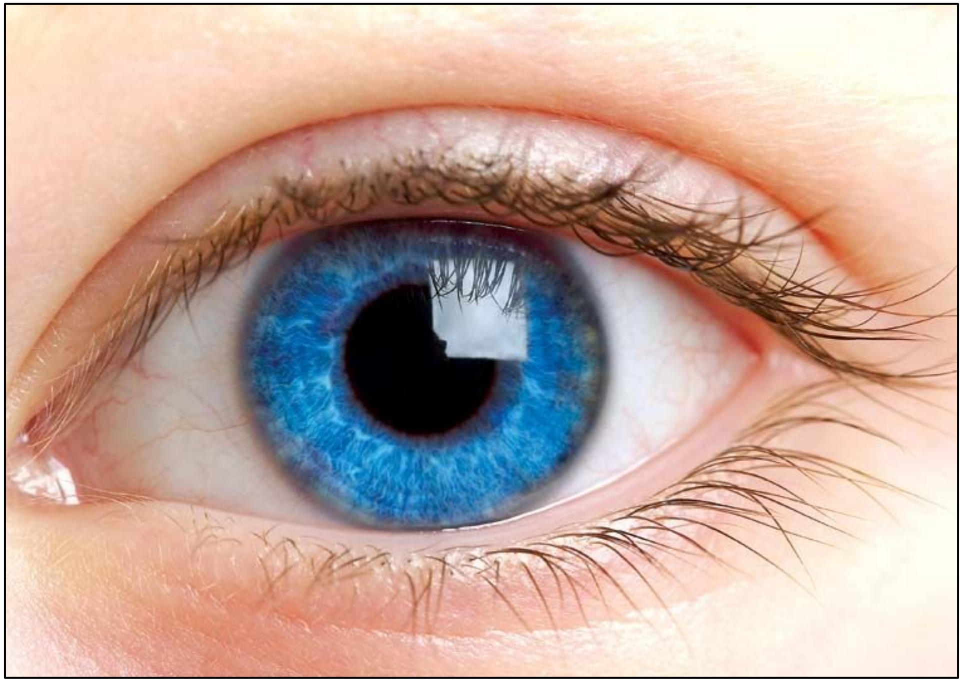

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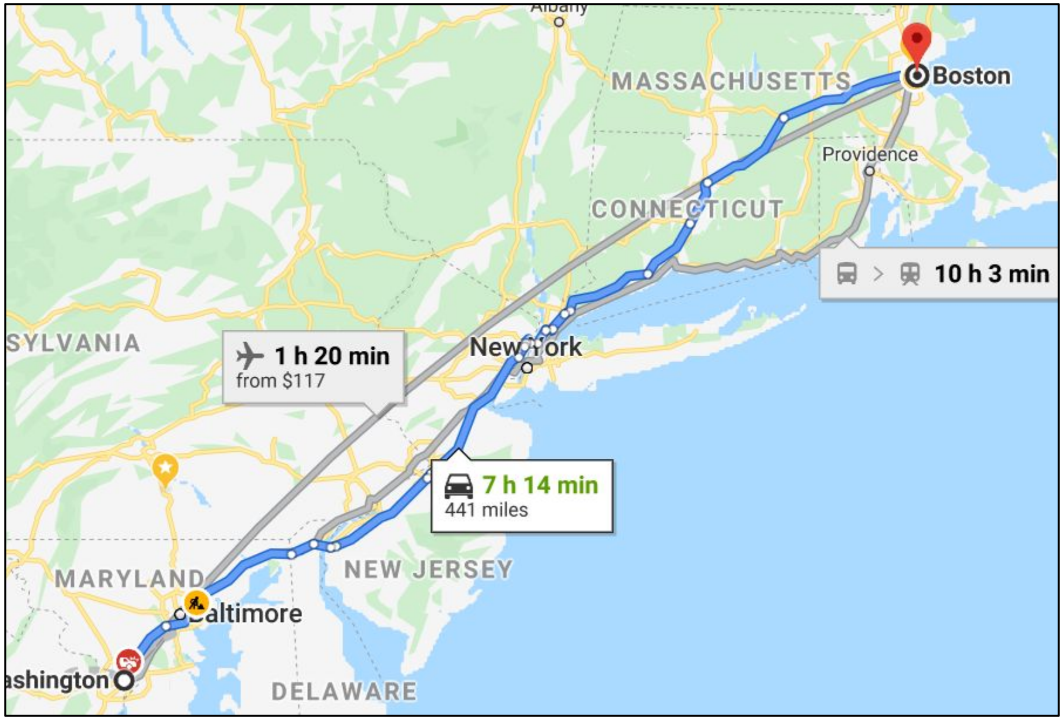
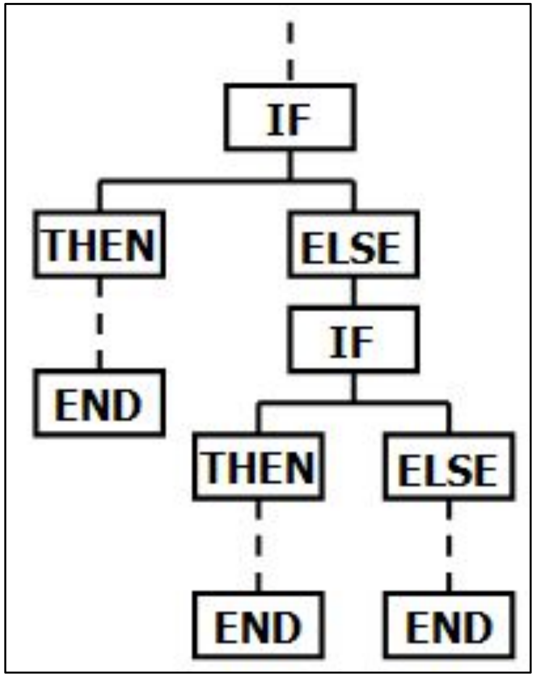
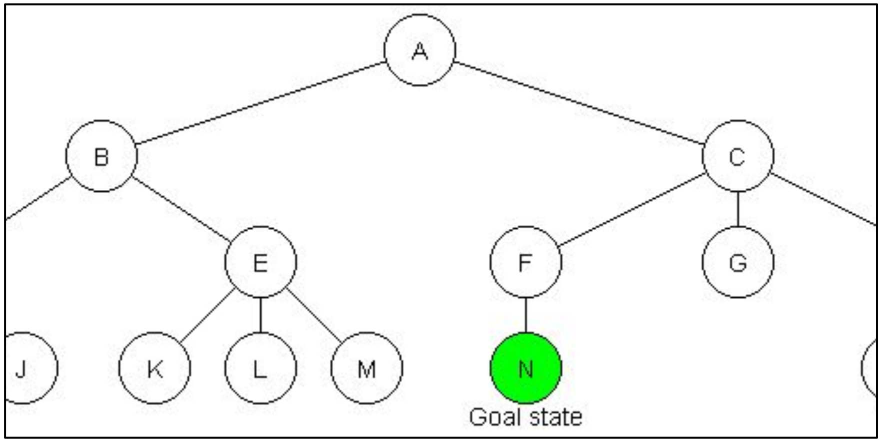


Typical “narrow” tasks include vision, language processing, and **planning**.

There are many ways to build AI,
including expert systems and tree search.





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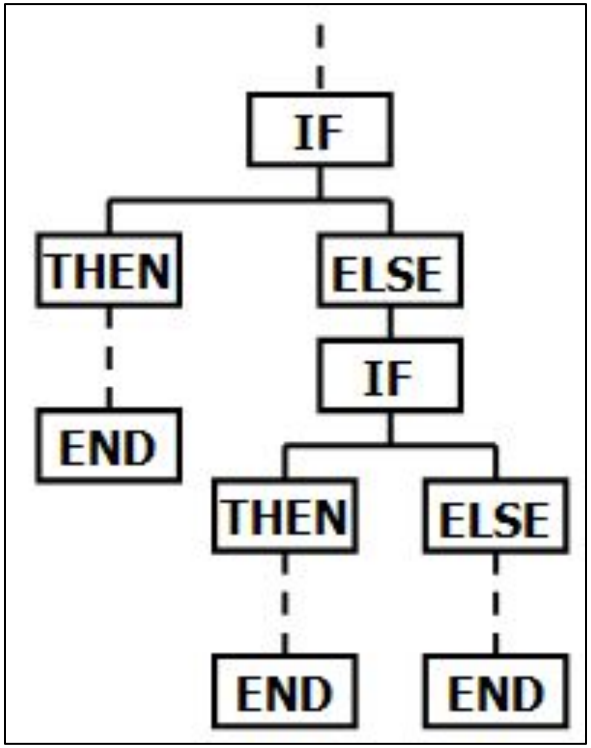

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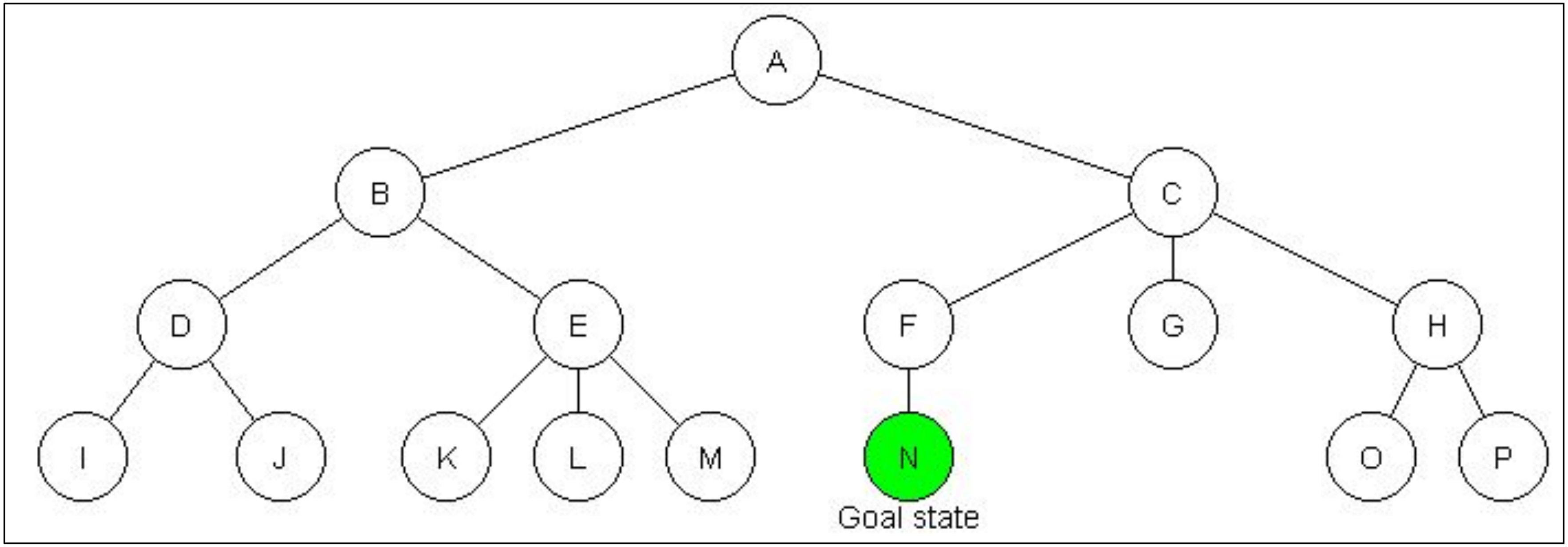
Introduction to Expert Systems

There are many ways to build AI,
including expert systems and [tree search.](#)



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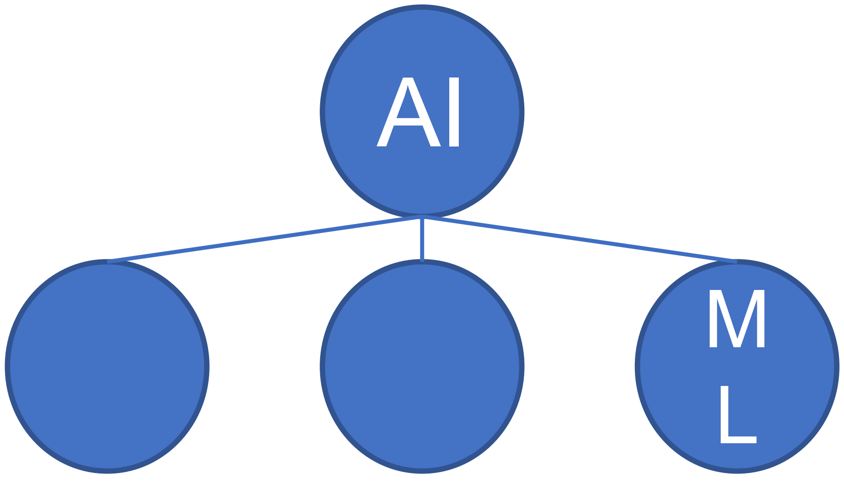
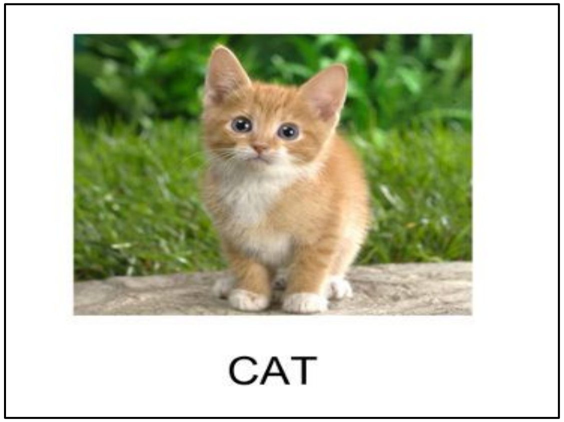
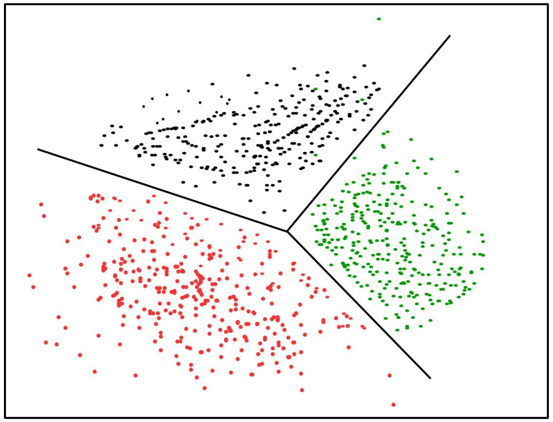
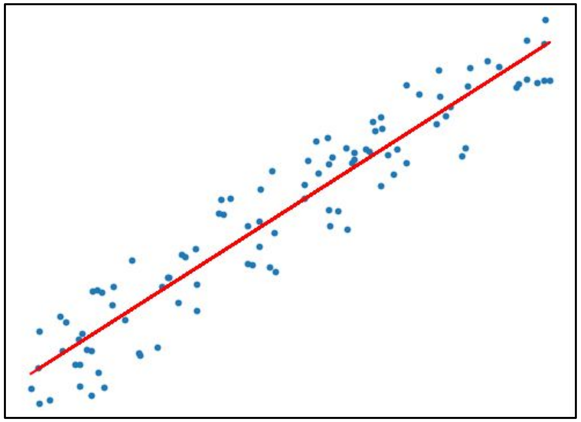

AI
M
L

Machine learning can perform many tasks,
i.e. classification, clustering, and regression.







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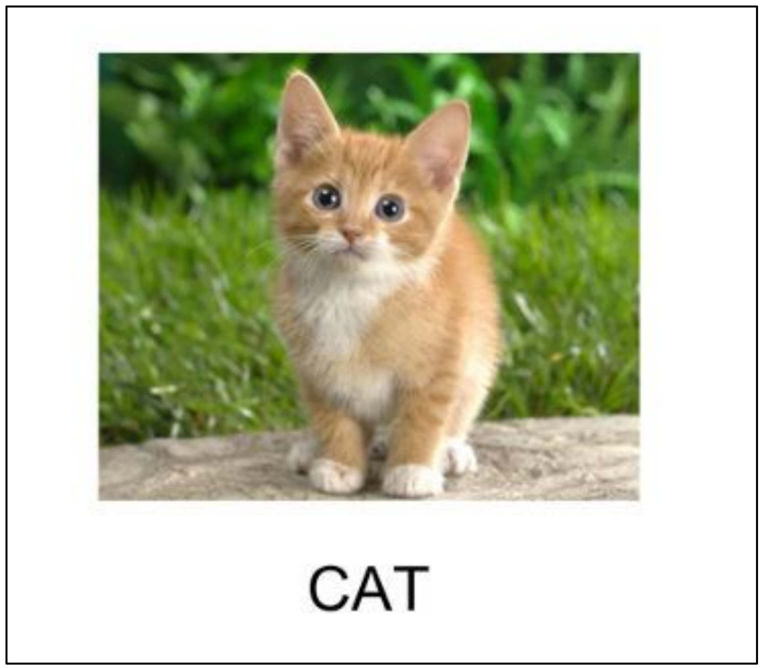

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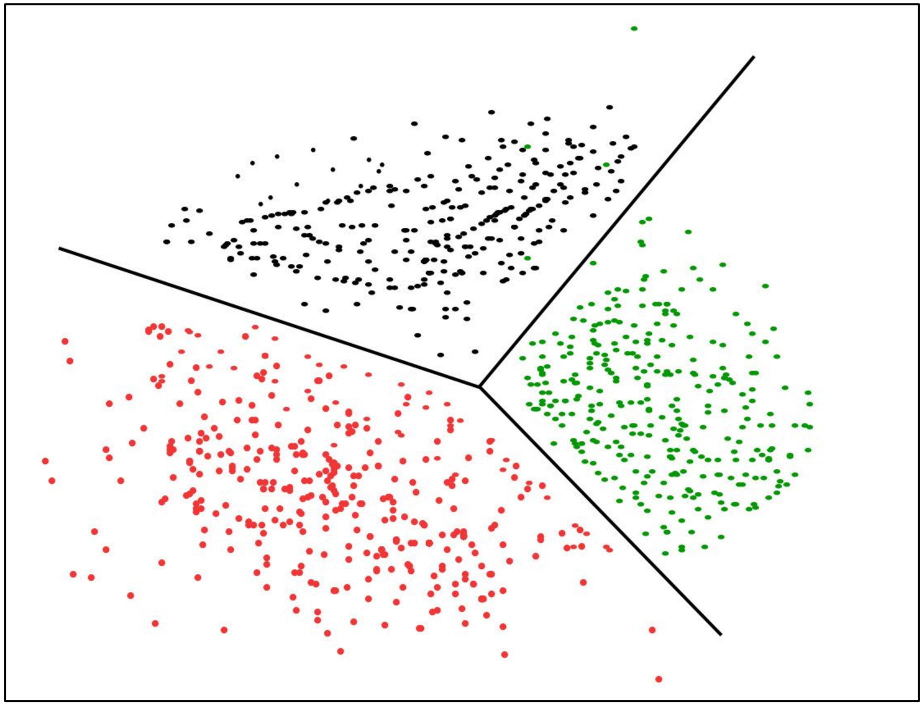

