Machine Learning – Testing and Artificial Intelligence

15-110 – Wednesday 04/17

Quizlet

Announcements

- **Check6-2** due **Friday at noon**
  - When testing your Check6-2 work, don't forget to uncomment the tests at the bottom of the file!

Learning Goals

- Describe how **training**, **validation**, and **testing** are used to build a model and measure its performance
- Recognize how AIs attempt to achieve **goals** by using a **perception, reason,** and **action** cycle
- Build **game trees** to represent the possible moves of a game
- Use the **minimax algorithm** to determine an AI's best next move in a game

From Training to Testing

Once we've trained a model using machine learning, we may want to evaluate that model to see how well it actually works.

We can do this by **testing** the model using the test data held in reserve.

Testing Machine Learning Models

Training Data, Validation Data, Testing Data

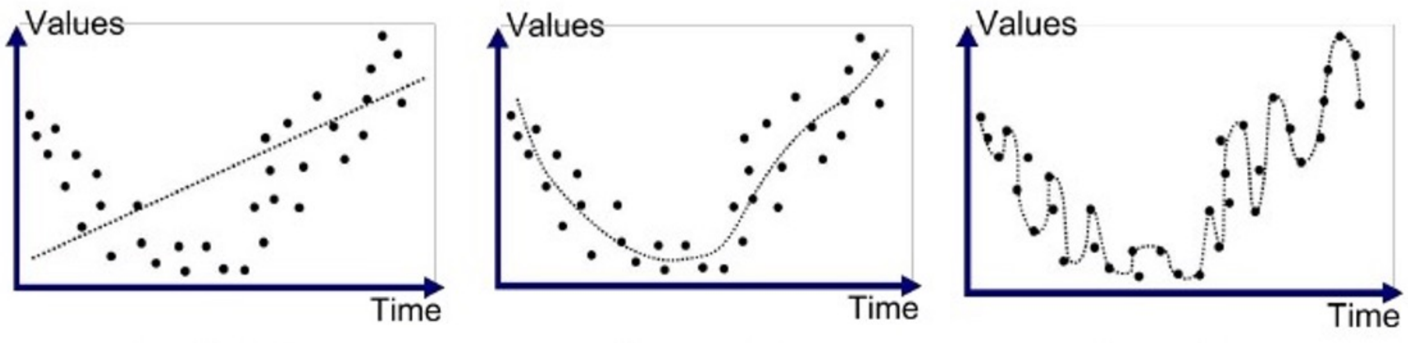
Once we've trained a model, we can use that model to make predictions about data. That means we don't want the model to **only** work on the data we provided originally - we want it to work on future data too.

We already separated our data into two sets: **training** data vs. **testing** data. When building algorithms professionally, you often want to create a third data set as well: the **validation** data set. This data set is used to help make the training work as well as possible before the final test is done.

Too Much Data Can Cause Overfitting

The **training data** is normally composed of the majority (maybe 70%) of the available dataset. This data is run through the machine learning algorithm to produce the model. The more training data there is, the more **accurate** the algorithm's model becomes.

This can go wrong if the algorithm over-optimizes the model. For example, it might identify a pattern that only exists within the training data, not in the general population – the pattern might just be noise. This is called **overfitting**. Overfitting can result in a model performing very well on training data, but poorly on test data.



Underfitted   Good Fit/Robust   Overfitted

Validation Data Identifies Overfitting

To detect and remove parameters in the model that cause overfitting, you can use **validation data**. This is a subset of the data (maybe 15%) that is **not** used when training the model. Instead, it will be used to **validate** the model during training.

The programmer repeatedly evaluates the model produced by the algorithm on the validation data to see how accurate it is. They can then modify certain parameters that are used by the algorithm to see which combination produces a model that works well on the training data *and* the validation data.

This is similar to how a teacher may provide students a set of practice problems to learn on, then provide a practice quiz with different problems where the students can test their knowledge.

Testing Data Provides Final Results

When the programmer thinks they've achieved an optimal model, the **testing data** is used to determine how accurate that model actually is. This is a portion of the data (maybe 15%) that was set aside at the beginning and never used during the training or validation process.

Unlike the validation data, which is evaluated multiple times, the model is run on the test data only **once**. We measure how close the predicted results are to the actual results. That score is the accuracy of the model.

You cannot train on your testing data if you want a fair test of the model!!!