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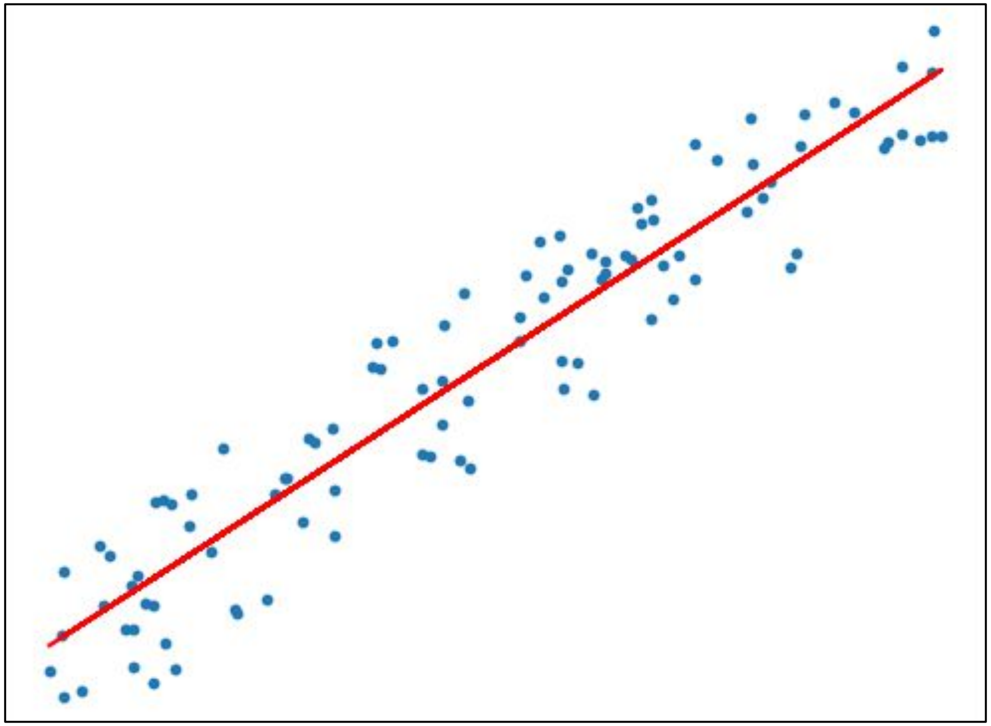

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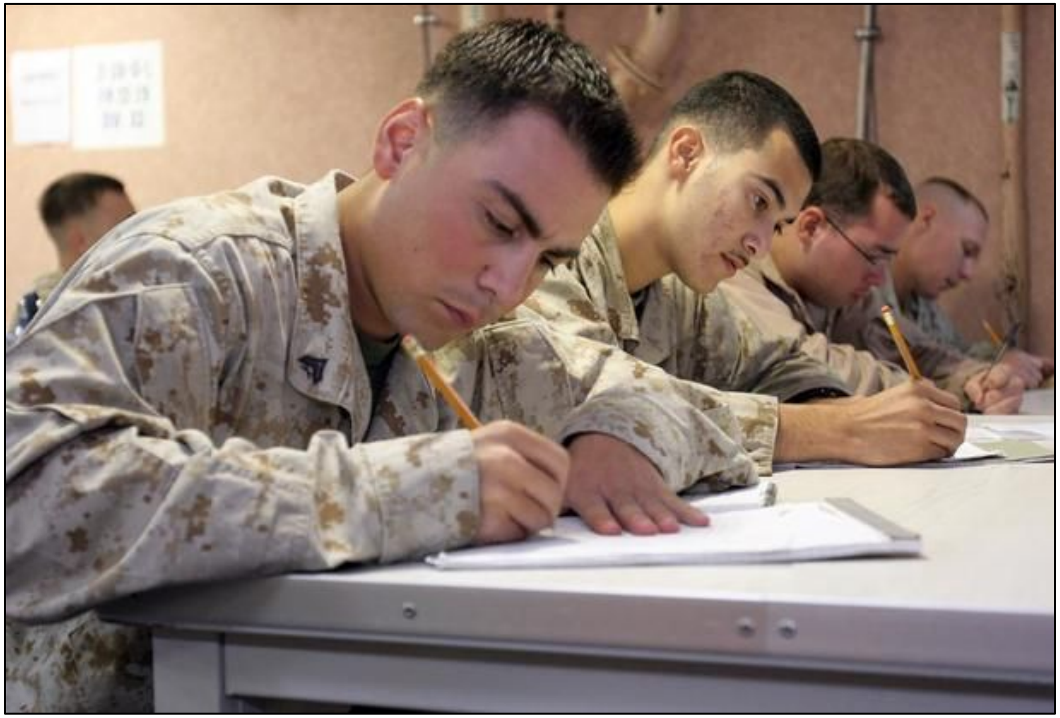

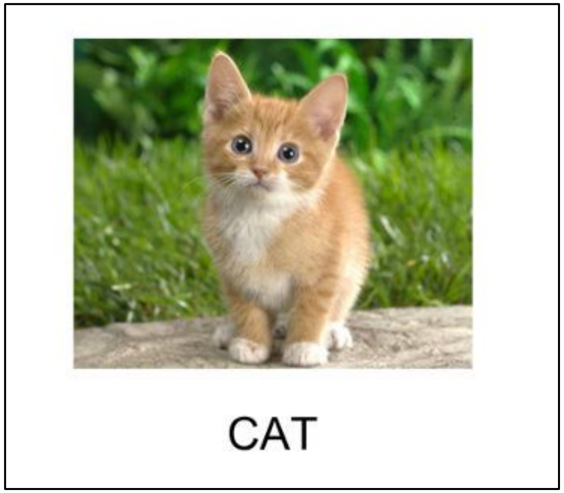

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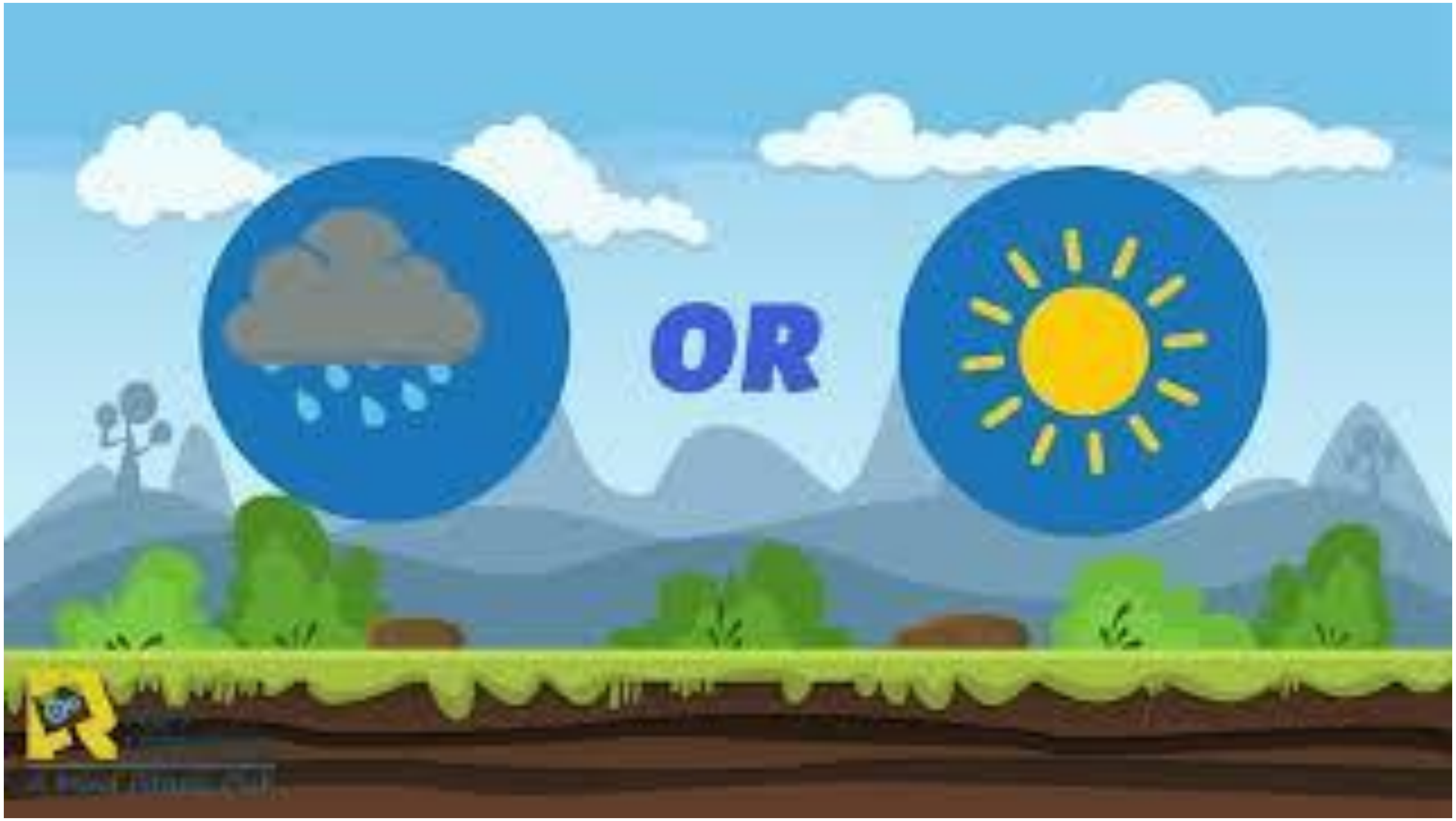

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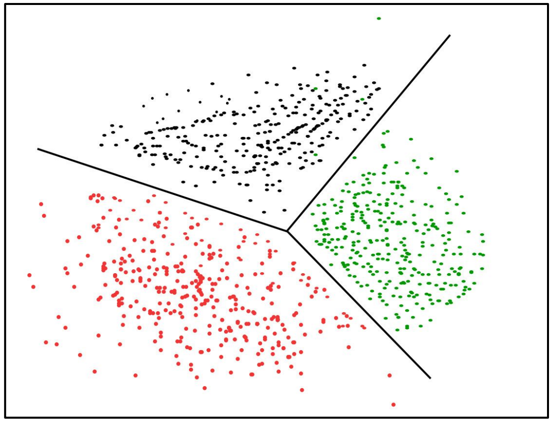

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Deep Learning Hardware

My computer

Spot the CPU! (central processing unit)

Spot the GPUs!

(graphics processing unit)

This image is in the public domain

NVIDIA vs AMD

CPU vs GPU

	Cores	Clock Speed	Memory	Price	Speed
CPU (Intel Core i7-7700k)	4 (8 threads with hyperthreading)	4.2 GHz	System RAM	$339	~540 GFLOPs FP32
GPU (NVIDIA GTX 1080 Ti)	3584	1.6 GHz	11 GB GDDR5 X	$699	~11.4 TFLOPs FP32

CPU: Fewer cores, but each core is much faster and much more capable; great at sequential tasks

GPU: More cores, but each core is much slower and "dumber"; great for parallel tasks

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TPU NVIDIA TITAN V	5120 CUDA, 640 Tensor	1.5 GHz	12GB HBM2	$2999	~14 TFLOPs FP32 ~112 TFLOP FP16
TPU Google Cloud TPU	?	?	64 GB HBM	$6.50 per hour	~180 TFLOP

CPU: Fewer cores, but each core is much faster and much more capable; great at sequential tasks

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TPU: Specialized hardware for deep learning

CPU vs GPU

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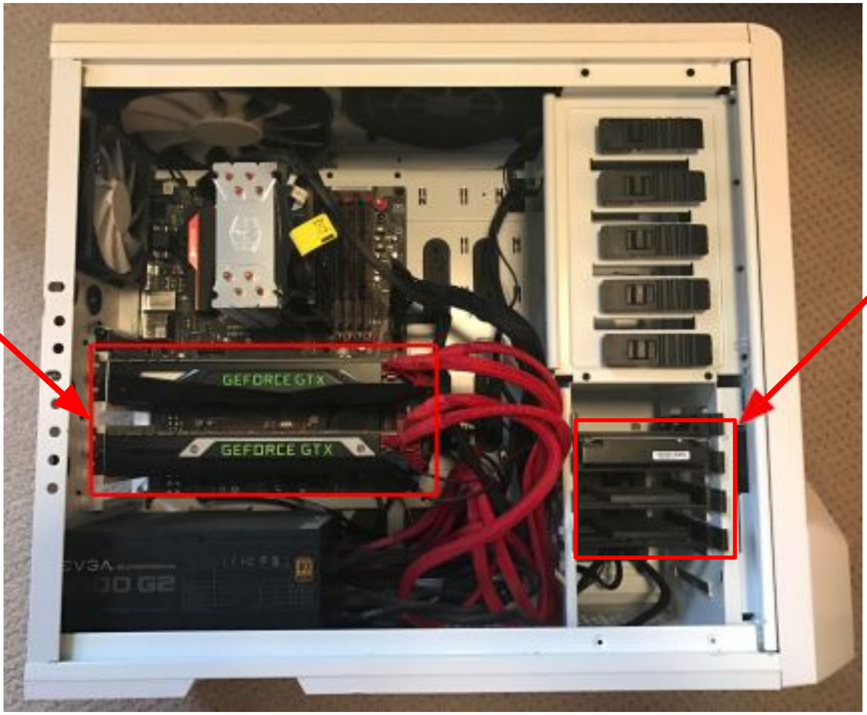
NOTE: TITAN V isn't technically a "TPU" since that's a Google term, but both have hardware specialized for deep learning

CPU / GPU Communication

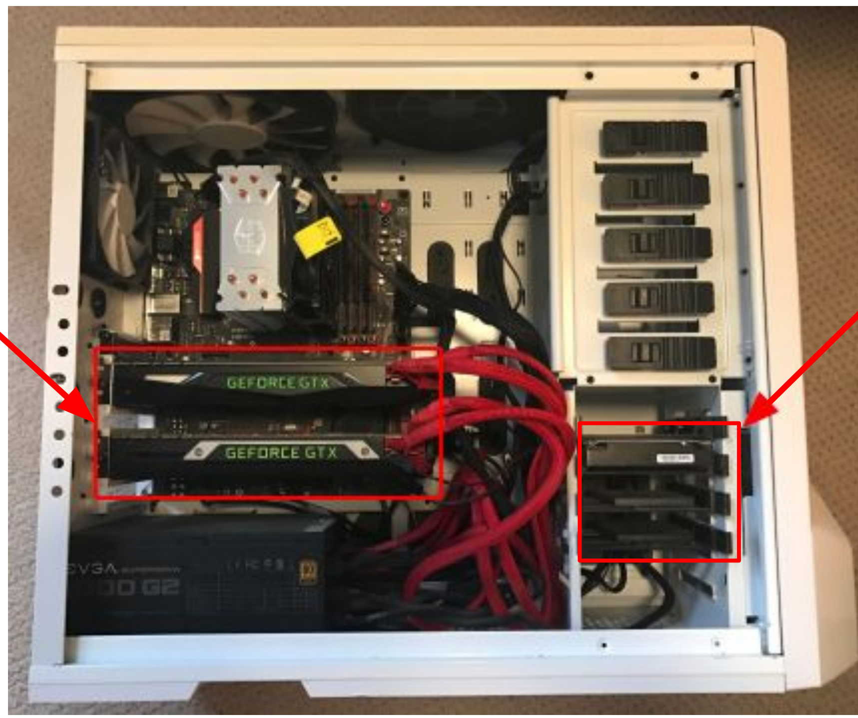
Model is here



Data is here

CPU / GPU Communication

Model is here



Data is here

If you aren't careful, training can bottleneck on reading data and transferring to GPU!

Solutions:

- Read all data into RAM
- Use SSD instead of HDD
- Use multiple CPU threads to prefetch data

Deep Learning Software

A zoo of frameworks!

Caffe
(UC Berkeley)

Caffe2
(Facebook)

Torch
(NYU /
Facebook)

PyTorch
(Facebook)

Theano
(U Montreal)

TensorFlow
(Google)

PaddlePaddle
(Baidu)

Chainer

MXNet
(Amazon)
Developed by U Washington, CMU, MIT, Hong Kong U, etc but main framework of choice at AWS

CNTK
(Microsoft)

Deeplearning4j

And others...

A zoo of frameworks!

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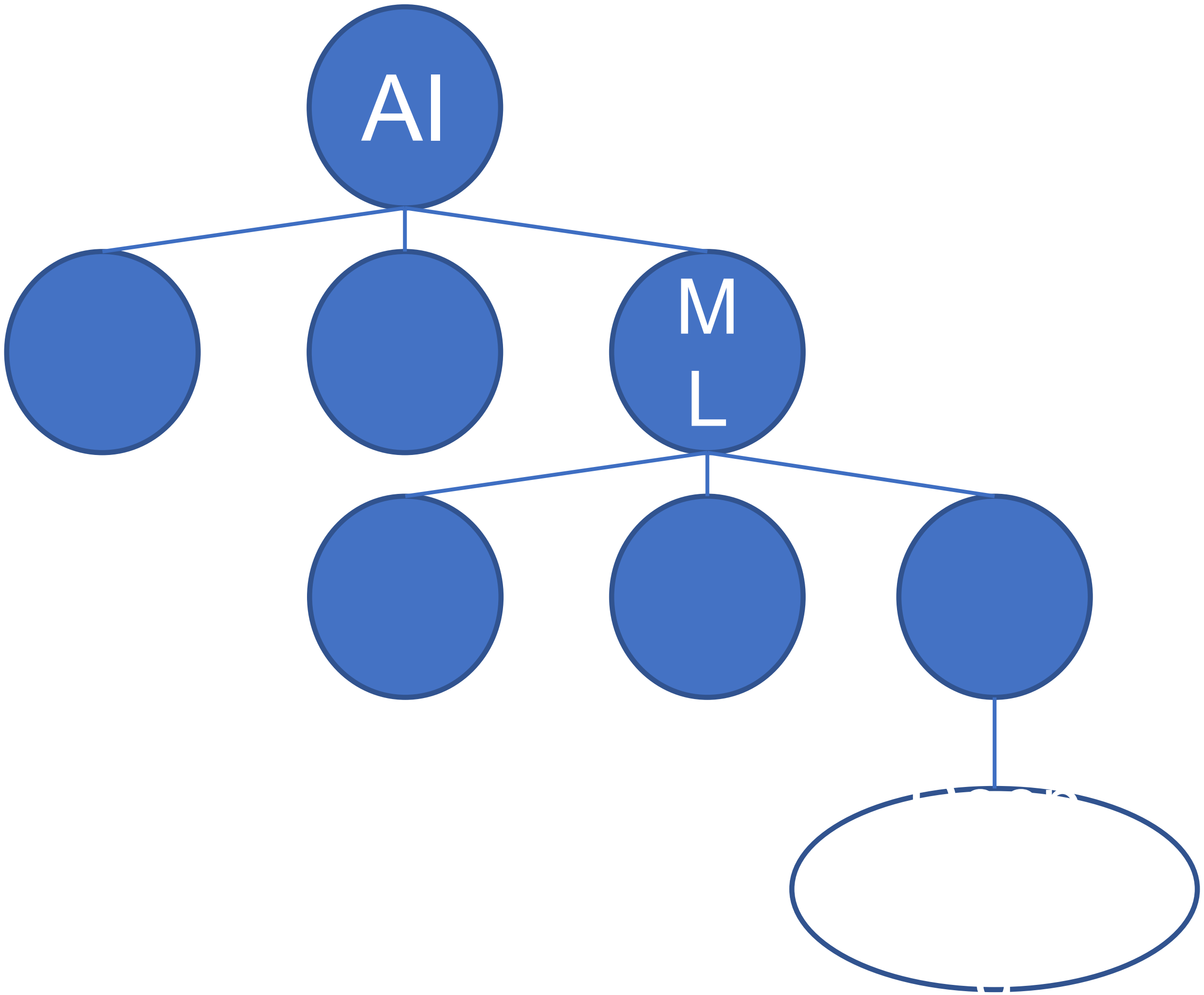
And others...