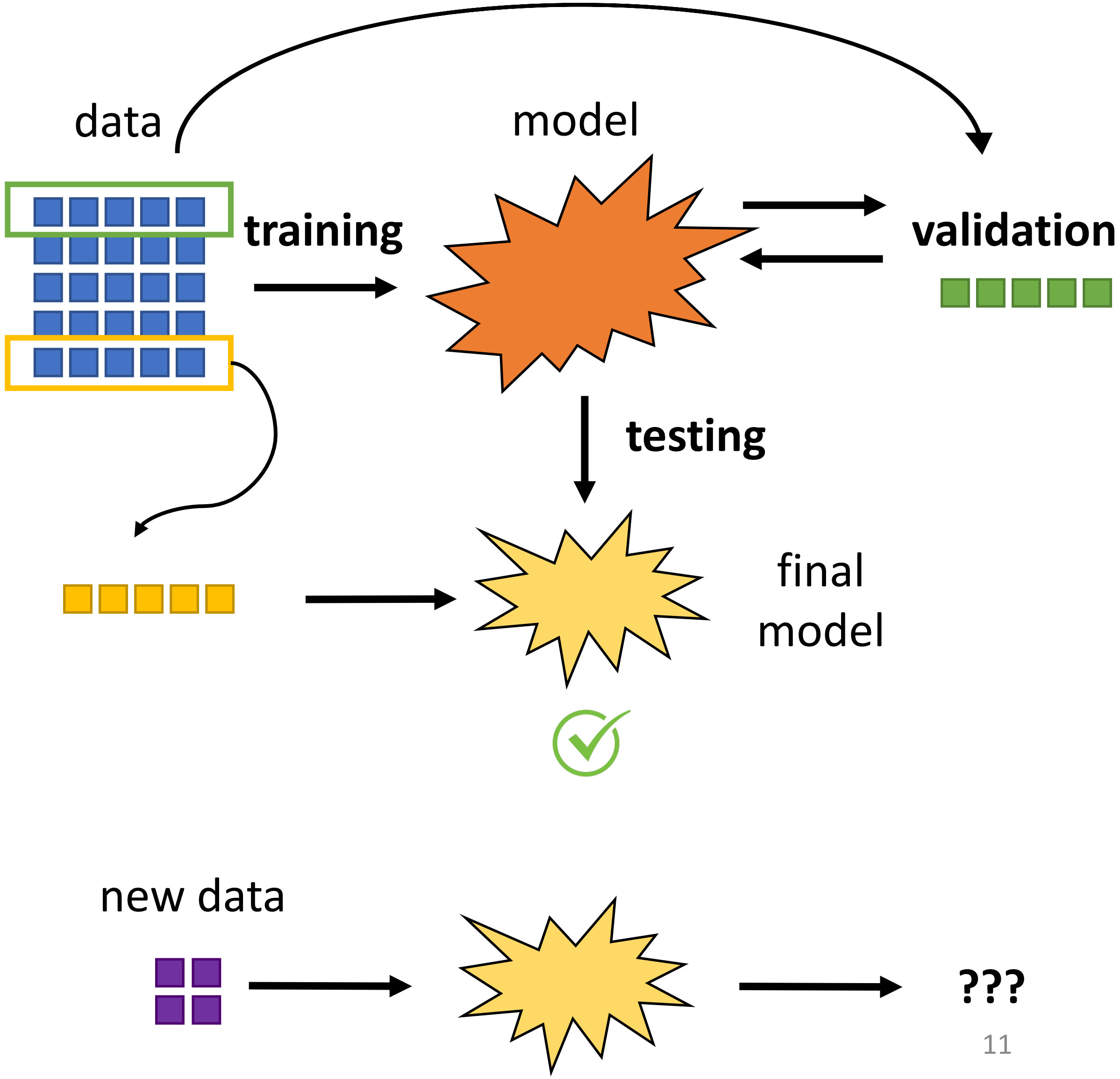
Example: Bad Training Process

What happens if we use our validation and test data to train as well?

The algorithm will get the opportunity to observe patterns in the additional data. It will optimize the model to include those patterns, even through validation.

When the model is tested, it will of course be accurate because the model was optimized to notice the correct patterns.

But if we try to use the model on new, unlabeled data later on, the patterns may no longer be valid. We don't know for sure because all the labeled data was used for training.



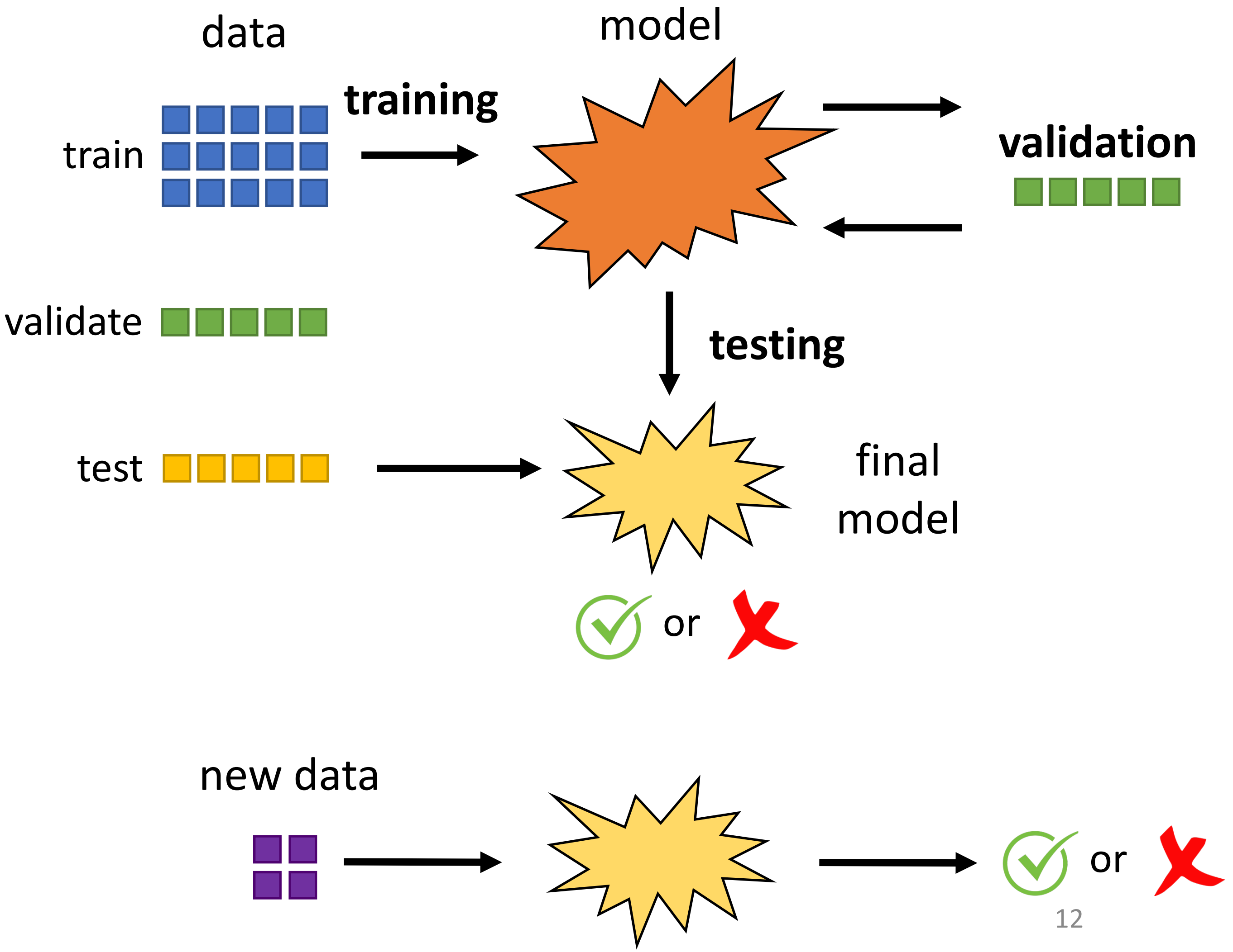
Example: Good Training Process

A better process: split the data into training, validation, and testing sets.

We'll train on **only** the training set and repeatedly test on the validation set. This should remove some of the overfitting from the training data.

When we're done, we'll test on the test set **once**. That produces our final result. It might be good, or it might be bad; it depends on how the model turned out.

However, the new data should have about the same accuracy as the test data, since the model never saw the test data before. There's less uncertainty.



Artificial Intelligence

Machine Learning Supports Artificial Intelligence

Now that we have machine learning algorithms, what can we do with them?

One option is to use them to support **artificial intelligence**. Let's talk more about what that means!

What is Artificial Intelligence?

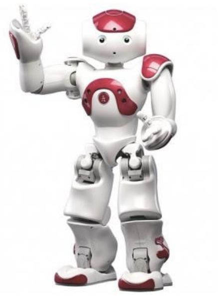
Artificial Intelligence (AI) is a branch of computer science that studies techniques which allow computers to do things that, when humans do them, are considered evidence of intelligence.

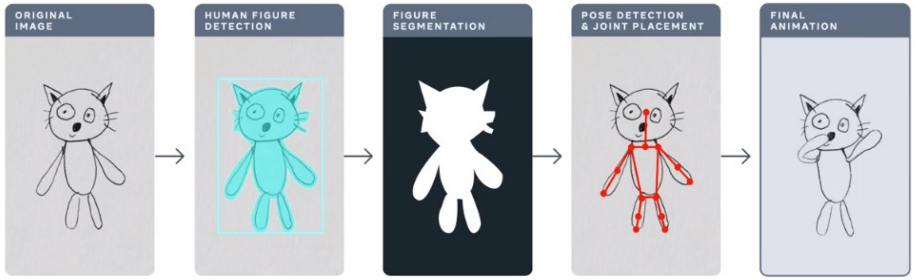
However, it's extremely hard to build a machine with **general intelligence-** that is, a machine that can do everything a human can do. We're still far away from this goal, as it includes many difficult tasks (visual and auditory perception, language understanding, reasoning, planning, and more).

Most modern AI applications are **specialized**; they do one specific task, and they do it very well. We call an AI application trained for a specific task an **agent**.

Examples of AI Agents

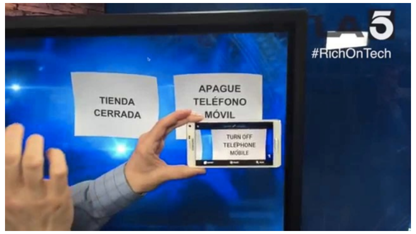
We've built AI agents that can play games, run robots, and animate children's drawings.

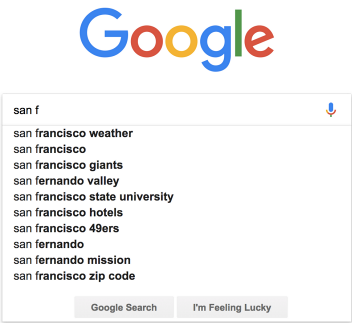


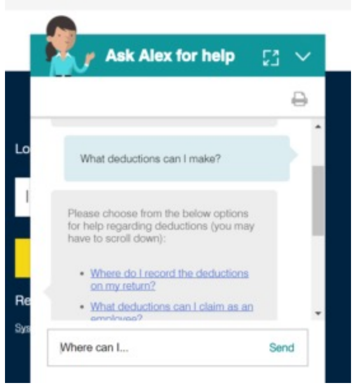


AI is also used to translate text, predict what you'll type, and answer questions on websites.