My Advice:

PyTorch is my personal favorite. Clean API, dynamic graphs make it very easy to develop and debug. Can build model in PyTorch then export to Caffe2 with ONNX for production / mobile

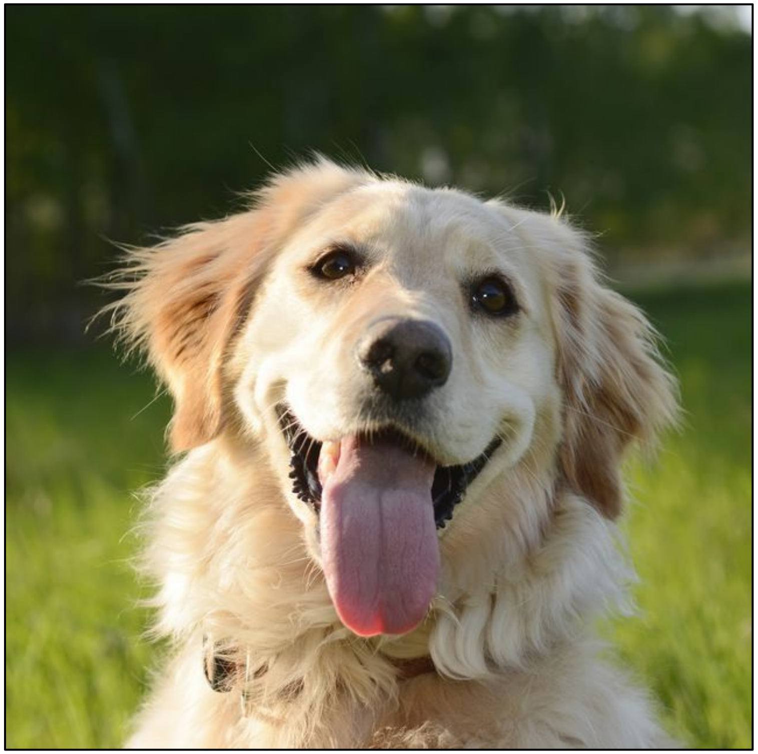
TensorFlow is a safe bet for most projects. Not perfect but has huge community, wide usage. Can use same framework for research and production. Probably use a high-level framework. Only choice if you want to run on TPUs.


AI
ML

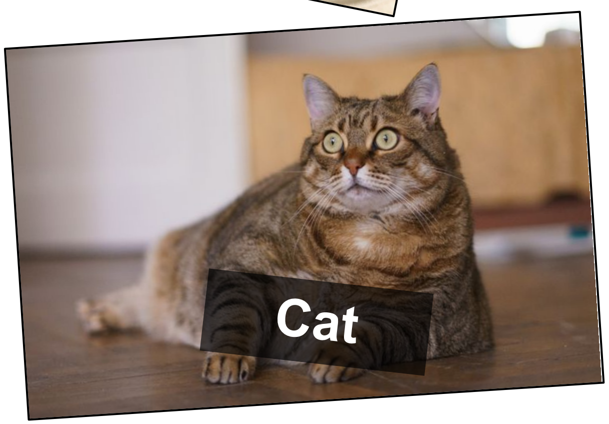
With the right data and the right model, machine learning can solve many problems.

But finding the right data and training the right model
can be difficult.

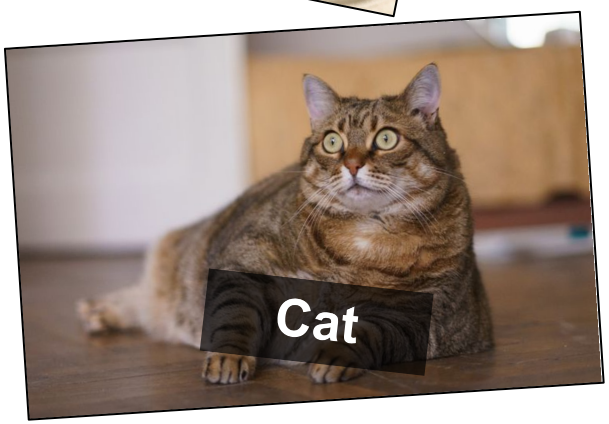
1. Define a problem.



2. Find data.



3. Clean data.



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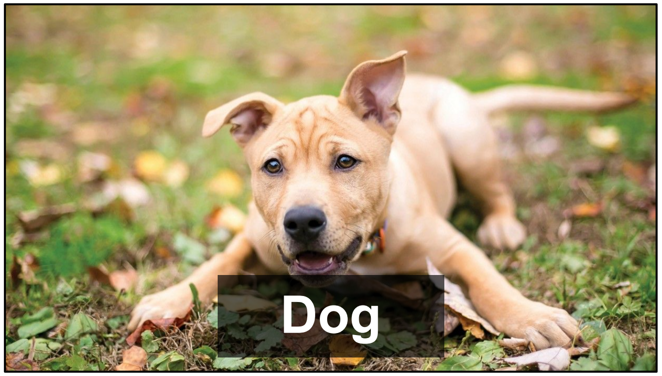


4. Choose a model.

Dogs	Cats
<u>Always</u> <u>Sometimes</u>	<u>Always</u> <u>Sometimes</u>

5. Train the model.

Cat

5. Train the model.

Cat

5. Train the model.

Dog

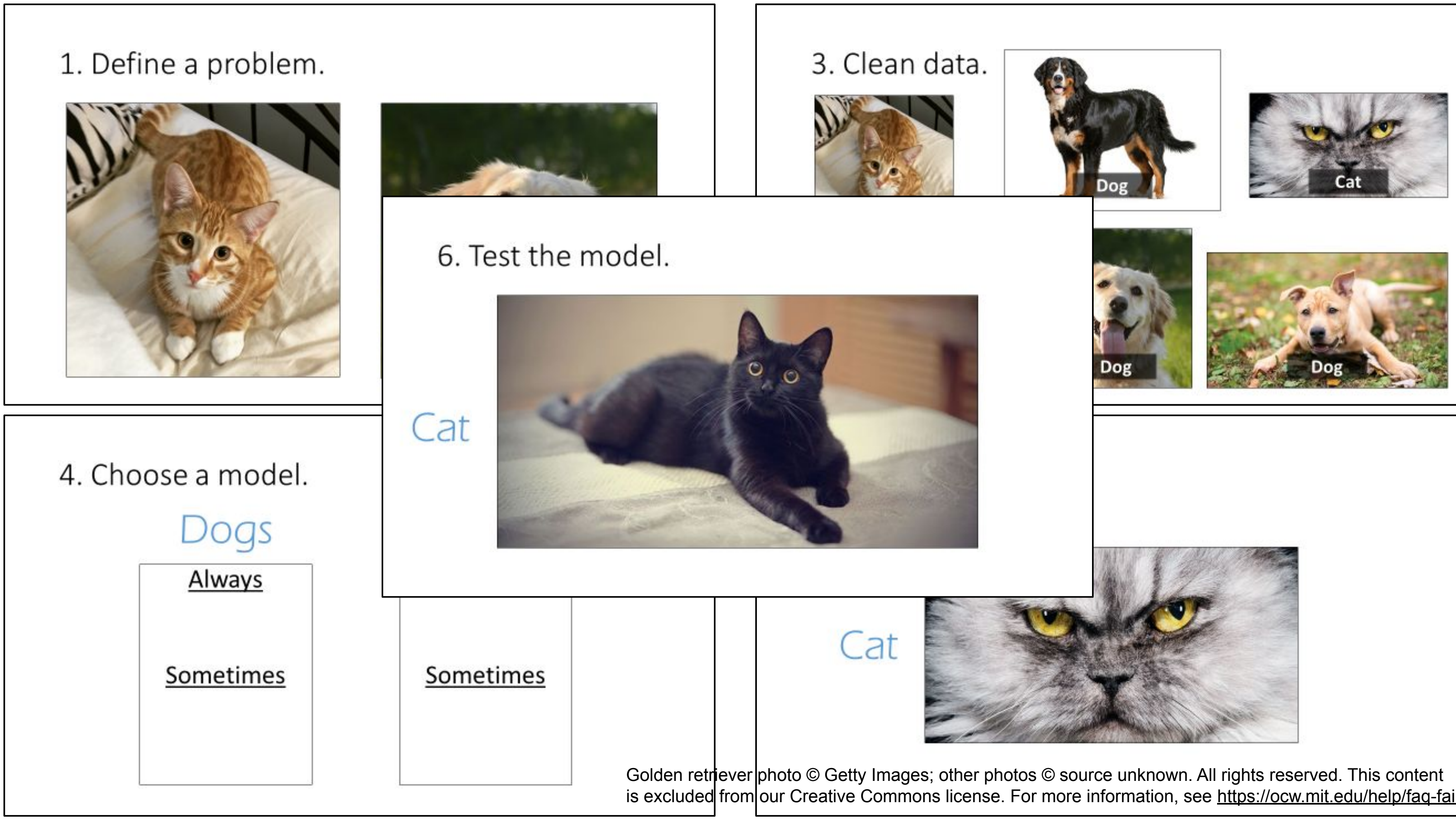
5. Train the model.

Dog

6. Test the model.

Cat

7. Deploy the model.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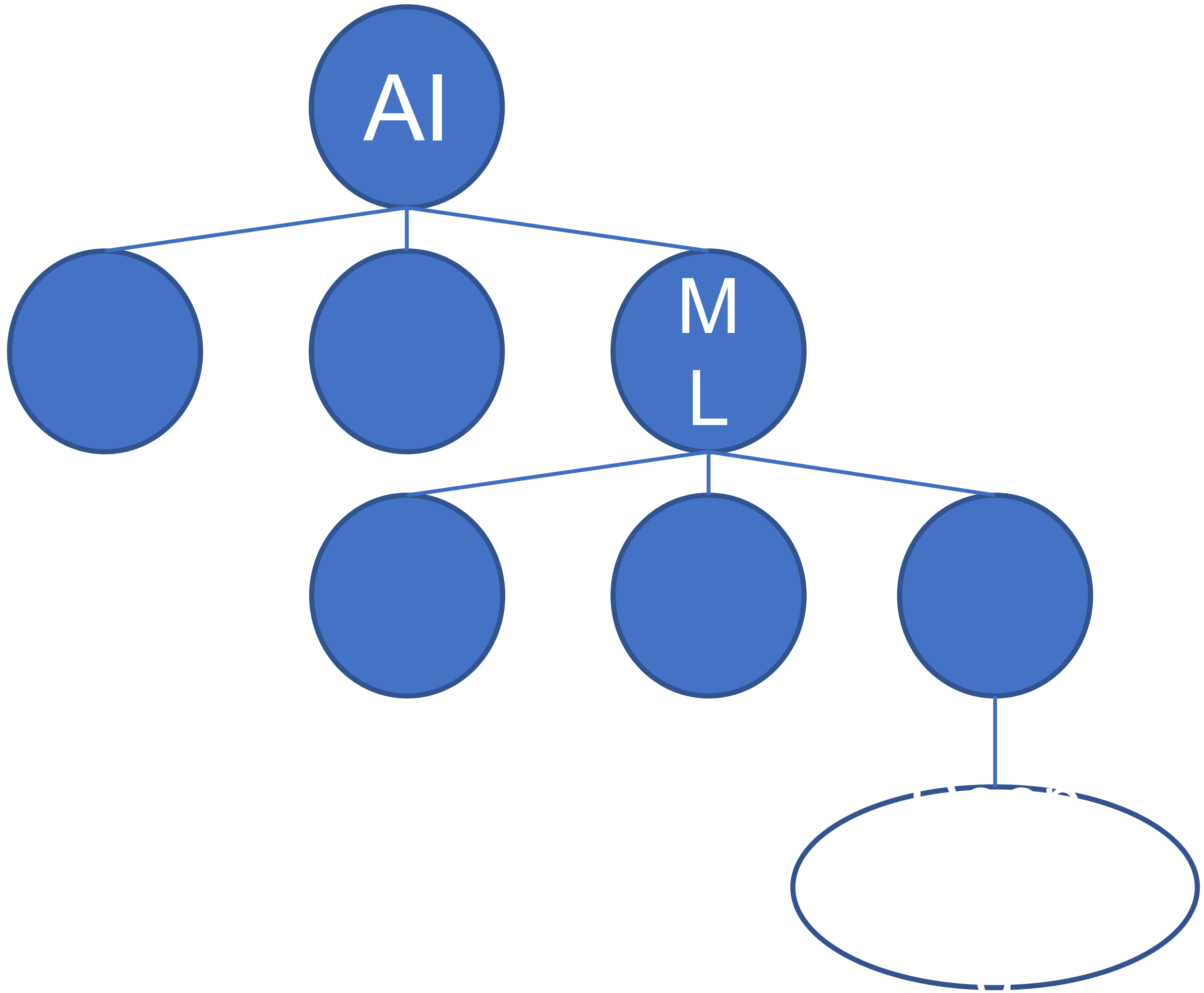
AI
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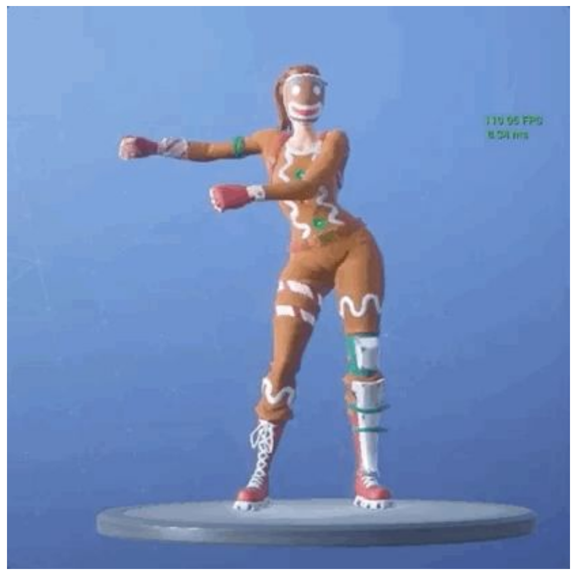
L

What is this movement?
What are they doing?

Gif via Giphy

What is this movement?
What are they doing?

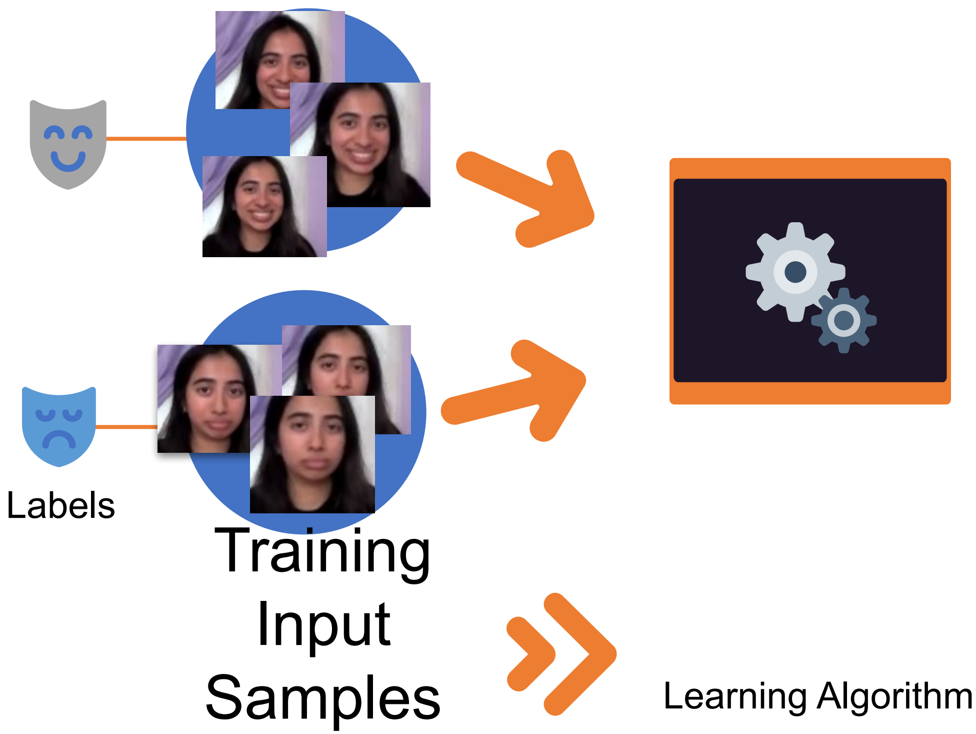


Gif via Giphy

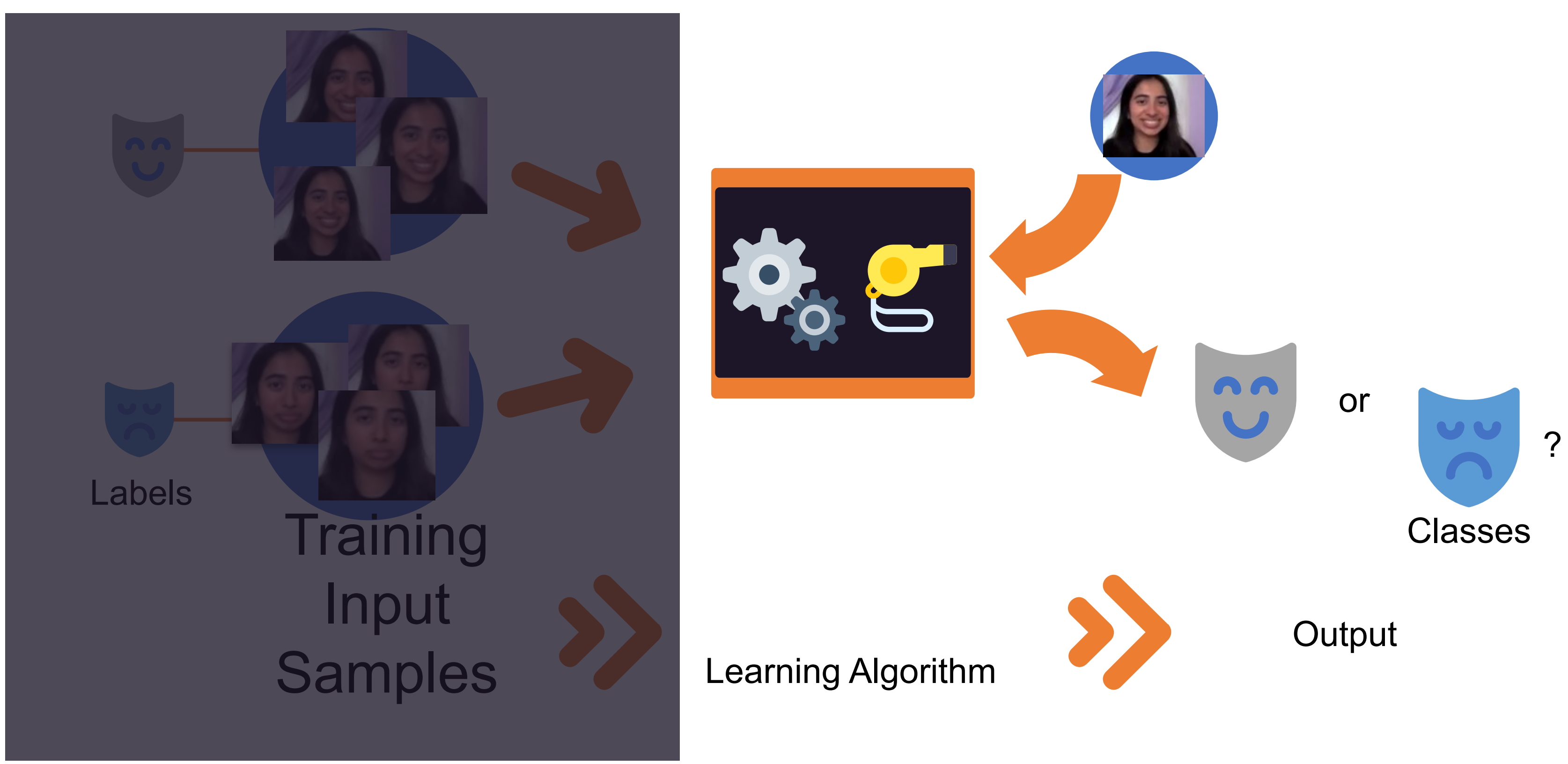
What is this movement?
What are they doing?