What do these agents have in common? Each agent we build has a specific **goal**, the thing it is trying to do.







Perception, Reason, and Action

Perception, Reason, and Action

An AI agent attempts to reach its goal by cycling through three steps: **perceive** information, **reason** about it, then **act** on it.

This is similar to how humans and animals work! We constantly take in information from our senses, process it, and decide what to do (consciously or unconsciously) based on that 'data'.

An agent's main task is to determine a **series of actions** that can be taken to accomplish its goal.

Perception: What Data Can Be Gathered?

First, the agent needs to **perceive** information about the state of the problem its solving.

This can range from data inputted directly by the user to contextual information about other actions the user has taken. For example, an autocomplete AI agent might use data both about what the user is currently typing *and* about what they've typed before.

Agents that interact with the real world can perceive information through **sensors**, pieces of hardware that collect data and send it to the agent.

Reason: What Should be Done Next?

Second, the AI agent needs to **reason** about the data it has collected, to decide what should be done next to move closer to the goal.

Reasoning uses **algorithms**, including **machine learning algorithms**. The agent often creates a **model representation** of the world based on the task it needs to solve and the data it has collected so far. It can then search through all the possible actions it can take to inform its decision.

A general goal of reasoning is to make decisions **quickly**, so that tasks can be accomplished efficiently. You don't want a self-driving car to take long to decide whether or not to stop!

Action: Here's What to Do

Finally, the AI agent needs to **act**, to produce a change in the state of the problem. All actions should lead the agent closer to its goal.

Actions don't need to reach the goal *immediately*, and often can't. As long as some progress is made, the agent can continue cycling through perceiving, reasoning, and acting until the goal is reached.

Agents that interface with the real world (robots) use **actuators** to make changes. This can be complicated (moving a robot arm) or simple (turning up the heat on the thermostat).

Example: IBM Watson

IBM's AI agent Watson was designed to play (and win!) the game Jeopardy. Its **goal** was to answer Jeopardy problems with a question. How did it work?

Watson **perceived** the questions by receiving them as text, then broke them down into keywords using natural language processing.

It used that information to search documents in its database, looking for the most relevant information. With that information, Watson used **reasoning** to determine how confident it was that the answer it found was correct.

If Watson decided to answer, it would **act** by organizing the information into a sentence, then pressing the buzzer with a robotic 'finger'.

Search Supports Artificial Intelligence

In Watson (and many other artificial intelligence applications), the key to being able to perceive and act quickly lies in **fast search algorithms**.

Being able to search quickly makes it possible for an AI agent to look through hundreds of thousands of possible actions to find which action will work best. This is what makes it possible for Watson to find a correct answer so quickly, or for a self-driving car to identify when it needs to stop immediately.

We've discussed many data structures and algorithms to support search already. We'll now describe two final ideas used by AI agents to support fast search- **game trees** and **minimax**.

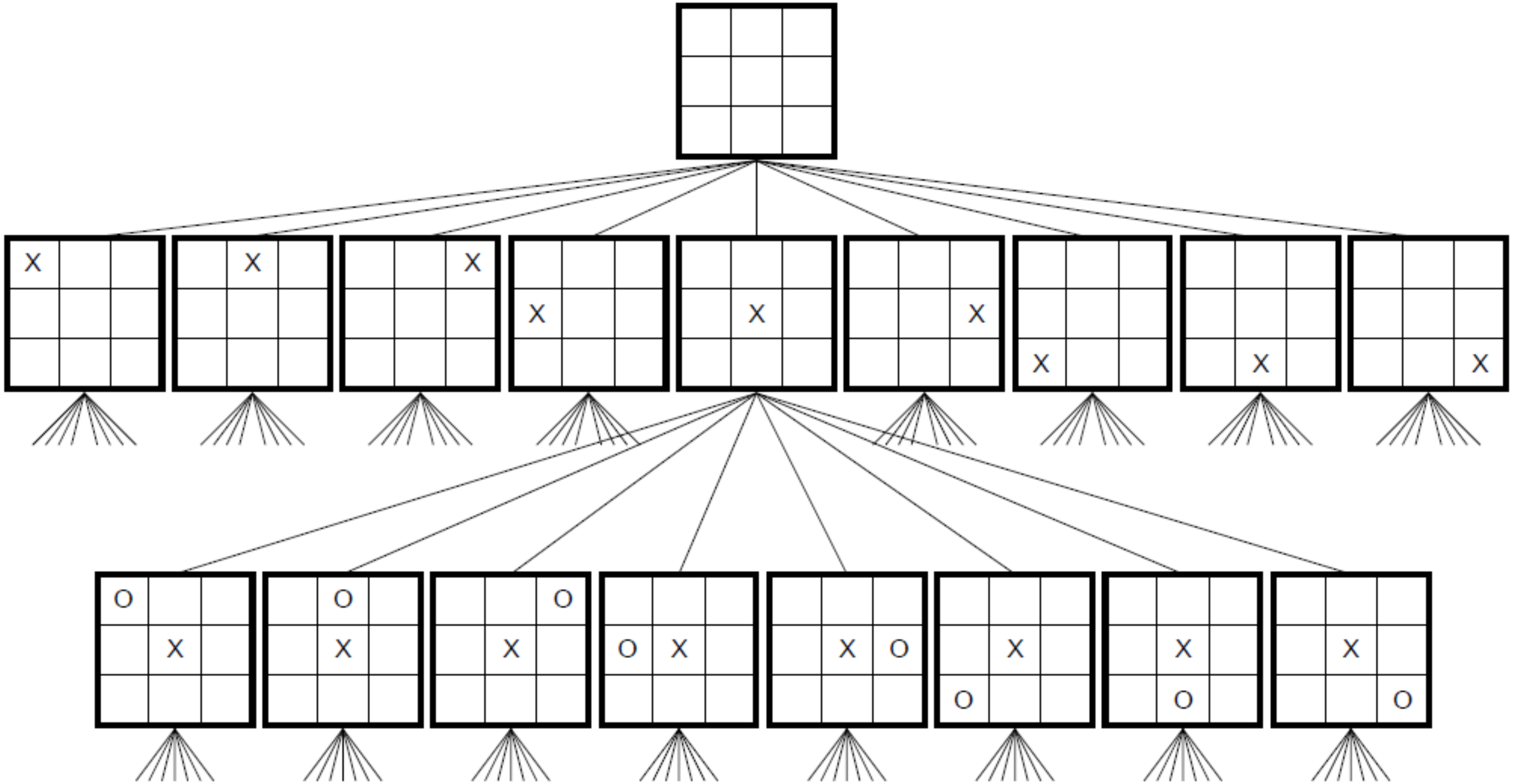
Game Trees and Minimax

Game Trees Represent Possible World States

To search data about possible actions and results quickly, an AI agent first needs to organize that data in a sensible way. Let's focus on a simple example: a two-player game between an AI agent and a human.

A game tree is a tree where the nodes are **game states** and the edges are **actions** made by the agent or the opposing player. Game trees let the agent represent all the possible outcomes of a game.

For example, the game tree for Tic-Tac-Toe looks like this...



Full board here: https://xkcd.com/832/

Reading a Game Tree

The **root** of a game tree is the current state of the game. That can be the start state (as in the previous example), or it can be a game state after some moves have been made.

The **leaves** of the tree are the final states of the game, when the AI agent wins, loses, or ties.

The **edges** between the root and the first set of children are the possible moves the agent can make. Then the next set of edges (from the first level of children to the second) are the moves the opponent can make. These alternate all the way down the tree.

Game Trees are Big

How many possible outcomes are there in a game of Tic-Tac-Toe?

Let's assume that all nine positions are filled. That means the **depth** of the tree is 10 (there are nine moves, so we count the root + 9 results of actions). There are 9 options for the first move, 8 for the second (for each of those nine states), 7 for the third, etc... that's **9!**, which is 362,880.

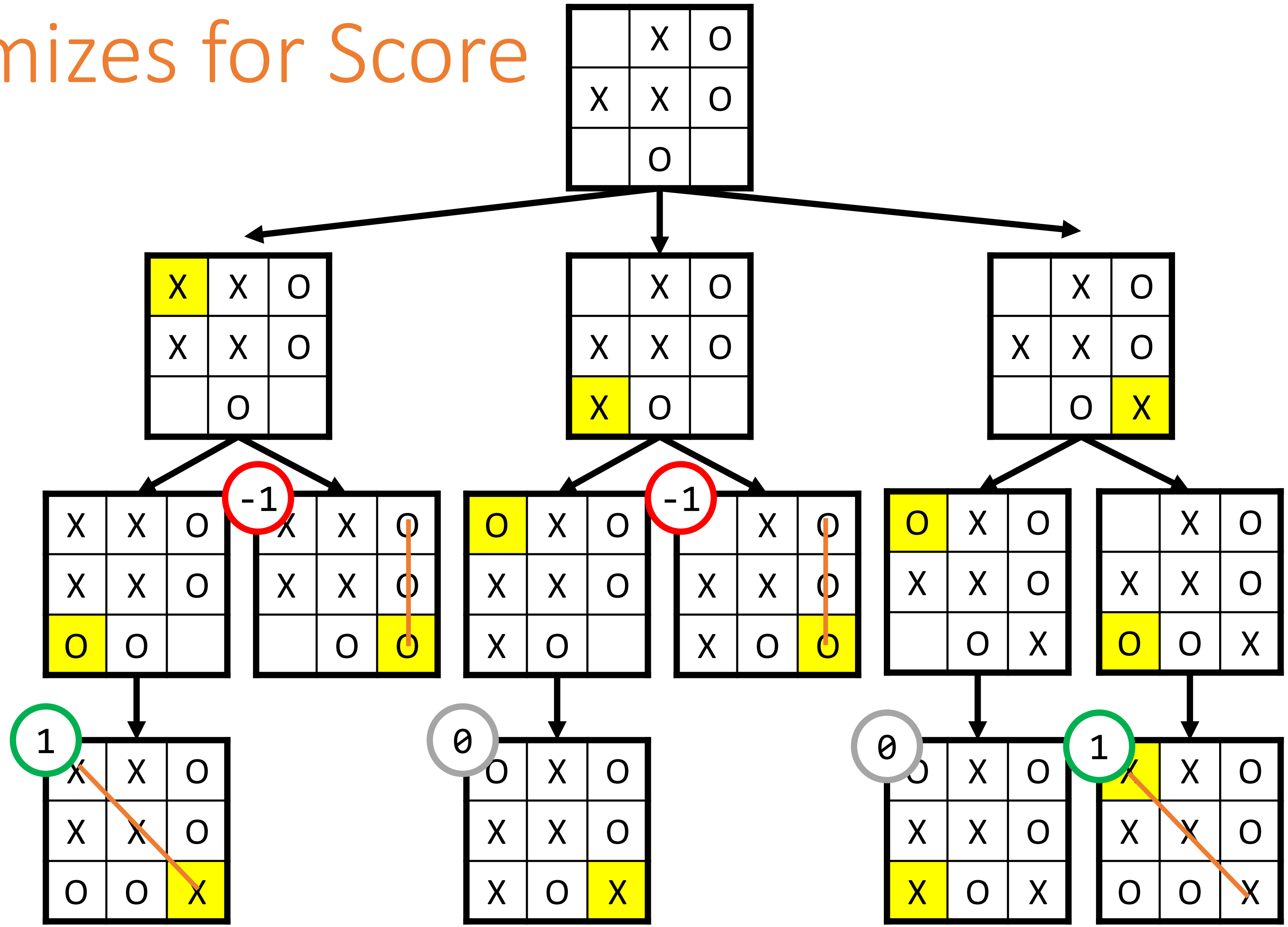
This number is a bit larger than the real set of possibilities (some games end early), but it's a good approximation.