Gif via Giphy

How do Machine Learning systems recognize what they see?

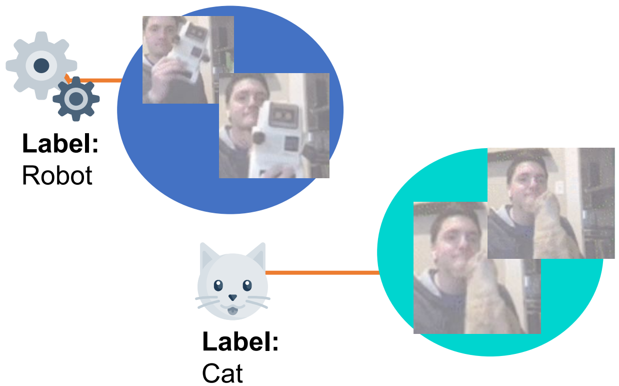


How do Machine Learning systems recognize what they see?



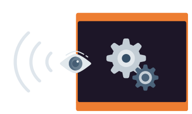
Robot, laptop, cat?

This is an AI system that tells you whether it sees: A robot, a laptop, or a cat.



Training Input Data

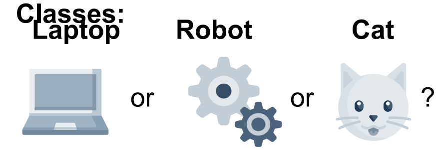
Pictures of Brian holding up his **robot**, laptop, or cat, and their labels



Learning

Patterns that identify the visual characteristics of Brian's robot, laptop, and cat

Output Classes:



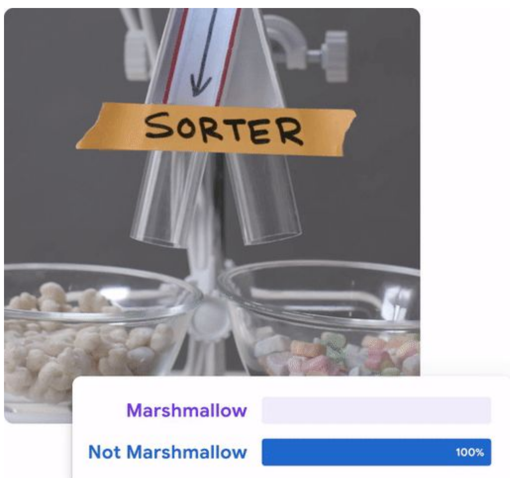
Output

A label that says whether it sees a robot, laptop or cat.

Guess the Training Data!

This AI system sorts Marshmallows from other cereal!

What would the Training Data input be for this system's Machine Learning Model?



[via Google Teachable Machine]

Label:
????

Label:
?????

Training
Input Data

What was this Machine Learning Model trained on?

Output Classes:

Laptop or Robot or Cat ?

Output

Learning

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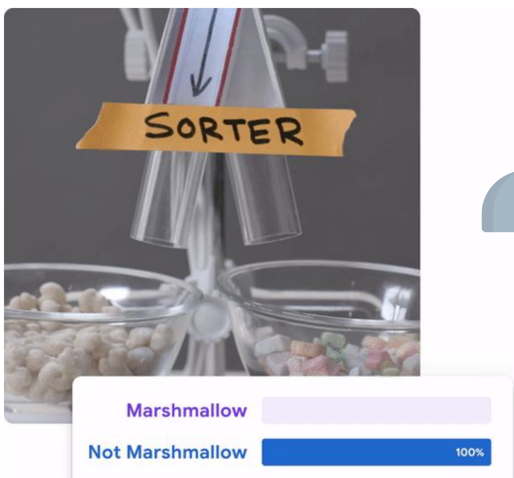
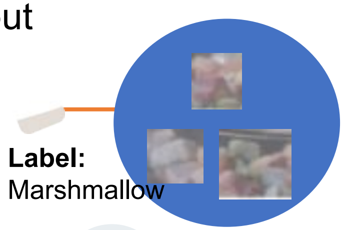
This AI system sorts Marshmallows from other cereal!

What would the Training Data input be for this system's Machine Learning Model?



[via Google Teachable Machine]



Label:
Marshmallow

Label:
Not
Marshmallow

Training
Input Data

This Machine Learning Model was trained on pictures of marshmallows and "not marshmallows" (other cereal)

Learning

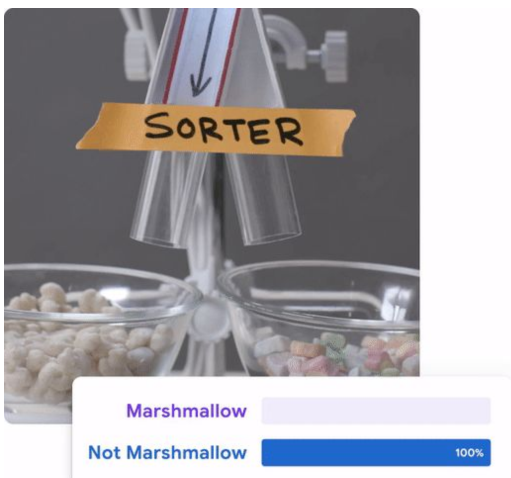
Output Classes:

Laptop or **Robot** or **Cat** ?

Output

How does a computer know what a marshmallow is?

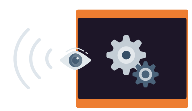
What are some features of a marshmallow that the Machine Learning Model might learn?



via Google Teachable Machine

Training
Input Data

[redacted]s Machine Learning Model was trained on pictures of marshmallows and "not marshmallows" (other cereal)



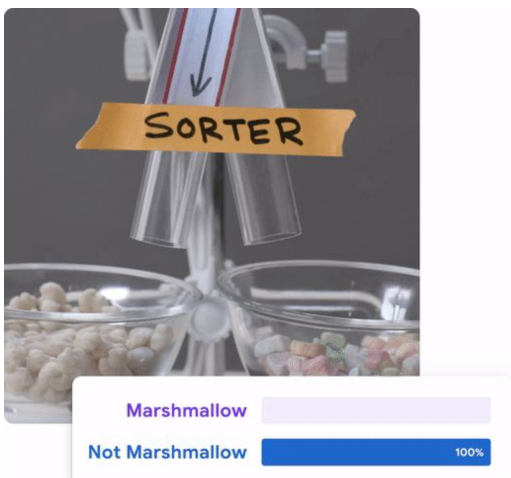
Learning

Output Classes:

Laptop or Robot or Cat ?

Output

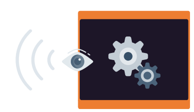
How does a computer know what a marshmallow is?



[via Google Teachable Machine]

Training
Input Data

[redacted]s Machine Learning Model was trained on pictures of marshmallows and “not marshmallows” (other cereal)



Learning

The model ultimately learns how features of cereal (color, shape, texture) differentiate between cereal bits

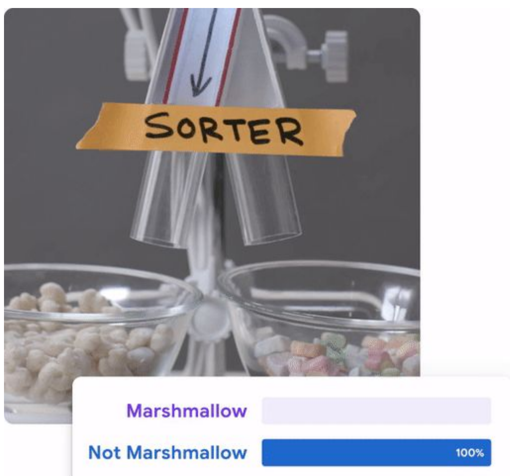
Output Classes:

Laptop or **Robot** or **Cat** ?

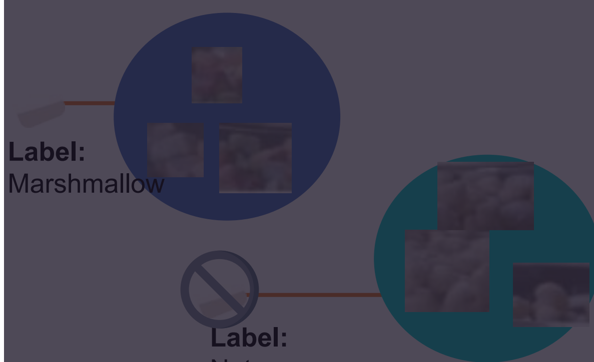
Output

What are the sorter's Output Classes?

What can the fully-trained Machine Learning Model now tell us about new images of cereal bits?



[via Google Teachable Machine]

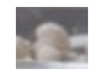


Training Input Data

[redacted]is Machine Learning Model was trained on pictures of marshmallows and "not marshmallows" (other cereal)

Learning

The model ultimately learns how features of cereal (color, shape, texture) differentiate between cereal bits



Output Classes:

____ or ____

Output

What are the sorter's Output Classes?

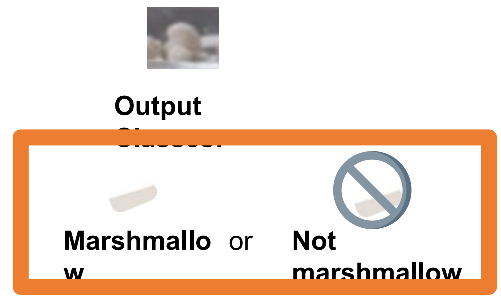
via Google Teachable Machine

Training
Input Data

[redacted]s Machine Learning Model was trained on pictures of marshmallows and "not marshmallows" (other cereal)

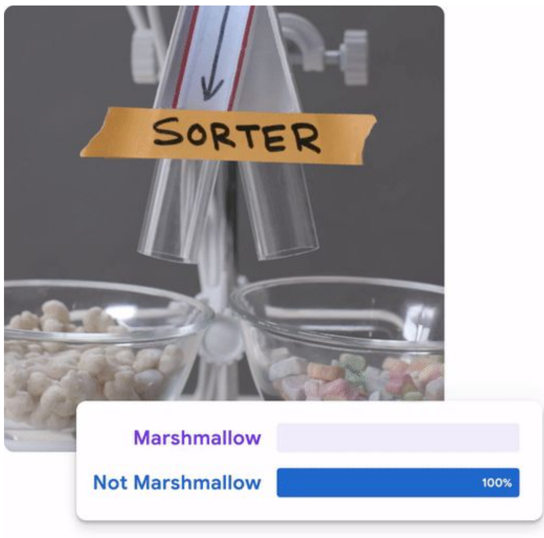
Learning

The model ultimately learns how features of cereal (color, shape, texture) differentiate between cereal bits

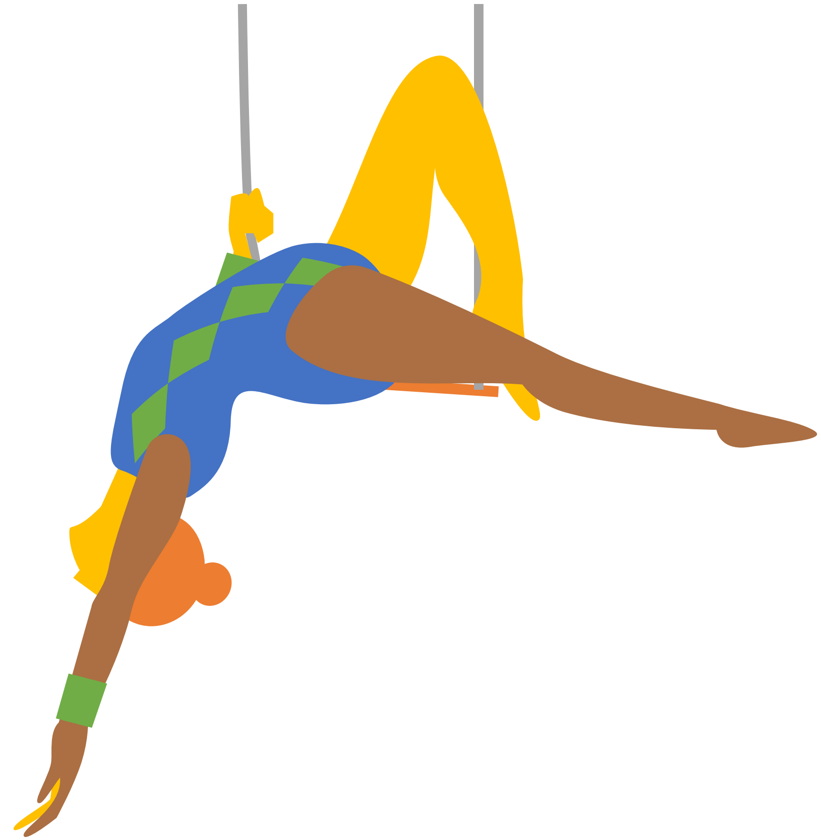


Output

Teachable Machine!

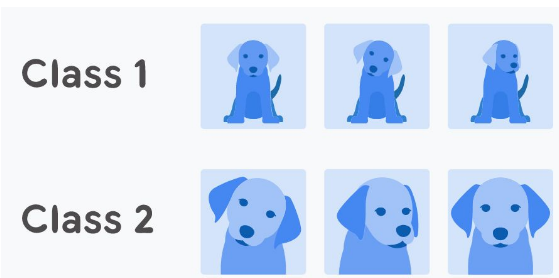


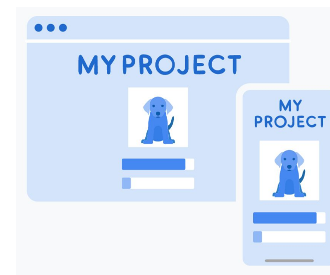
via Google Teachable Machine



https://teachablemachine.withgoogle.com/

Training a Machine Learning Model





Training
Input Samples

Learning Algorithm

Output

Training a Machine Learning Model

IceMelt:

Modeling and Predicting Climate Change

Ages 14 - 18

MAYFLOWER
A.S.T.E.M.
ACADEMY

Goals for this course

- Gathering data from an online data source
- Visualize the data using a line graph on a phone app
- Discuss patterns or trends you see
- Develop a mathematical model to make sense of the data and make predictions about the future of climate-related phenomena
- Use a generative AI chatbot to provide analysis and put climate predictions in context
- **Next steps:** Brainstorm a new phone app you could create to analyze data relevant to a problem you want people to know about.

Lesson 1: Visualize Climate Data

MAYFLOWER
A.S.T.E.M.
ACADEMY

Selena loves to skate anytime she isn’t in school. So she wants to know how many days of good ice there will be in the future.

Using an app she built, Selena enters the date that ice first forms at her local lake in the fall, and then in the spring she enters the date that ice thaws. The app shows the total days the lake was frozen over the winter. The app then adds her data to historical records kept by her city going back 70 years.

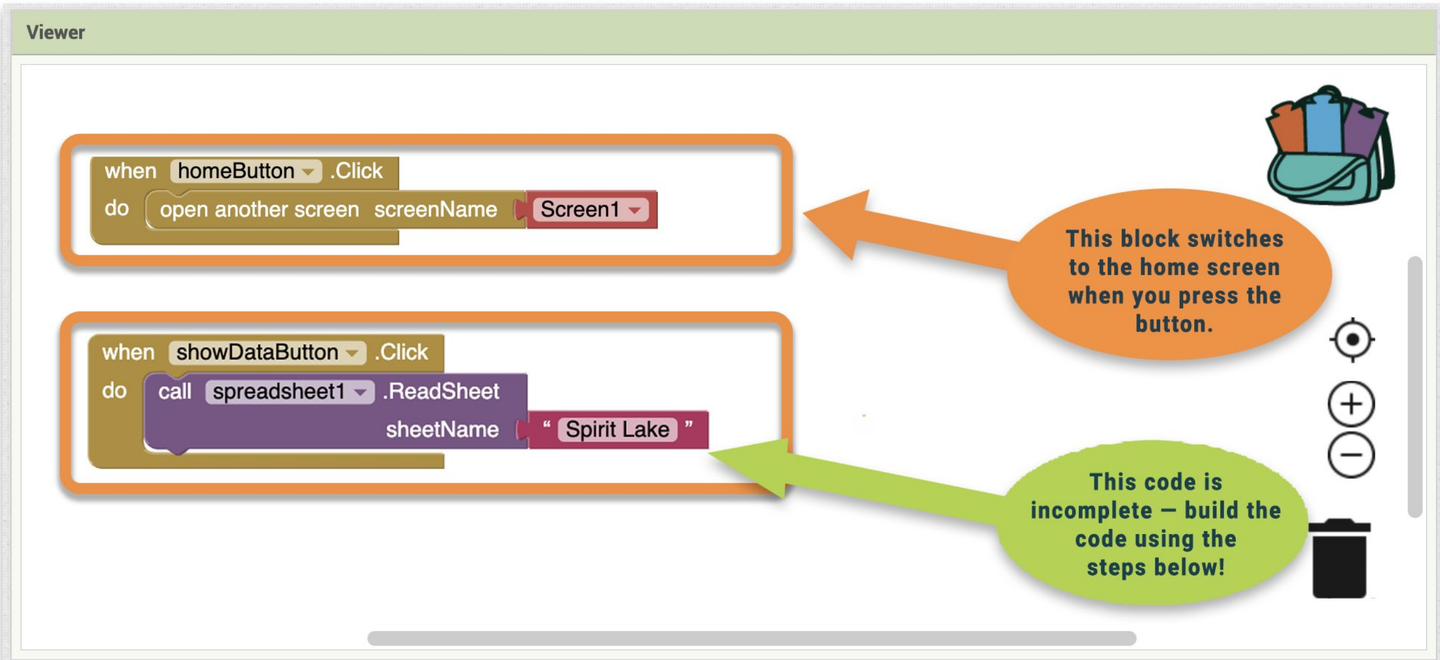
Follow Selena as she builds an app that makes sense of her local lake's annual changes. What she really wants to know: How many days of good skating will her local lake have in the future?

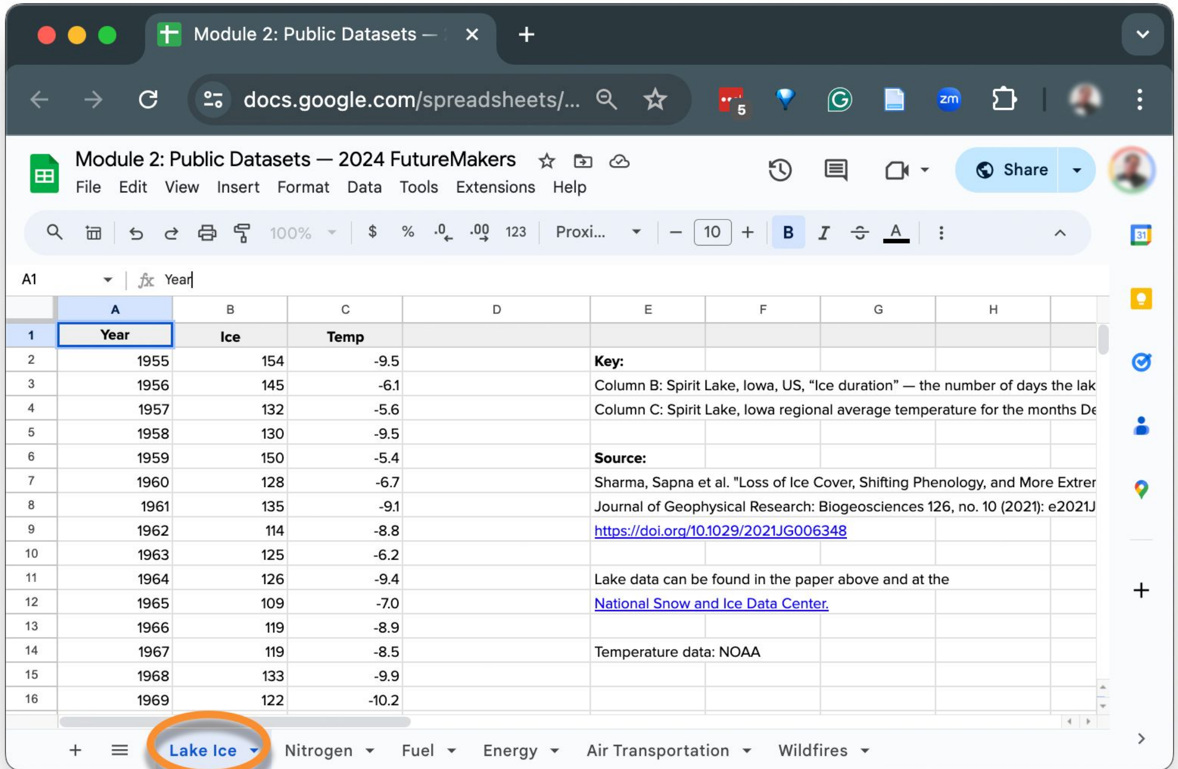
The Challenge: Making Sense of Raw Data

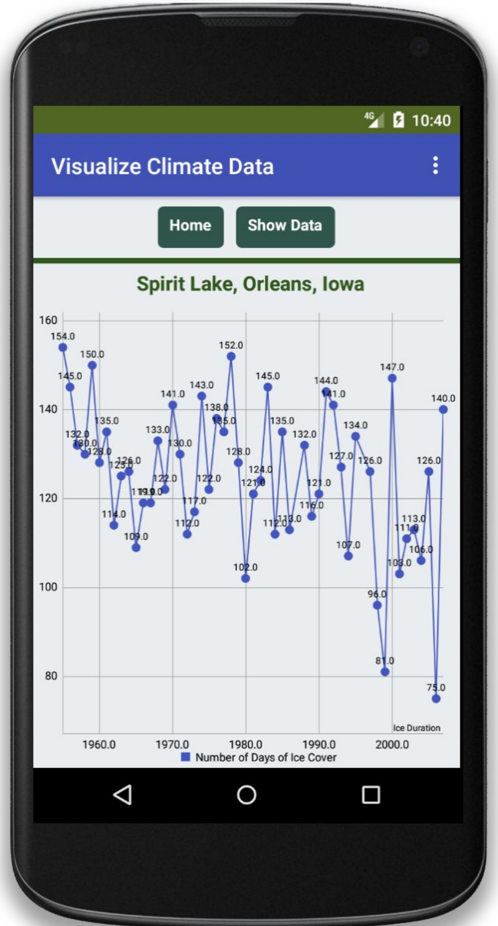
	A	B	C
1	**Year**	**Ice**	**Temp**
2	1955	154	-9.5
3	1956	145	-6.1
4	1957	132	-5.6
5	1958	130	-9.5
6	1959	150	-5.4
7	1960	128	-6.7
8	1961	135	-9.1

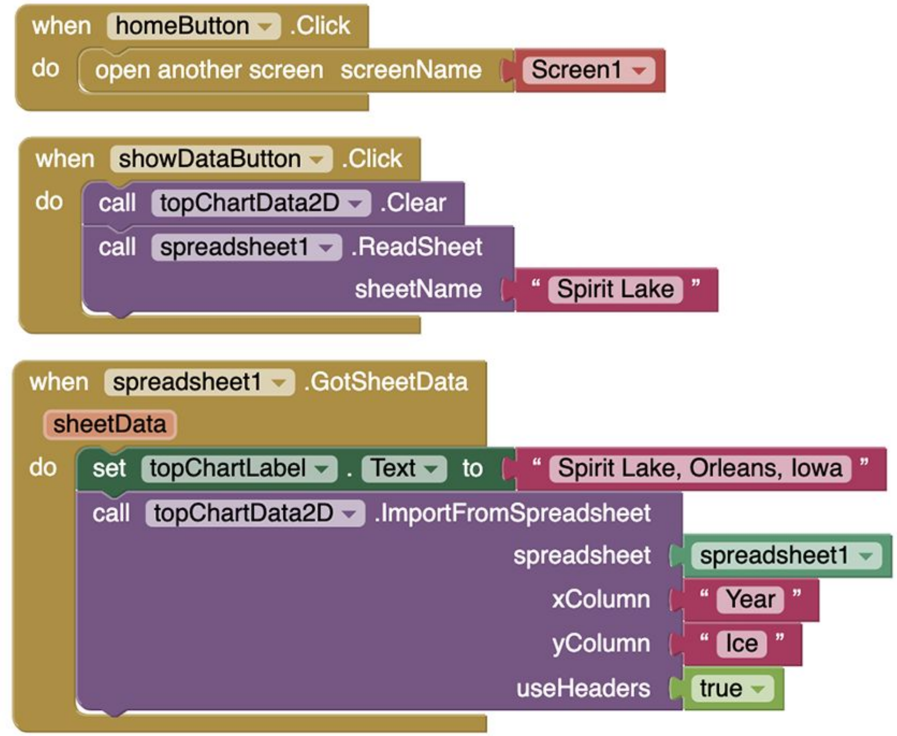
What Does It Do?
Review the Lesson 1 User Interface

What Does it Do? Review the Lesson 1 code



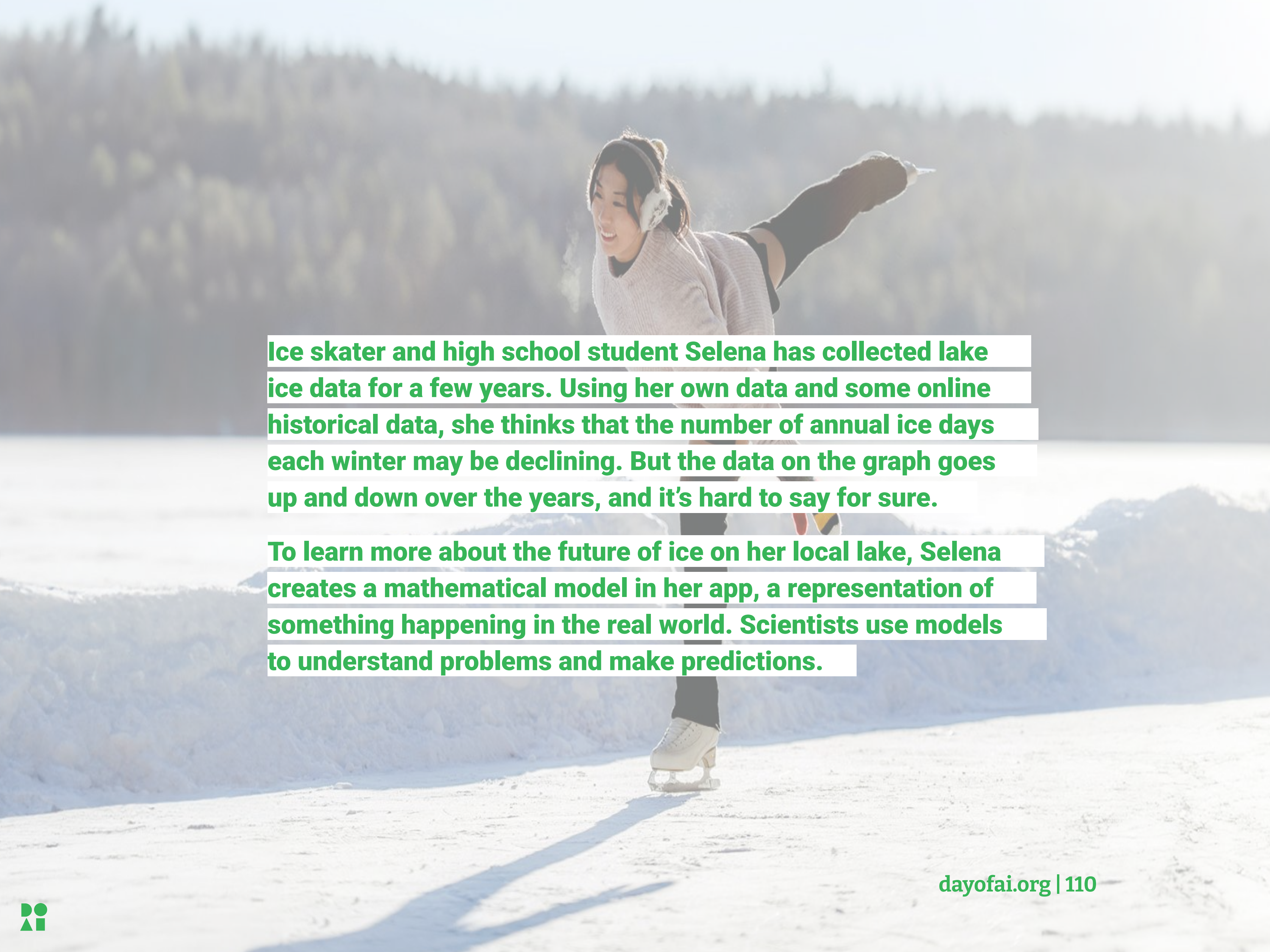

Module 2: Public Datasets —
docs.google.com/spreadsheets/...
Module 2: Public Datasets — 2024 FutureMakers
File Edit View Insert Format Data Tools Extensions Help
Share
Year
Ice
Temp
1955 154 -9.5
1956 145 -6.1
1957 132 -5.6
1958 130 -9.5
1959 150 -5.4
1960 128 -6.7
1961 135 -9.1
1962 114 -8.8
1963 125 -6.2
1964 126 -9.4
1965 109 -7.0
1966 119 -8.9
1967 119 -8.5
1968 133 -9.9
1969 122 -10.2
Key:
Column B: Spirit Lake, Iowa, US, “Ice duration” — the number of days the lak
Column C: Spirit Lake, Iowa regional average temperature for the months De
Source:
Sharma, Sapna et al. "Loss of Ice Cover, Shifting Phenology, and More Extrer
Journal of Geophysical Research: Biogeosciences 126, no. 10 (2021): e2021J
https://doi.org/10.1029/2021JG006348
Lake data can be found in the paper above and at the
National Snow and Ice Data Center.
Temperature data: NOAA
Lake Ice
Nitrogen
Fuel
Energy
Air Transportation
Wildfires


10:40
Visualize Climate Data
Home
Show Data
Spirit Lake, Orleans, Iowa
Ice Duration
Number of Days of Ice Cover


when homeButton .Click
do open another screen screenName Screen1
when showDataButton .Click
do call topChartData2D .Clear
call spreadsheet1 .ReadSheet
sheetName " Spirit Lake "
when spreadsheet1 .GotSheetData
sheetData
do set topChartLabel . Text to " Spirit Lake, Orleans, Iowa "
call topChartData2D .ImportFromSpreadsheet
spreadsheet spreadsheet1
xColumn " Year "
yColumn " Ice "
useHeaders true

Lesson 2: Create a Model with Climate Data

MAYFLOWER
A.S.T.E.M.
ACADEMY

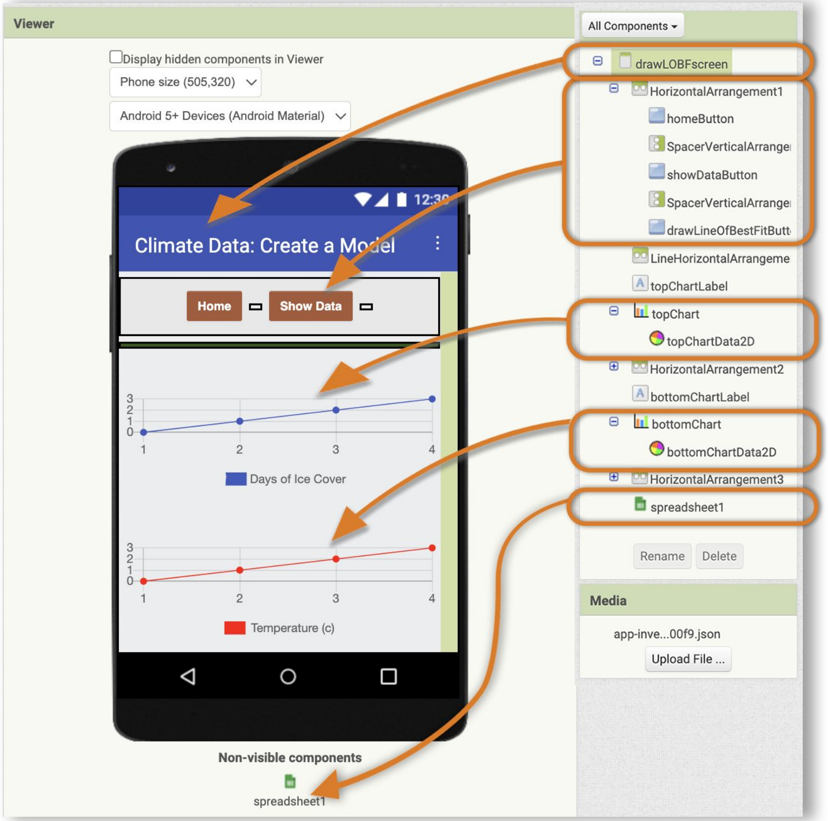


Ice skater and high school student Selena has collected lake ice data for a few years. Using her own data and some online historical data, she thinks that the number of annual ice days each winter may be declining. But the data on the graph goes up and down over the years, and it's hard to say for sure.

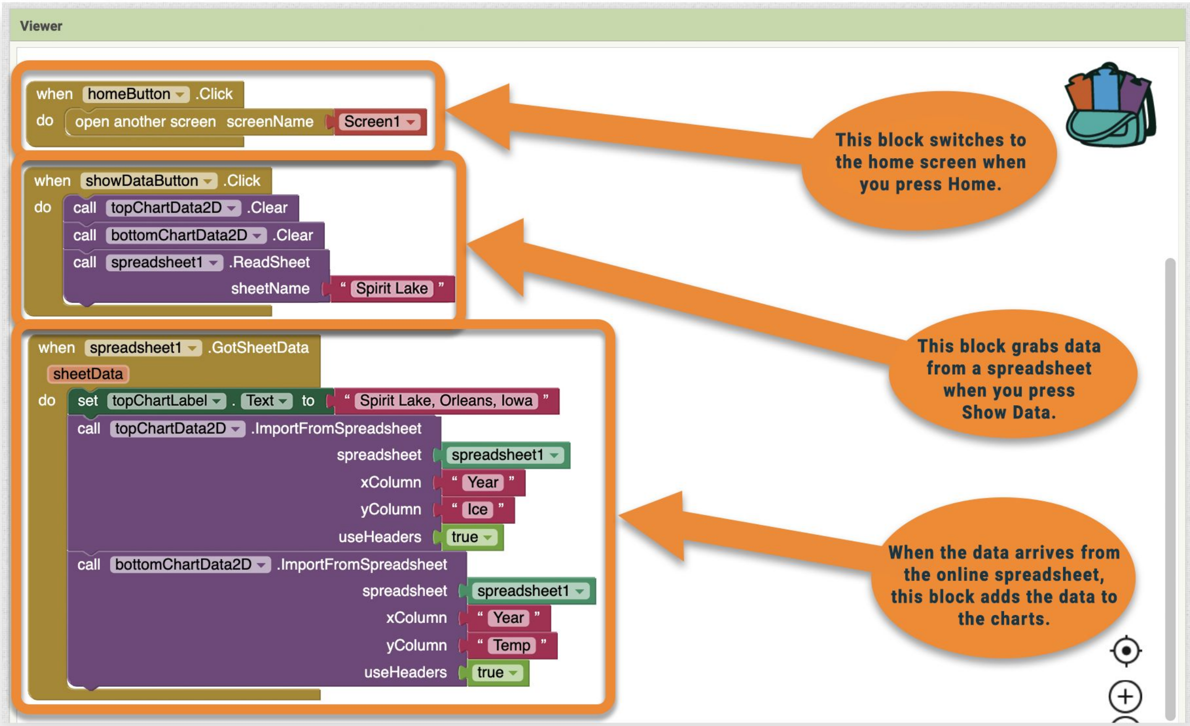
To learn more about the future of ice on her local lake, Selena creates a mathematical model in her app, a representation of something happening in the real world. Scientists use models to understand problems and make predictions.