How can the agent choose the best set of moves to make out of all these options?

Minimax Optimizes for Score

The **minimax** algorithm can be used to maximize the final 'score' of a game for an AI agent.

In Tic-Tac-Toe, we'll say that the score is 1 if the computer wins, 0 if there's a tie, and -1 if the human wins.



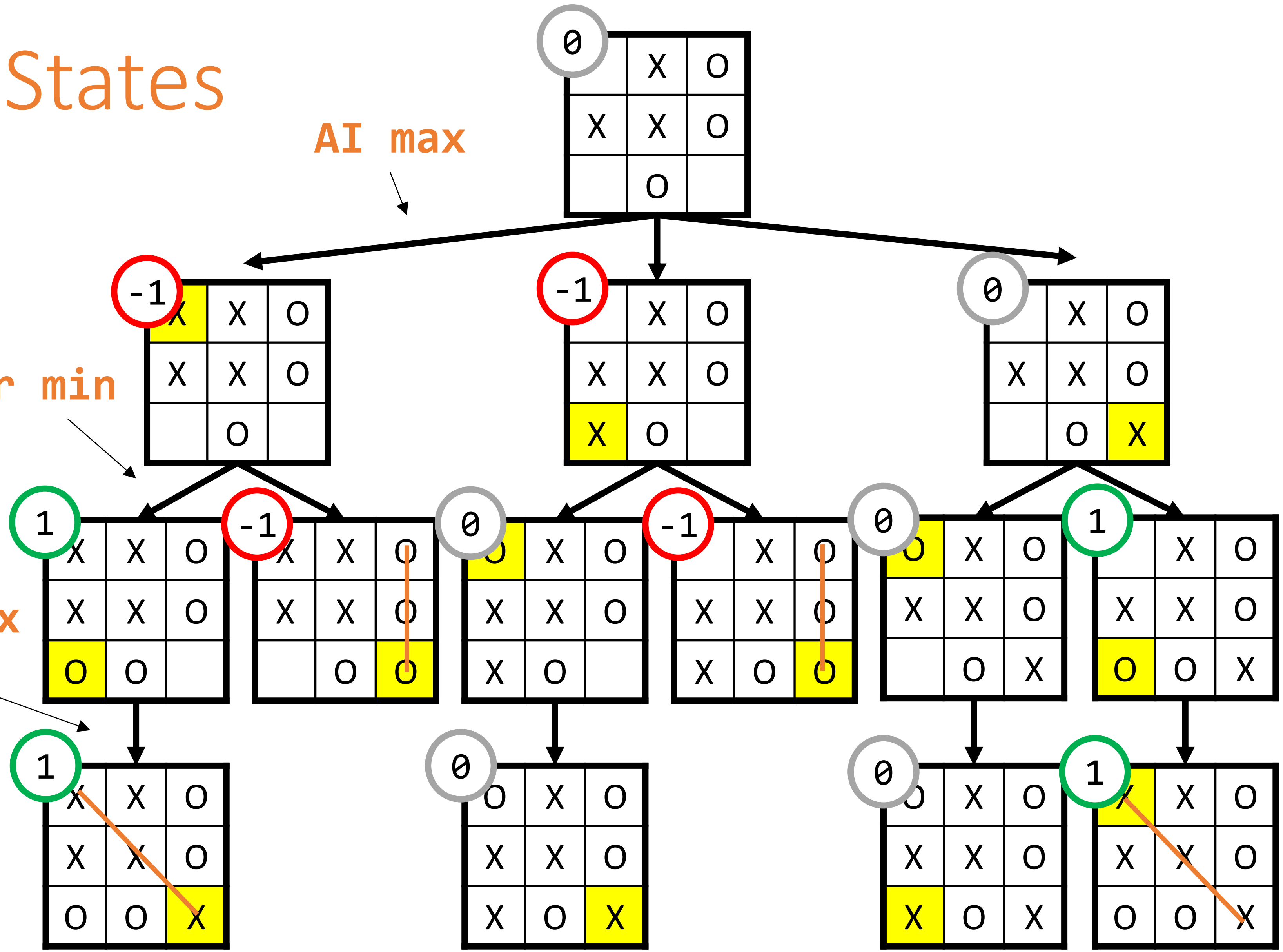
Scoring Game States

How do we score the intermediate states? Look at the scores of the state's children.