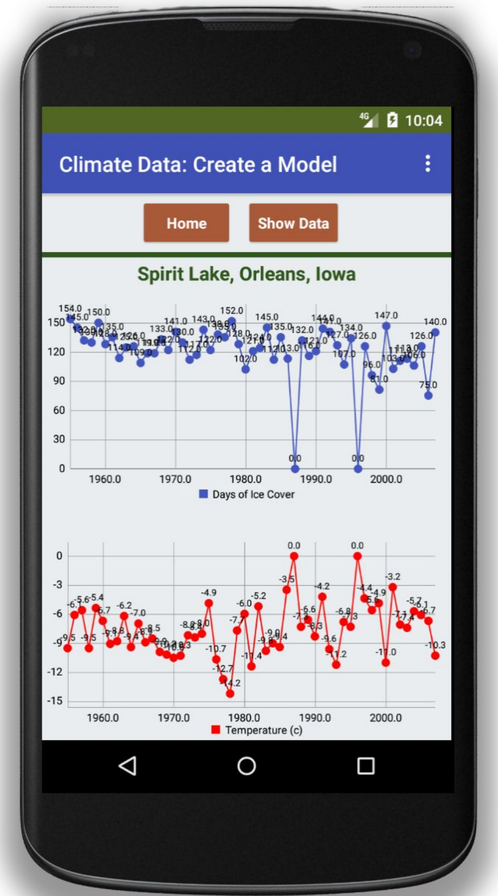
What Does It Do?

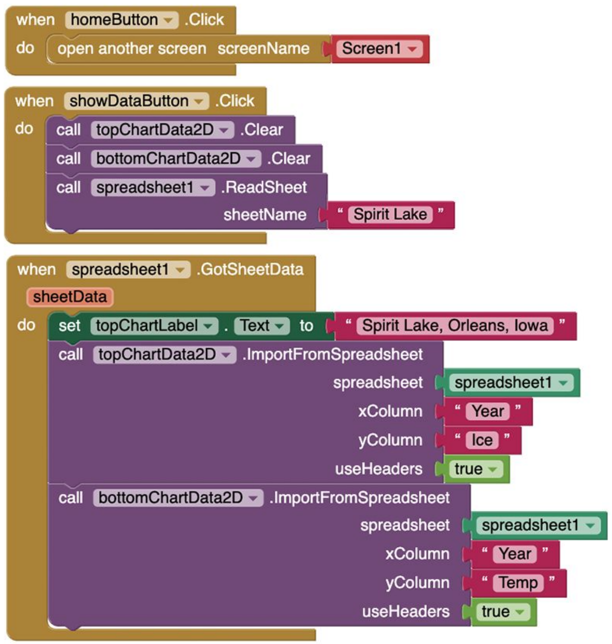
Review the Lesson 2 User Interface

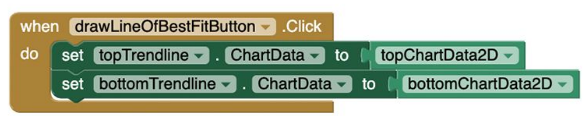


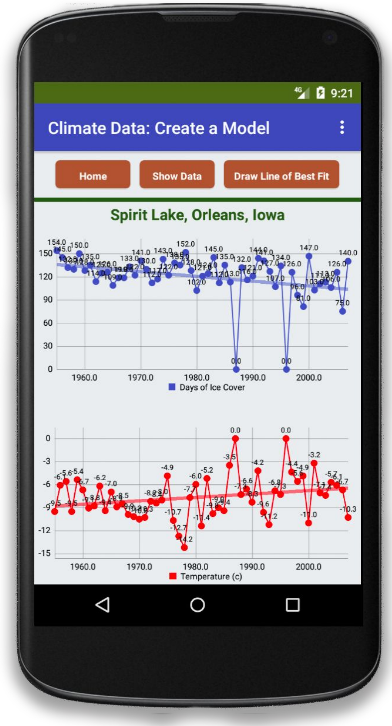
What Does it Do? Review the Lesson 2 code



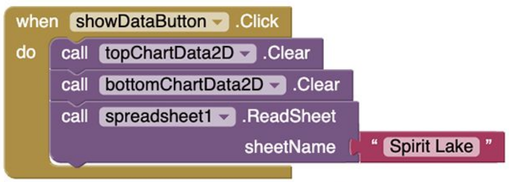

10:04
Climate Data: Create a Model
Home
Show Data
Spirit Lake, Orleans, Iowa
Days of Ice Cover
Temperature (c)


when homeButton .Click
do open another screen screenName Screen1
when showDataButton .Click
do call topChartData2D .Clear
call bottomChartData2D .Clear
call spreadsheet1 .ReadSheet
sheetName " Spirit Lake "
when spreadsheet1 .GotSheetData
sheetData
do set topChartLabel . Text to " Spirit Lake, Orleans, Iowa "
call topChartData2D .ImportFromSpreadsheet
spreadsheet spreadsheet1
xColumn " Year "
yColumn " Ice "
useHeaders true
call bottomChartData2D .ImportFromSpreadsheet
spreadsheet spreadsheet1
xColumn " Year "
yColumn " Temp "
useHeaders true

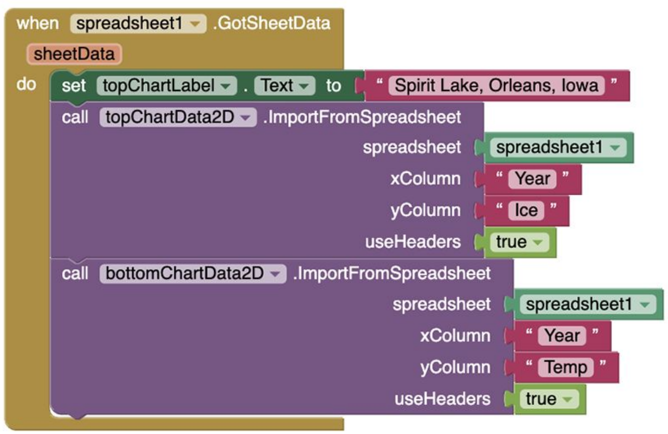

when drawLineOfBestFitButton .Click
do set topTrendline . ChartData to topChartData2D
set bottomTrendline . ChartData to bottomChartData2D


9:21
Climate Data: Create a Model
Home
Show Data
Draw Line of Best Fit
Spirit Lake, Orleans, Iowa
1960.0
1970.0
1980.0
1990.0
2000.0
Days of Ice Cover
Temperature (c)

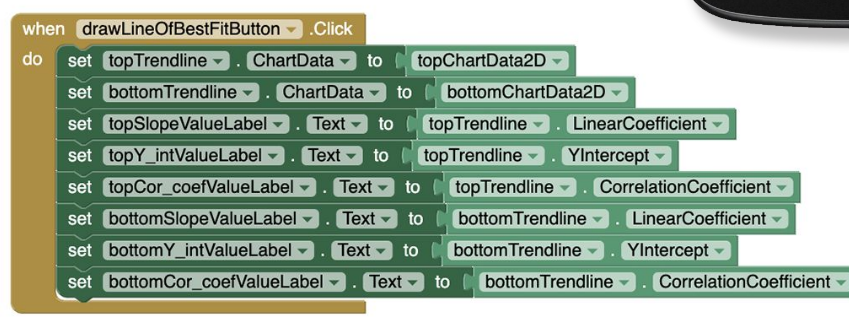
when homeButton .Click
do open another screen screenName Screen1



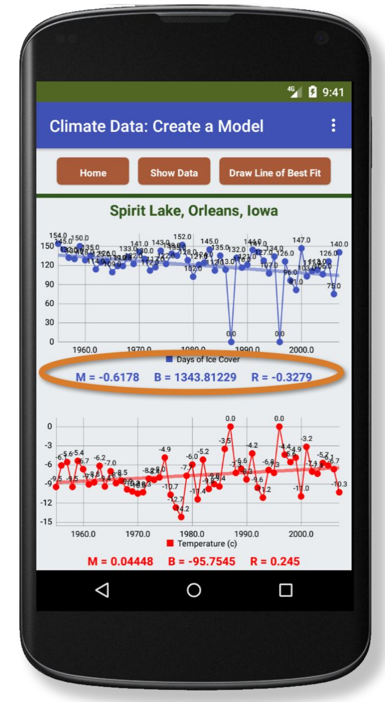
when showDataButton .Click
do call topChartData2D .Clear
call bottomChartData2D .Clear
call spreadsheet1 .ReadSheet
sheetName "Spirit Lake"



when spreadsheet1 .GotSheetData
sheetData
do set topChartLabel . Text to "Spirit Lake, Orleans, Iowa"
call topChartData2D .ImportFromSpreadsheet
spreadsheet spreadsheet1
xColumn "Year"
yColumn "Ice"
useHeaders true
call bottomChartData2D .ImportFromSpreadsheet
spreadsheet spreadsheet1
xColumn "Year"
yColumn "Temp"
useHeaders true



when drawLineOfBestFitButton .Click
do set topTrendline . ChartData to topChartData2D
set bottomTrendline . ChartData to bottomChartData2D
set topSlopeValueLabel . Text to topTrendline . LinearCoefficient
set topY_intValueLabel . Text to topTrendline . YIntercept
set topCor_coefValueLabel . Text to topTrendline . CorrelationCoefficient
set bottomSlopeValueLabel . Text to bottomTrendline . LinearCoefficient
set bottomY_intValueLabel . Text to bottomTrendline . YIntercept
set bottomCor_coefValueLabel . Text to bottomTrendline . CorrelationCoefficient



9:41
Climate Data: Create a Model
Home
Show Data
Draw Line of Best Fit
Spirit Lake, Orleans, Iowa
Days of Ice Cover
M = -0.6178 B = 1343.81229 R = -0.3279
Temperature (c)
M = 0.04448 B = -95.7545 R = 0.245

Lesson 3: Clean the Data

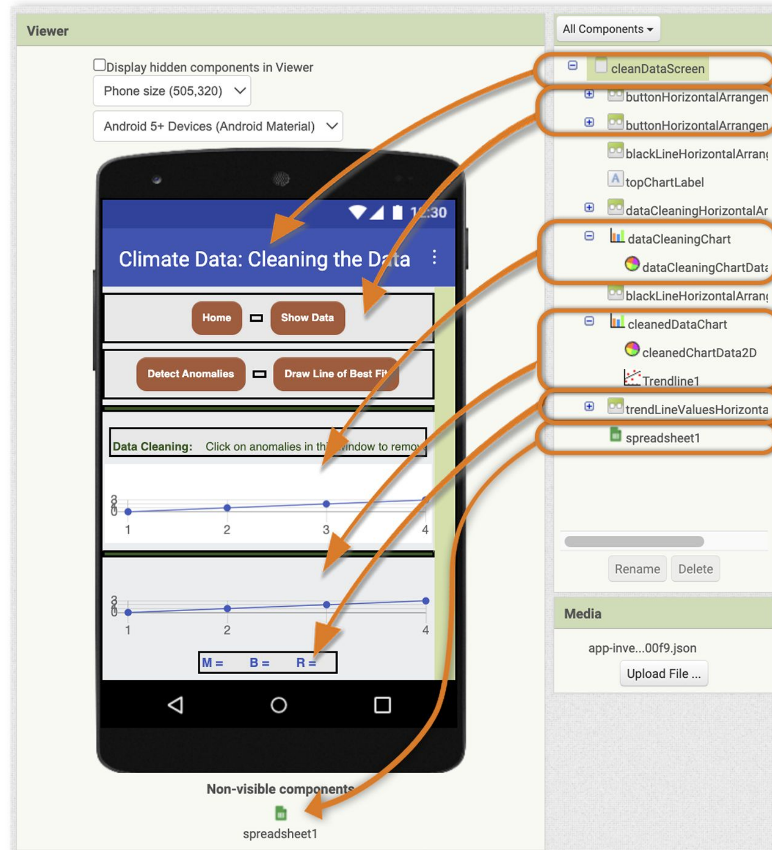
MAYFLOWER
A.S.T.E.M.
ACADEMY

Ice skater and high school student Selena found a problem with her data — a bunch of 0s in the middle of the graph (mainly in the 1980s and 1990s). But her neighbors don't remember any winters when there was no ice at all. She suspects these might be errors or gaps in the data.

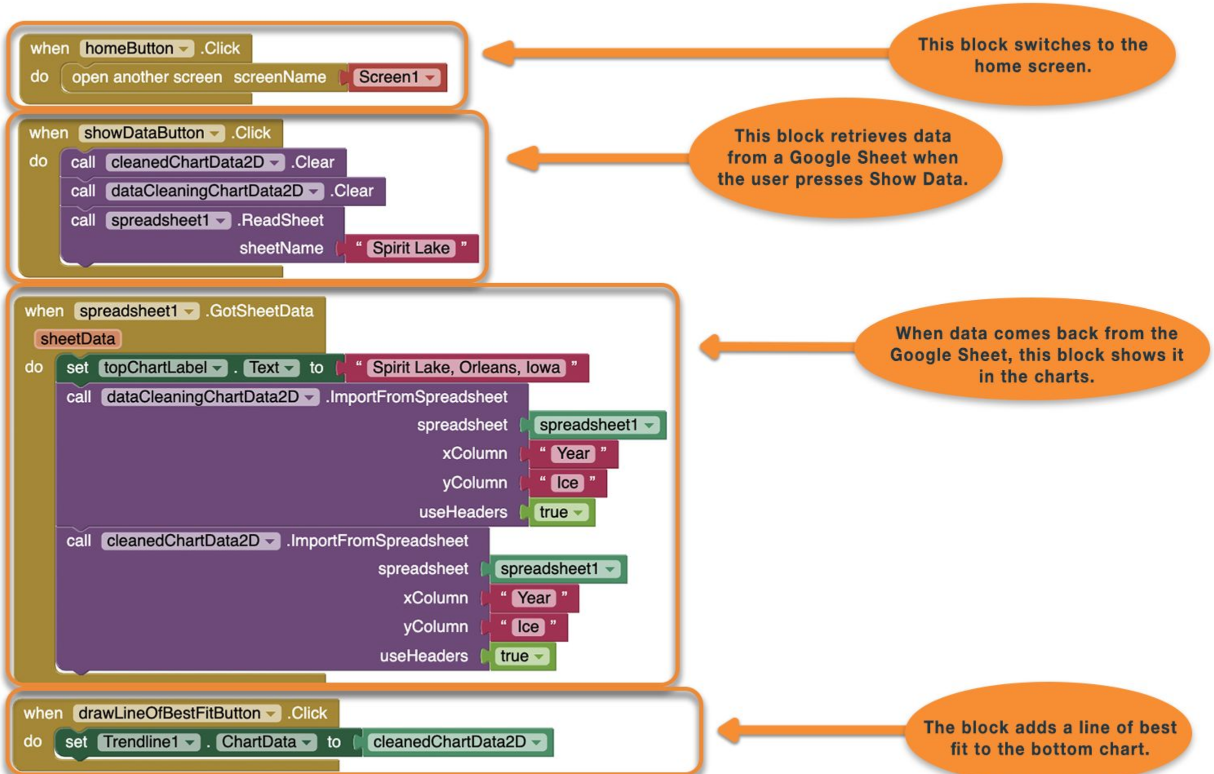
Follow along with Serena as she cleans her data of anomalies and makes new, more optimistic predictions about winter ice on her local lake.

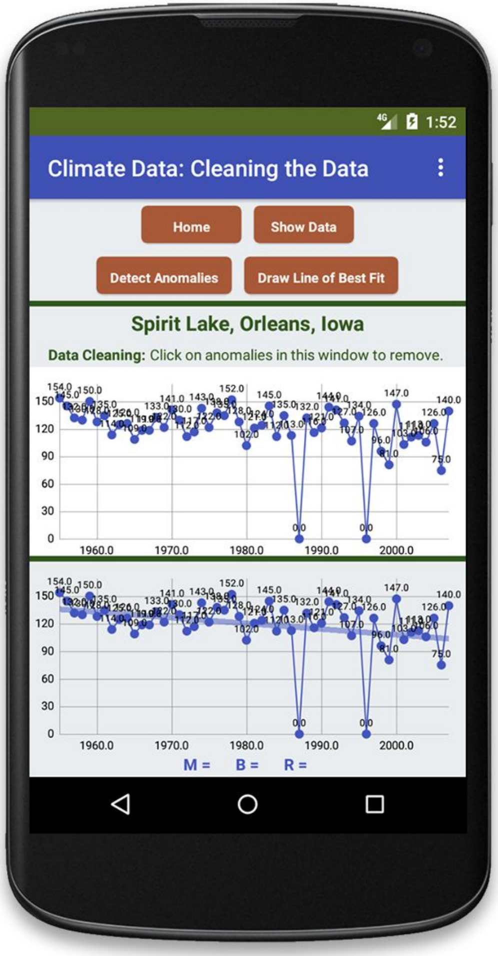
What Does It Do?

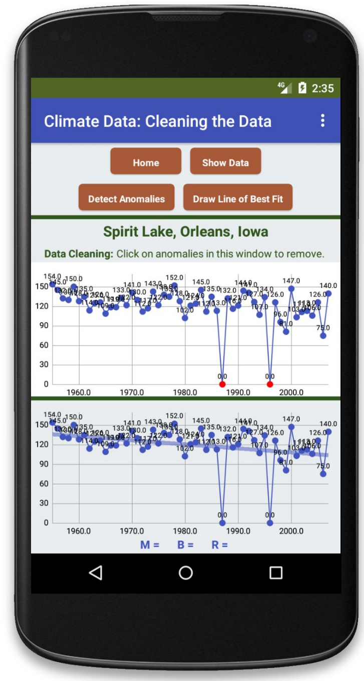
Review the Lesson 3 User Interface

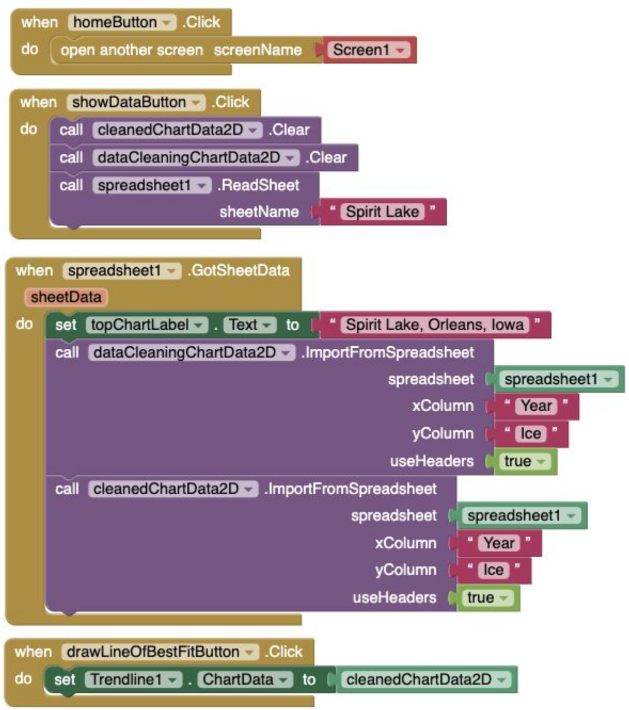


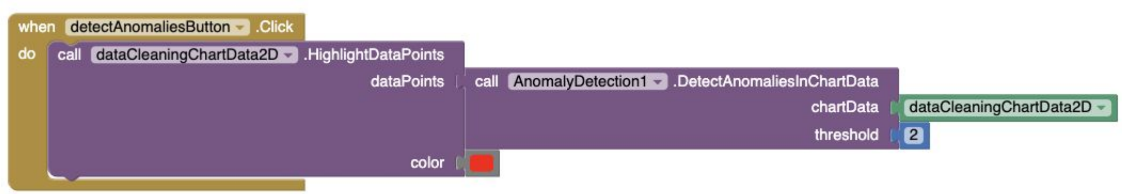
What Does it Do? Review the Lesson 3 code