If the next move is made by the agent, take the **maximum** of the scores.

If it's made by the opponent, take the **minimum**.

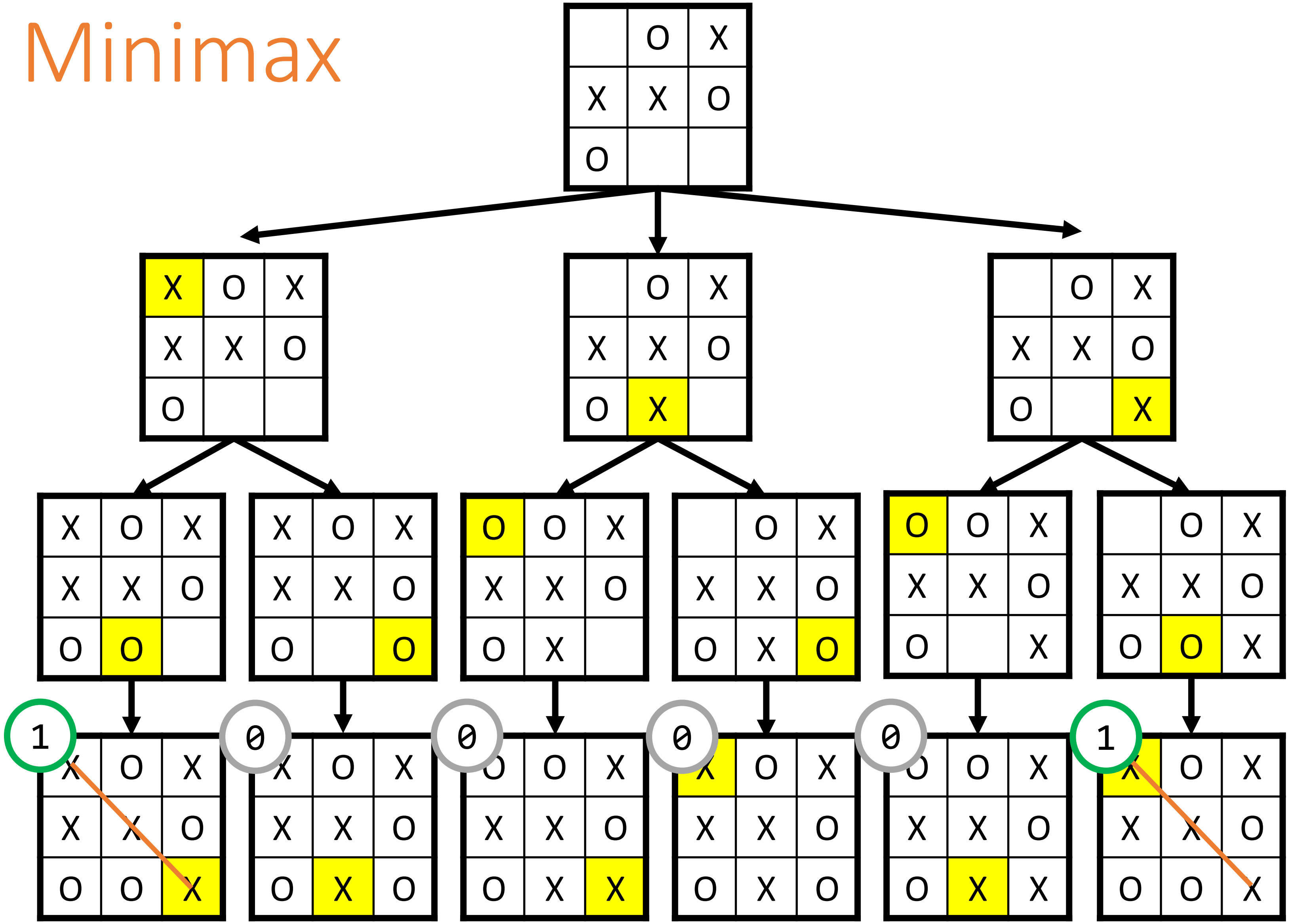
Start from the leaves and build up to the root.



Activity: Apply Minimax

You do: given the tree to the right, apply minimax to find the score of the root node.

Note that the first action is taken by the AI agent.



Minimax Algorithm

```
# Need to use a general tree- "children" instead of "left" and "right"
def minimax(tree, isMyTurn):
    if len(tree["children"]) == 0:
        return score(tree["contents"]) # base case: score of the leaf
    else:
        results = [] # recursive case: get scores of all children
        for child in tree["children"]:
            # switch whose turn it will be for the children
            results.append(minimax(child, not isMyTurn))
        if isMyTurn == True:
            return max(results) # my turn? maximize!
        else:
            return min(results) # opponent's turn? minimize!

def score(state):
    ??? # this depends on the agent's goal
```

Complexity of Minimax

How efficient is minimax? It needs to visit **every node** of the tree, so if the tree has n nodes, it runs in O(n) time.

However, complete game trees are **huge;** more complex games have much larger trees. For example, in Chess there's an average of 35 possible next moves per turn, with an average of 100 turns per game. That means there are 35^{100} possible states to check – way too many!!

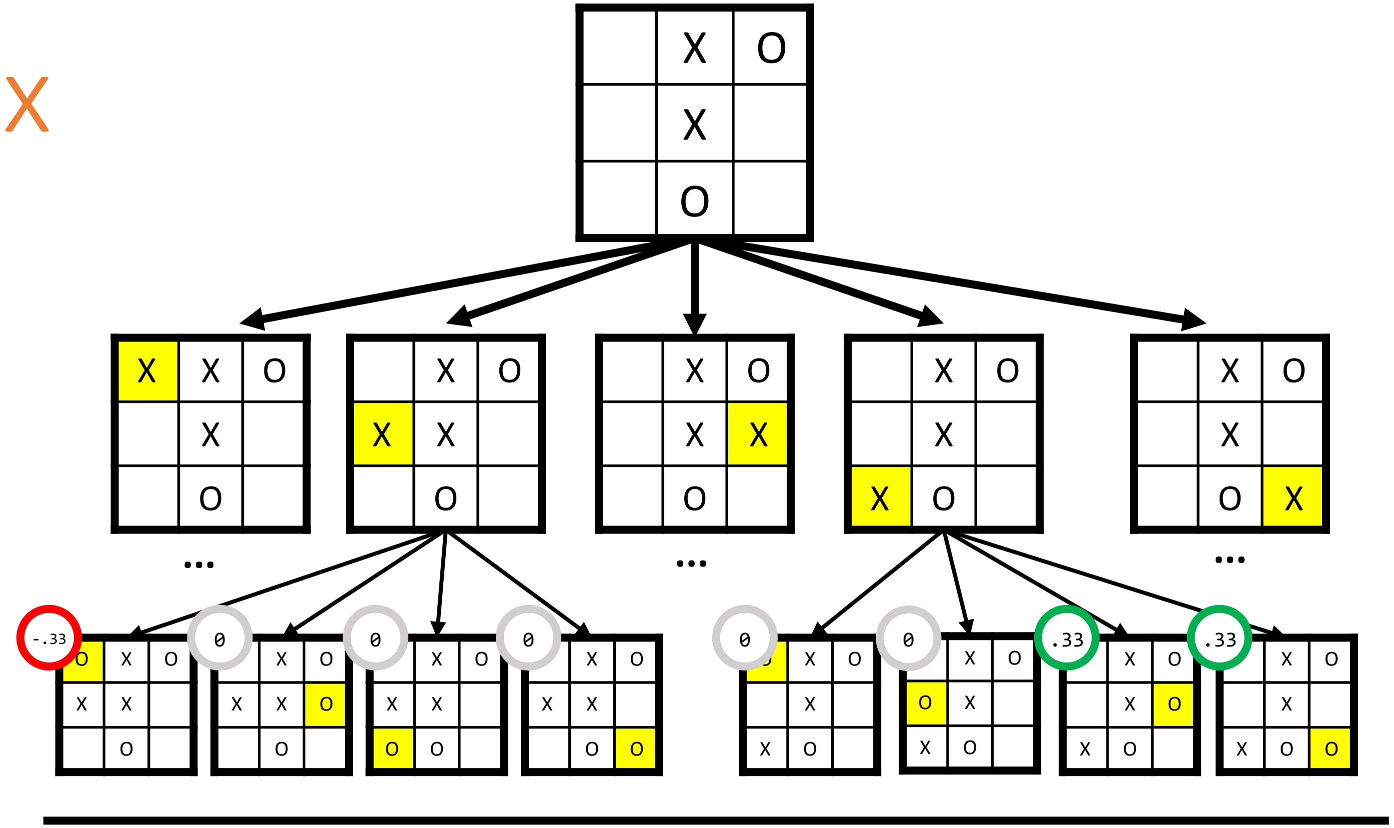
In general, AI agents will try to constrain the size of a game tree by using **heuristics**, as we discussed in the Tractability lecture.

Heuristics in Minimax

The main flaw in minimax is the size of the game tree. We can address this by having the computer move down a set number of levels in the game tree, then stop, even if it has not reached an end state.

For states that are not leaves, use a heuristic to **score** the state based on the current setup of the game. Then the agent can use minimax to find the next-best move based on the heuristic scores.

If the heuristic is well-designed, its score should approximate the real result and minimax should still produce a good result!



stop here

Heuristic:

$$\frac{\text{number of possible X wins - number of possible O wins}}{\text{total number of non-tie results}}$$

Sidebar: Game AIs

Algorithms like minimax and the use of heuristics have made it possible for AI agents to beat world champions at games like Chess, Go, and Poker.

Why did it take 19 years to get from Chess to Go? Go has many more next moves than Chess, so it needed more advanced algorithms (including Monte Carlo randomization and machine learning!).

These AI agents will keep improving as computers grow more powerful and we design better algorithms.

DeepBlue beat chess grandmaster Garry Kasparov in 1997

AlphaGo beat 9-dan ranked Go champion Lee Sedol in 2016

Learning Goals

- Describe how **training**, **validation**, and **testing** are used to build a model and measure its performance

- Recognize how AIs attempt to achieve **goals** by using a **perception, reason,** and **action** cycle

- Build **game trees** to represent the possible moves of a game

- Use the **minimax algorithm** to determine an AI's best next move in a game