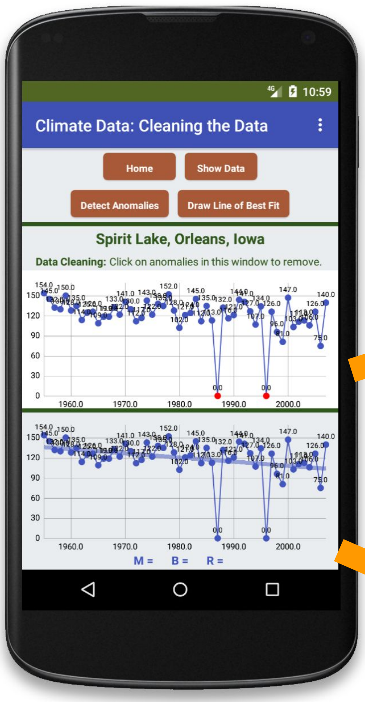



1:52
Climate Data: Cleaning the Data
Home
Show Data
Detect Anomalies
Draw Line of Best Fit
Spirit Lake, Orleans, Iowa
Data Cleaning: Click on anomalies in this window to remove.
1960.0
1970.0
1980.0
1990.0
2000.0
M =
B =
R =

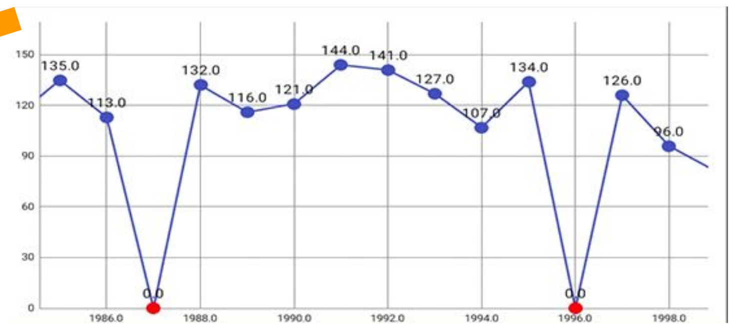

Climate Data: Cleaning the Data
Home
Show Data
Detect Anomalies
Draw Line of Best Fit
Spirit Lake, Orleans, Iowa
Data Cleaning: Click on anomalies in this window to remove.
M =
B =
R =

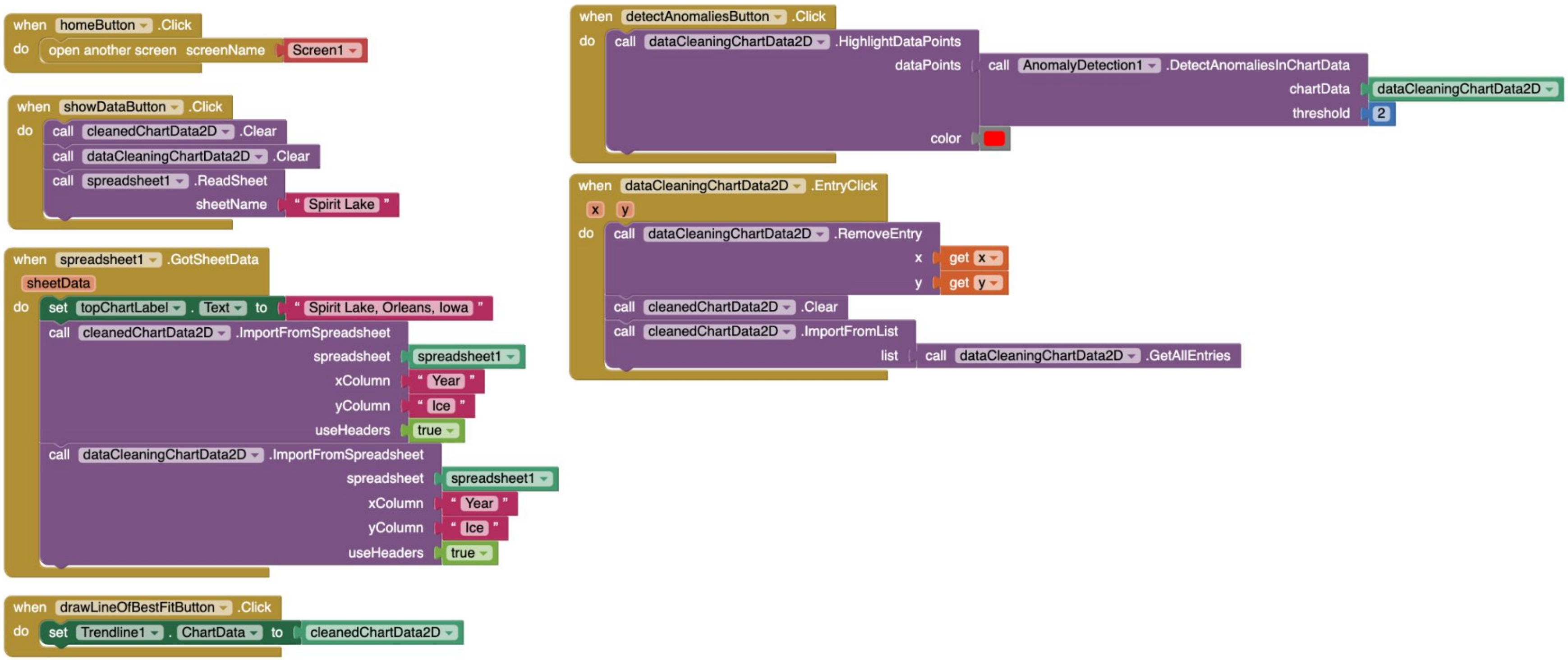

when homeButton .Click
do open another screen screenName Screen1
when showDataButton .Click
do call cleanedChartData2D .Clear
call dataCleaningChartData2D .Clear
call spreadsheet1 .ReadSheet
sheetName " Spirit Lake "
when spreadsheet1 .GotSheetData
sheetData
do set topChartLabel . Text to " Spirit Lake, Orleans, Iowa "
call dataCleaningChartData2D .ImportFromSpreadsheet
spreadsheet spreadsheet1
xColumn " Year "
yColumn " Ice "
useHeaders true
call cleanedChartData2D .ImportFromSpreadsheet
spreadsheet spreadsheet1
xColumn " Year "
yColumn " Ice "
useHeaders true
when drawLineOfBestFitButton .Click
do set Trendline1 . ChartData to cleanedChartData2D

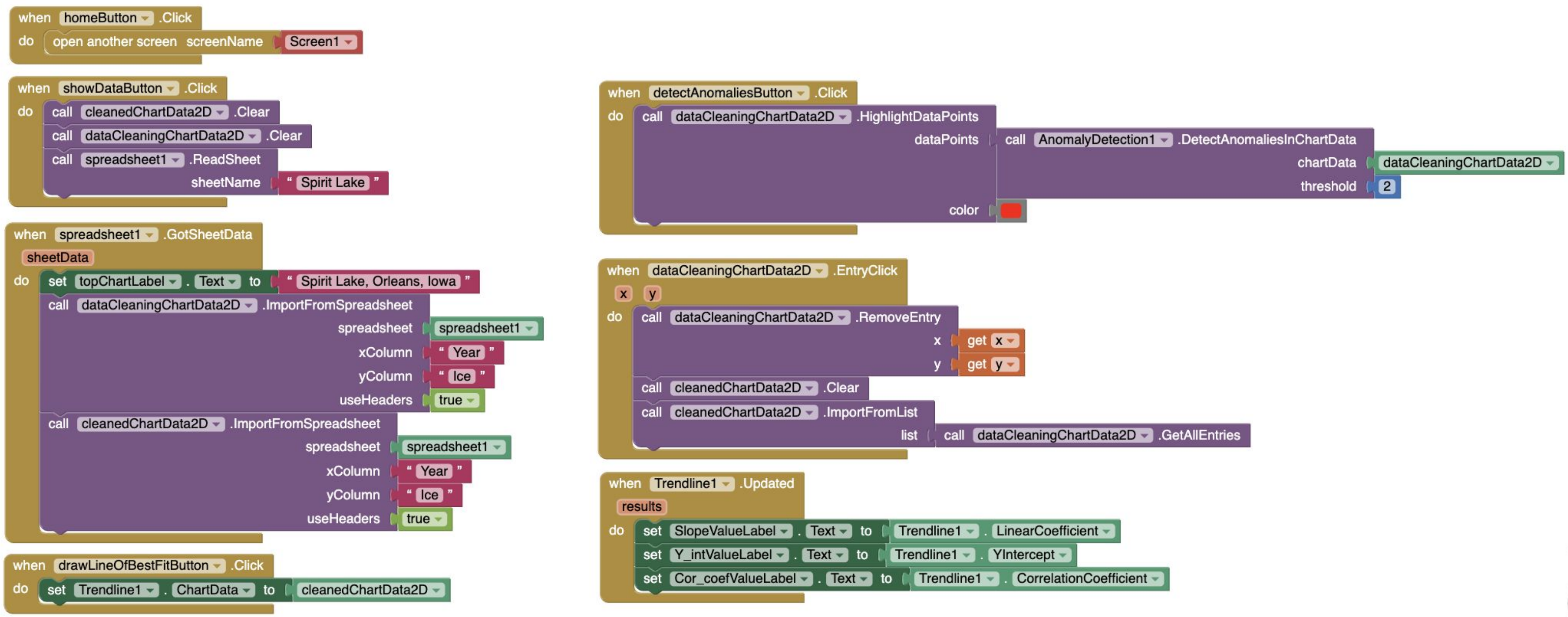

when detectAnomaliesButton .Click
do call dataCleaningChartData2D .HighlightDataPoints
dataPoints call AnomalyDetection1 .DetectAnomaliesInChartData
chartData dataCleaningChartData2D
threshold 2
color



- **Use your fingers to zoom** in on the anomalies. Zooming will make it easier to remove them.




when homeButton .Click
do open another screen screenName Screen1
when showDataButton .Click
do call cleanedChartData2D .Clear
call dataCleaningChartData2D .Clear
call spreadsheet1 .ReadSheet
sheetName " Spirit Lake "
when spreadsheet1 .GotSheetData
sheetData
do set topChartLabel . Text to " Spirit Lake, Orleans, Iowa "
call cleanedChartData2D .ImportFromSpreadsheet
spreadsheet spreadsheet1
xColumn " Year "
yColumn " Ice "
useHeaders true
call dataCleaningChartData2D .ImportFromSpreadsheet
spreadsheet spreadsheet1
xColumn " Year "
yColumn " Ice "
useHeaders true
when drawLineOfBestFitButton .Click
do set Trendline1 . ChartData to cleanedChartData2D
when detectAnomaliesButton .Click
do call dataCleaningChartData2D .HighlightDataPoints
dataPoints call AnomalyDetection1 .DetectAnomaliesInChartData
chartData dataCleaningChartData2D
threshold 2
color
when dataCleaningChartData2D .EntryClick
x y
do call dataCleaningChartData2D .RemoveEntry
x get x
y get y
call cleanedChartData2D .Clear
call cleanedChartData2D .ImportFromList
list call dataCleaningChartData2D .GetAllEntries

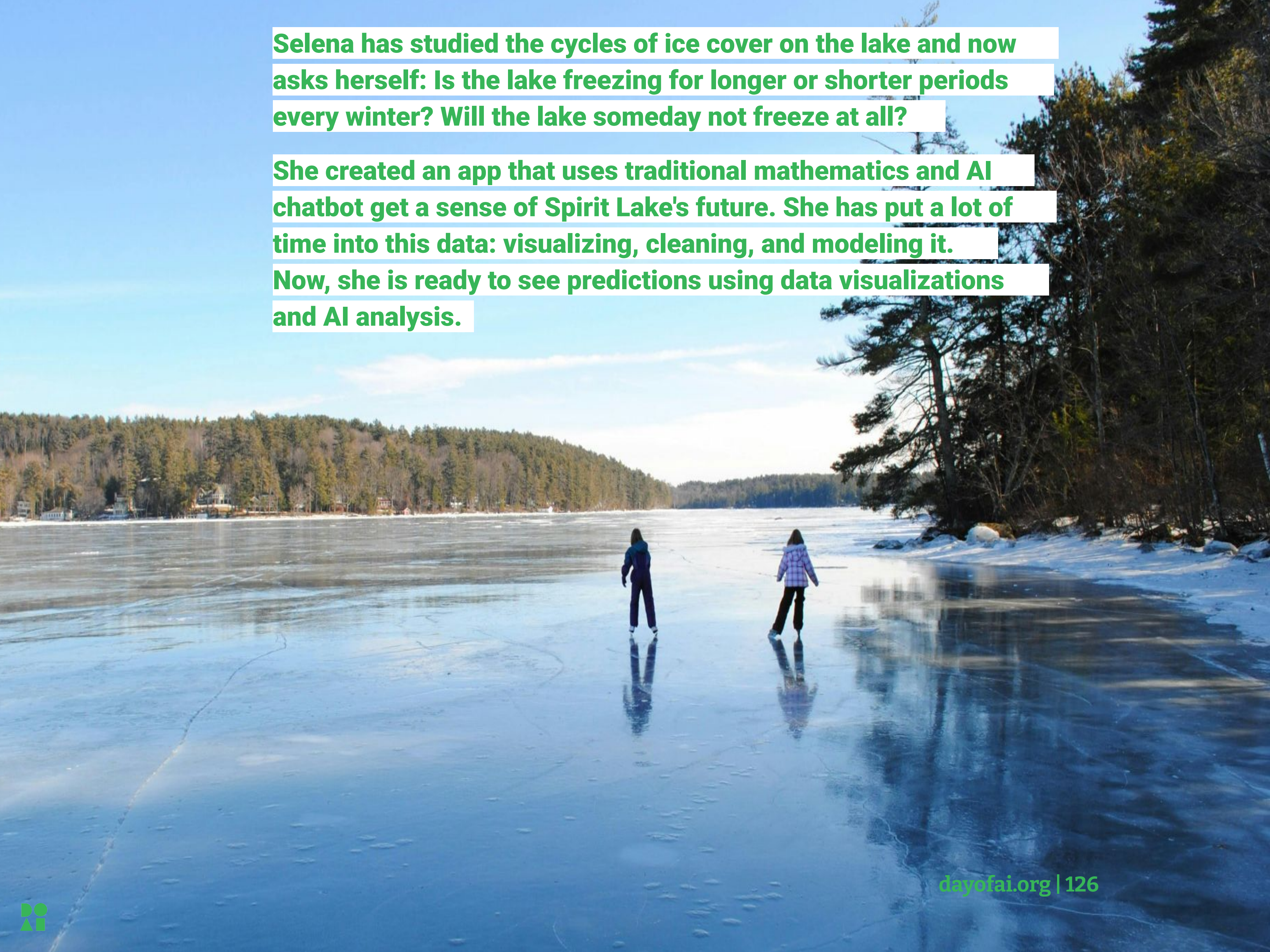

when homeButton .Click
do open another screen screenName Screen1
when showDataButton .Click
do call cleanedChartData2D .Clear
call dataCleaningChartData2D .Clear
call spreadsheet1 .ReadSheet
sheetName " Spirit Lake "
when spreadsheet1 .GotSheetData
sheetData
do set topChartLabel . Text to " Spirit Lake, Orleans, Iowa "
call dataCleaningChartData2D .ImportFromSpreadsheet
spreadsheet spreadsheet1
xColumn " Year "
yColumn " Ice "
useHeaders true
call cleanedChartData2D .ImportFromSpreadsheet
spreadsheet spreadsheet1
xColumn " Year "
yColumn " Ice "
useHeaders true
when drawLineOfBestFitButton .Click
do set Trendline1 . ChartData to cleanedChartData2D
when detectAnomaliesButton .Click
do call dataCleaningChartData2D .HighlightDataPoints
dataPoints call AnomalyDetection1 .DetectAnomaliesInChartData
chartData dataCleaningChartData2D
threshold 2
color
when dataCleaningChartData2D .EntryClick
x y
do call dataCleaningChartData2D .RemoveEntry
x get x
y get y
call cleanedChartData2D .Clear
call cleanedChartData2D .ImportFromList
list call dataCleaningChartData2D .GetAllEntries
when Trendline1 .Updated
results
do set SlopeValueLabel . Text to Trendline1 . LinearCoefficient
set Y_intValueLabel . Text to Trendline1 . YIntercept
set Cor_coefValueLabel . Text to Trendline1 . CorrelationCoefficient

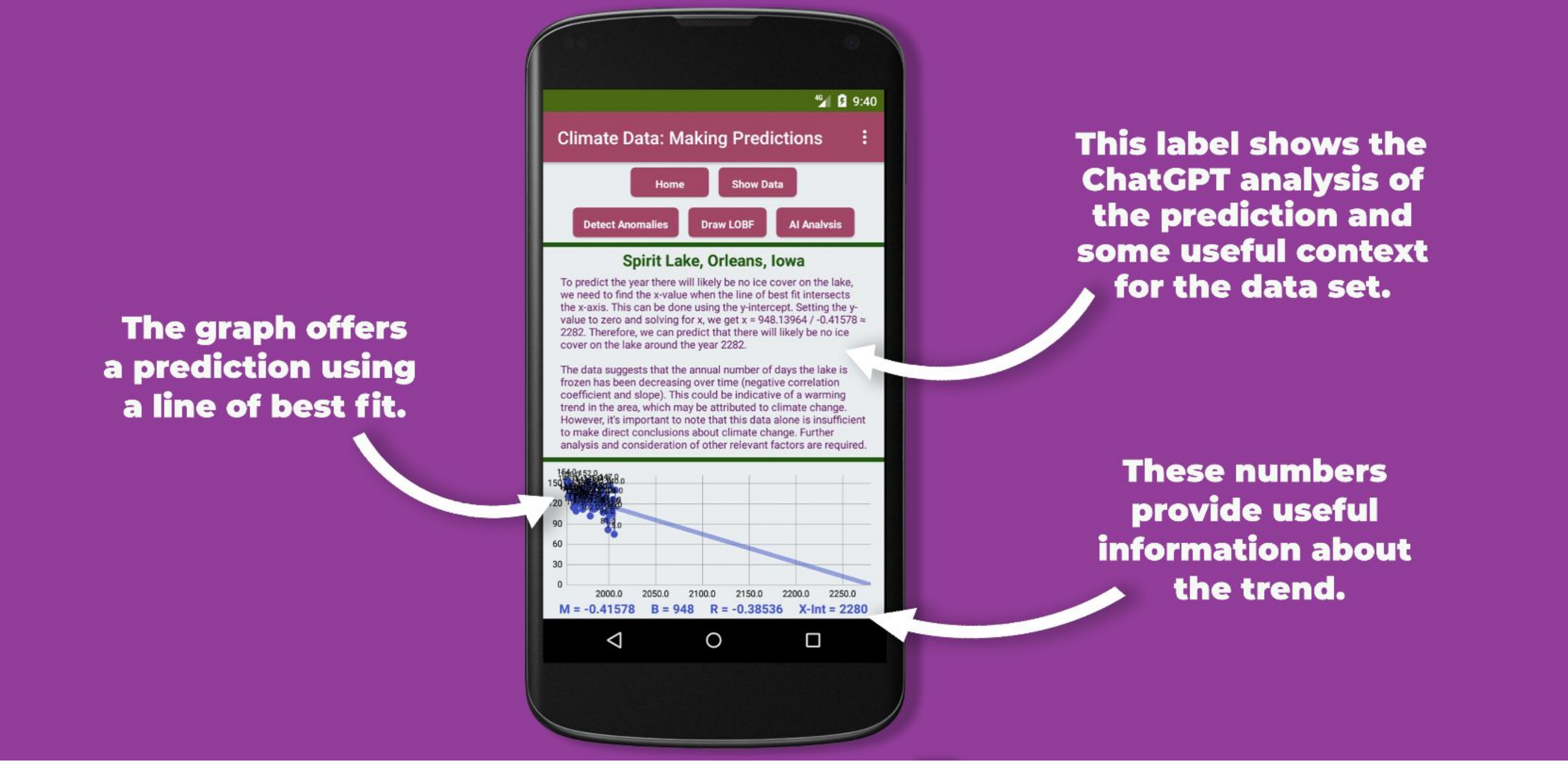
Lesson 4: Make Mathematical and AI Predictions with Climate Data

MAYFLOWER
A.S.T.E.M.
ACADEMY

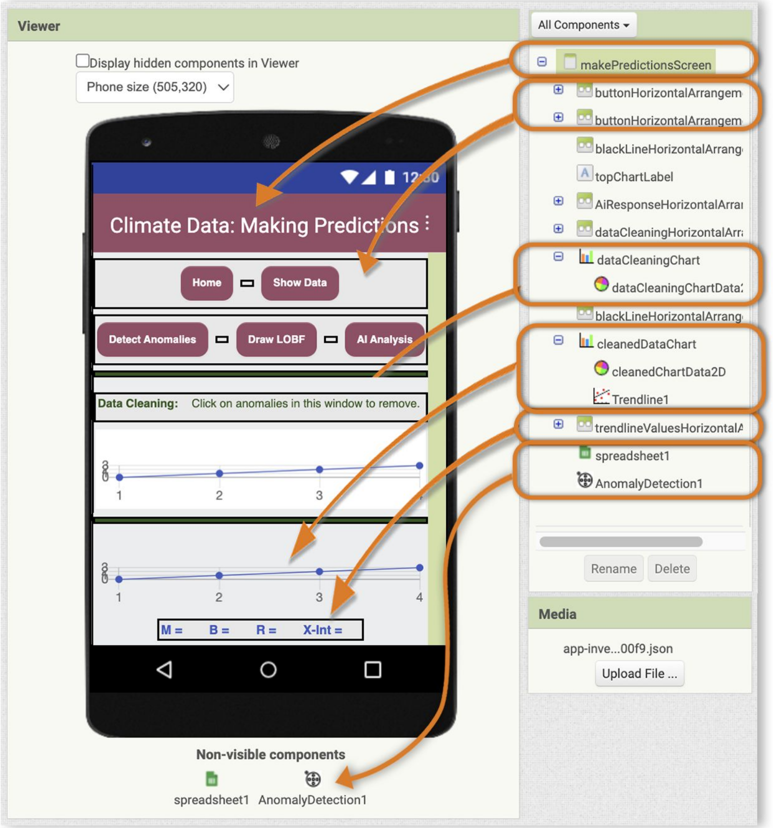
Selena has studied the cycles of ice cover on the lake and now asks herself: Is the lake freezing for longer or shorter periods every winter? Will the lake someday not freeze at all?

She created an app that uses traditional mathematics and AI chatbot get a sense of Spirit Lake's future. She has put a lot of time into this data: visualizing, cleaning, and modeling it. Now, she is ready to see predictions using data visualizations and AI analysis.

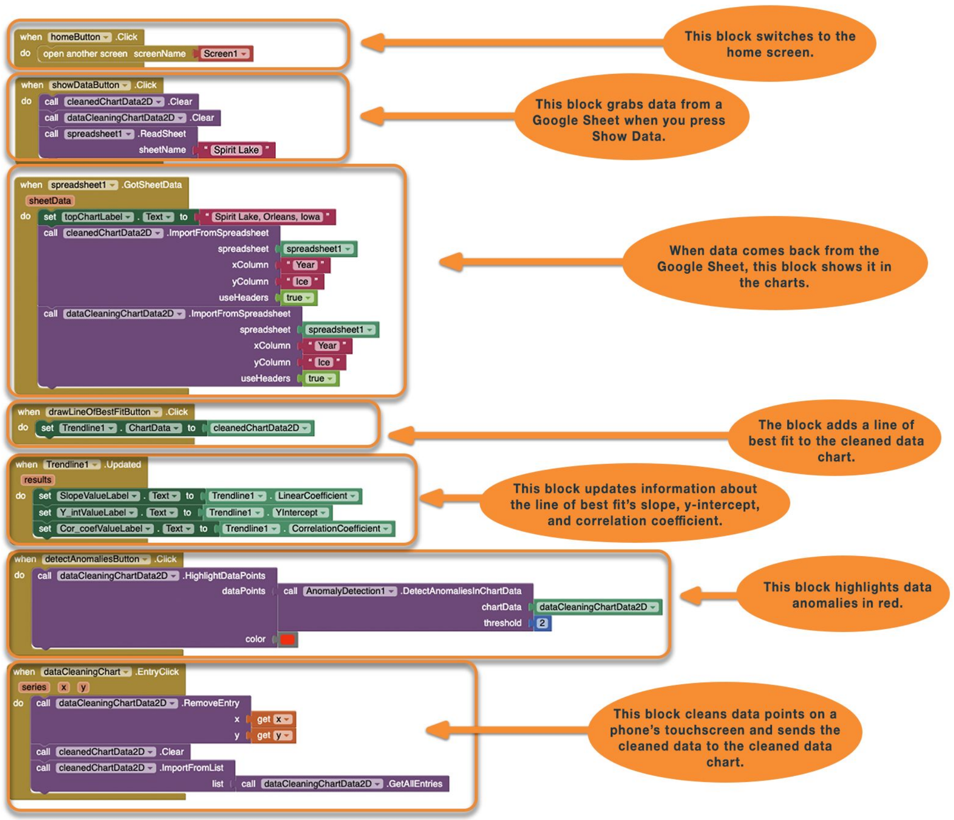



9:40
Climate Data: Making Predictions
Home
Show Data
Detect Anomalies
Draw LOBF
AI Analysis
Spirit Lake, Orleans, Iowa
To predict the year there will likely be no ice cover on the lake, we need to find the x-value when the line of best fit intersects the x-axis. This can be done using the y-intercept. Setting the y-value to zero and solving for x, we get x = 948.13964 / -0.41578 ≈ 2282. Therefore, we can predict that there will likely be no ice cover on the lake around the year 2282.
The data suggests that the annual number of days the lake is frozen has been decreasing over time (negative correlation coefficient and slope). This could be indicative of a warming trend in the area, which may be attributed to climate change. However, it's important to note that this data alone is insufficient to make direct conclusions about climate change. Further analysis and consideration of other relevant factors are required.
90
60
30
0
2000.0
2050.0
2100.0
2150.0
2200.0
2250.0
M = -0.41578
B = 948
R = -0.38536
X-Int = 2280
The graph offers a prediction using a line of best fit.
This label shows the ChatGPT analysis of the prediction and some useful context for the data set.
These numbers provide useful information about the trend.

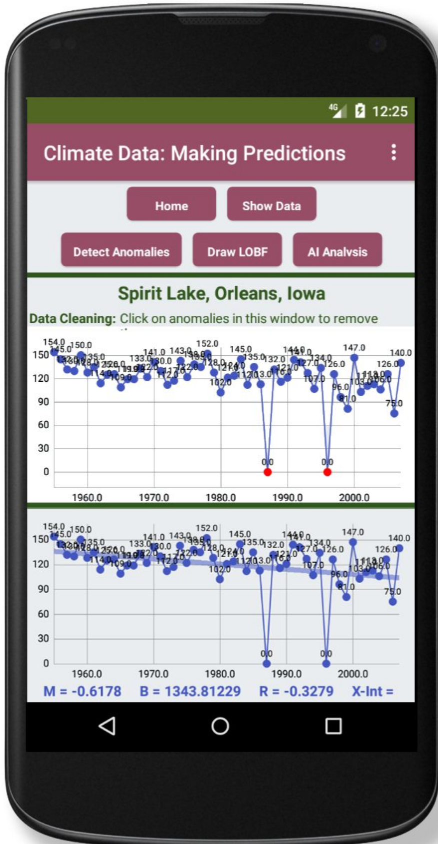
What Does It Do?
Review the Lesson 4 User Interface



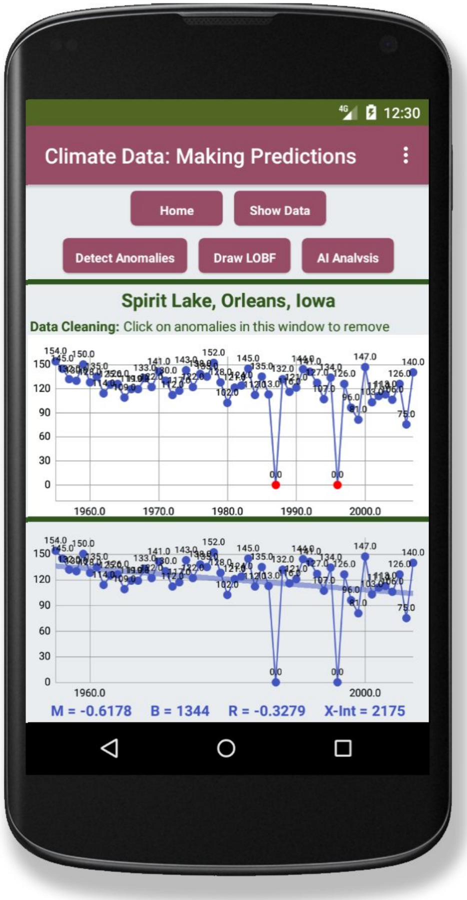
What Does it Do? Review the Lesson 4 code



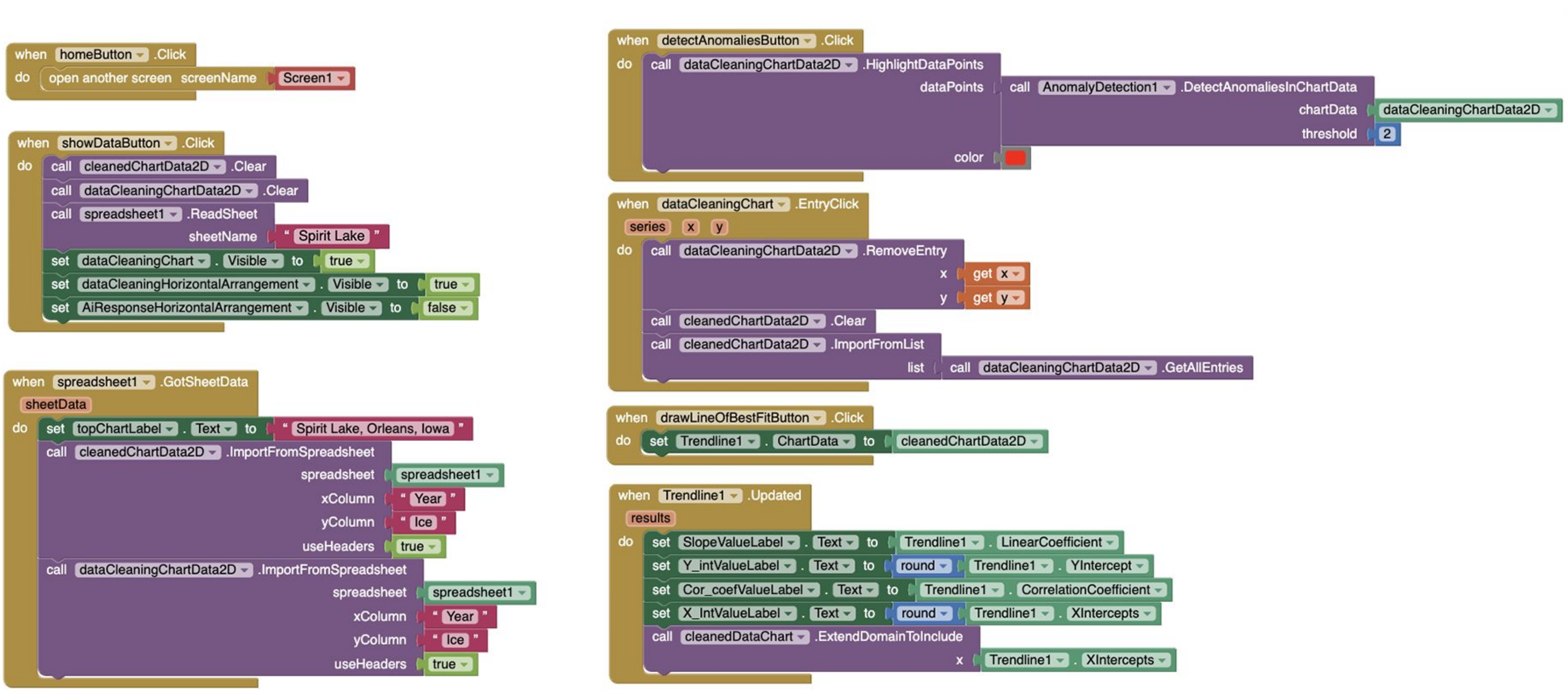
Lesson 4, Part 1 Code the X-intercept Value

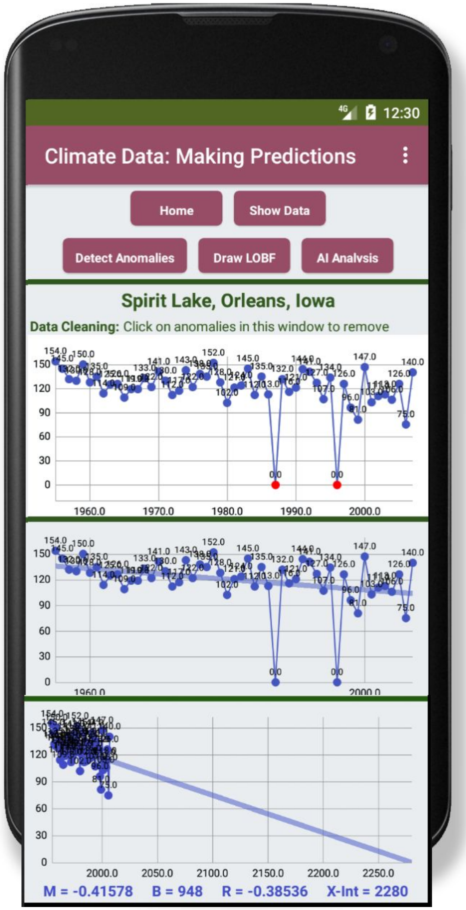


Lesson 4, Part 1 Screen

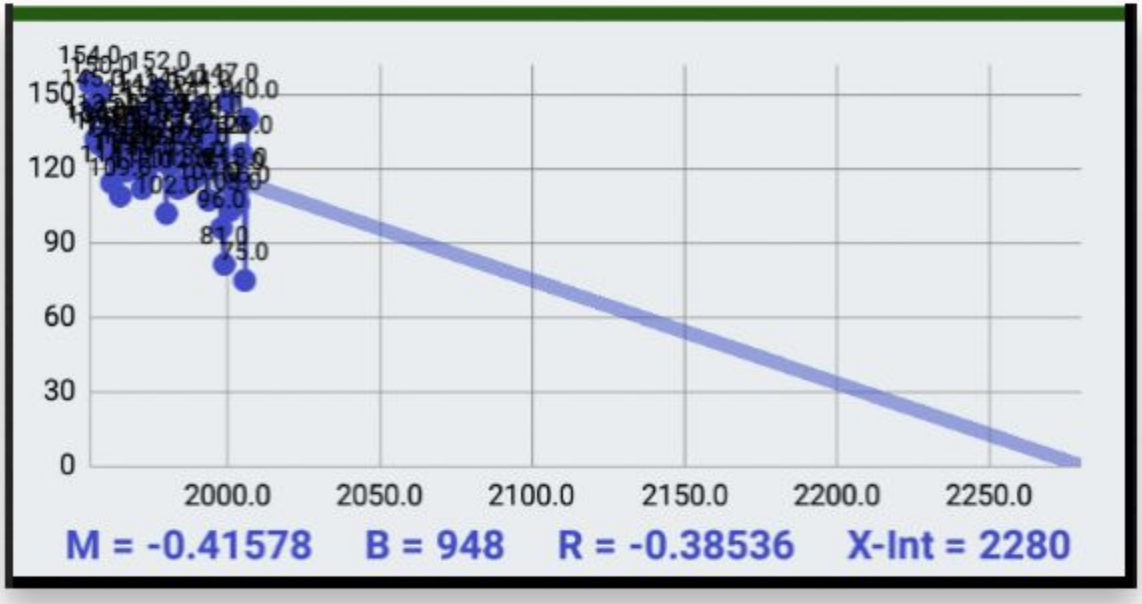


Lesson 4, Part 1 Code



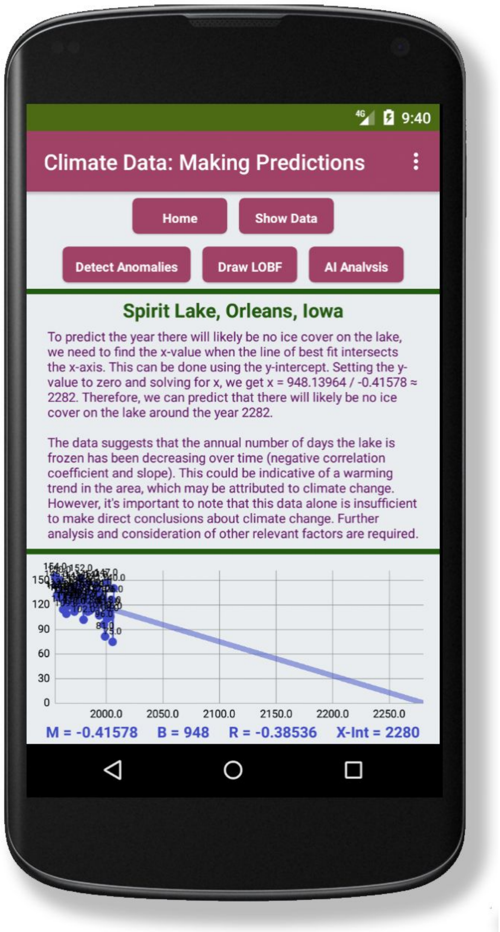


12:30
Climate Data: Making Predictions
Home
Show Data
Detect Anomalies
Draw LOBF
AI Analysis
Spirit Lake, Orleans, Iowa
Data Cleaning: Click on anomalies in this window to remove
M = -0.41578 B = 948 R = -0.38536 X-Int = 2280



150
120
90
60
30
0
2000.0
2050.0
2100.0
2150.0
2200.0
2250.0
M = -0.41578
B = 948
R = -0.38536
X-Int = 2280

Lesson 4, Part 1 Screen



Lesson 4, Part 2 Code